Topics on Non-Expert Economic Agents' Inflation Expectations

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Abstract

Non-expert economic agents' inflation expectations (NEEA IEs) have received a substantial critical examination by the central bank, given that they influence the monetary transmission mechanism. As a result, the central bank requires reliable source data on NEEA IEs that are available in near real-time. Furthermore, it is imperative for the central bank to efficiently manage NEEA IEs, mainly through central bank press releases (CBPRs). Nevertheless, most research on NEEA IEs has primarily used data from developed countries and is limited to addressing the unpredictable inflation conditions in developing countries. Given the significance of this subject, this thesis investigates three topics of NEEA IEs using Indonesian data. Chapter 1 investigates the most effective method for quantifying qualitative data in a volatile inflation condition. We also analyse the factors influencing the NEEA IEs by including the socioeconomic variables using regional data. Chapter 2 examines the value of information in news articles utilising Natural Language Processing (NLP) as an alternative data source for measuring NEEA IEs and alternative tools to predict inflation. Chapter 3 examines CBPRs' comprehensiveness, clarity, and sentiment features concerning their influence on NEEA IEs. We also investigate the impact of the consistency of CBPRs on the similarity between these releases and news articles.

List of Contents

List of Tables

List of Figures

Declaration

I declare that this thesis is a presentation of original work, and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as references.

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Introduction

"Inflation feeds in part on itself, so part of the job of returning to a more stable and more productive economy must be to break the grip of inflationary expectations" (Volcker 1979).

As implied by the quotation above from Volcker in 1979, managing inflation expectations (IEs hereafter) is crucial for achieving economic stability and productivity. The literature also recognises the importance of IEs in effectively carrying out monetary policy (Mankiw & Reis 2002; Carroll 2003; Bernanke 2016), especially since numerous central banks have moved to the Inflation Targeting Framework (ITF). The concerns of consumers, who are non-expert economic agents (NEEA hereafter), have received a critical examination by the central bank, given that they substantially influence the monetary transmission mechanism (Bernanke 2007; Blanchard *et al.* 2010; Armantier *et al.* 2015). Consequently, it is essential for the central bank to have reliable and meaningful source data on NEEA IEs. Most of the data used to analyse NEEA IEs is derived from consumer surveys. Nevertheless, the primary obstacle is the qualitative nature of the survey's response and the infrequency of their monthly or quarterly. Furthermore, to effectively manage NEEA IEs, central banks utilise communication strategies, primarily through central bank press releases (CBPRs hereafter); however, there is a lack of consensus about how CBPRs are transmitted to NEEA (Dräger *et al.* 2016). Most studies on NEEA IEs have focused mainly on data from developed countries and are limited to addressing unpredictable inflation conditions in developing countries. Given the importance of this subject, this thesis examines three main topics related to NEEA IEs using data from a developing country: investigating the most effective methods for quantifying the qualitative data from consumer surveys, examining the alternative NEEA IEs data representations with near-real-time frequency, and investigate how the CBPRs influence NEEA IEs.

Anderson (1952) was the first to develop a method for transforming qualitative into quantitative data using the balanced statistics method. Carlson and Parkin (1975) developed an approach using the probability method. The literature also showcases an alternate strategy for quantifying qualitative data through regression analysis (Pesaran 1984). Several research studies have examined the methods for quantifying qualitative data using the extended versions of the methodologies mentioned earlier. Nevertheless, the effectiveness of these methods, especially in unexpected and unstable inflation conditions in developing

countries, is still dubious. The data from developing countries also demonstrates notable differences compared to developed countries, frequently showcasing considerable variability in the socioeconomic condition, with a more pronounced gap between regions.

In Chapter 1, we explore techniques for quantifying qualitative data and analysing the characteristics of NEEA IEs using data from both national and regional sources in a developing country. This investigation offers fresh insights into implementing effective methods for quantifying qualitative data in unstable and unpredictable inflationary contexts and improves our understanding of how socioeconomic factors influence NEEA IEs. We employ primary data from Indonesia monthly consumer surveys conducted by Bank Indonesia from January 2009 to December 2019. Several methodological approaches are employed to quantify qualitative data and identify the most effective methods in volatile inflation data situations, including the balanced approach (BA hereafter), the probability method of Carlson-Parkin (CP hereafter), regression methods, and their extended versions. The main assumptions of the methods of quantifying qualitative data are symmetric threshold[1] and long-term unbiased assumptions[2]. Due to relatively high inflation conditions in developing countries, the symmetric threshold assumption may not accurately capture economic agents' responses. Moreover, due to its reliance on global economic conditions, the developing country's inflation is occasionally influenced by global variables, making it challenging to maintain a consistent policy regime. Therefore, given that the research is conducted in a country with unstable inflation conditions and susceptibility to external factors, we utilise the asymmetric threshold (AT hereafter) to relax the symmetric threshold; and regime-period unbiasedness (RPU hereafter) assumptions, relaxing the assumption of long-term unbiasedness. In order to examine the impact of socioeconomic factors on IEs in various regions, we also perform a panel data analysis utilising inflation, education and expenditure data as indicators of socioeconomic variables. The investigation revealed that the CP method performed better than the BA and regression methods[3]. The CP method, extended to include the AT and RPU assumptions, produced the most advantageous result. This study discovered that NEEA IEs are impacted by inflation, level of education, and

[1] A symmetric threshold refers to a situation where the indifference threshold is equally balanced between the lower and upper thresholds, ranging from zero. The NEEA use a threshold to establish their IEs. If the NEEA anticipate that prices will generally fall below the lower threshold, it indicates a decrease in prices (deflation). Conversely, if prices are expected to exceed the upper threshold, it suggests a general increase in prices (inflation).

[2] Long-term unbiasedness refers to the condition in which the NEEA IEs, on average, align with the actual inflation for the entire data period used in the research.

[3] In terms of the metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Diebold-Mariano Test (DM-Test).

expenditure. Research indicated that increasing inflation affects an increase in IEs. Conversely, the results indicate that higher education levels lead to lower IEs among economic agents. The similar impact also indicates that increasing expenditure tends to decrease IEs. We believe this study discovery will offer novel perspectives and improve the comprehension of different methodologies for analysing IEs.

Concerning investigating near-real-time representations of NEEA IEs data, news articles could be a viable alternative as they are generated more frequently than surveys. Natural Language Processing (NLP hereafter) is a technique that may transform textual information from news articles into meaningful insights. To date, NLP has had little application in economics compared to its potential, especially in IEs. Within the scarce body of literature, Angelico *et al.* (2022) performed a study that investigated the economic agents' IEs using NLP. They applied dictionary-based and topic modelling on Italian tweets to determine the economic agents' IEs. Although the work utilised NLP to evaluate textual data and model NEEA IEs, there is a gap in knowledge on the impact of news articles on these expectations. According to Conrad *et al.* (2022) and Gardt *et al.* (2022), economic agents still depend on traditional media, including news articles, to obtain information on inflation. Therefore, employing news articles to represent the NEEA IEs is valuable.

In Chapter 2, we explore the optimal approach for extracting meaningful information from news articles to mimic consumer surveys as a representation of NEEA IEs. This study also examines alternative tools for predicting the inflation rate. To our knowledge, this work is the first study utilising news articles to represent NEEA IEs using supervised learning of NLP in developing country data. We utilise a primary dataset comprising news articles in Bahasa Indonesia from January 2009 to December 2018. In our NLP approach, we employ a range of supervised learning such as Support Vector Classifier (SVC hereafter), Naive Bayes, K-Nearest Neighbors (KNN hereafter), and Decision Trees, as well as semi-supervised learning utilising dictionary-based methods. This approach is used to identify the most effective methods for representing NEEA IEs and predicting inflation rates. This study employed the main keywords, "*inflasi*" (inflation) and "*harga*" (price), to narrow down the pertinent data about IEs. We analyse how information affects the NEEA IEs by assessing the articles' titles and bodies separately. We compare four distinct forecast horizons: one month, three months, six months, and twelve months. This study discovered that the news articles provide valuable information on NEEA IEs. The NLP study demonstrates that SVC in supervised learning surpasses the other models in terms of performance. Applying the semi-supervised learning of the dictionary-based method shows that a bespoke dictionary prioritising essential words

is more effective in extracting meaningful information from news articles. Applying the CP method with the extended version indicates that the six-month forecast horizons produce the best outcomes. The findings demonstrated that news articles can be transformed into NEEA IEs and utilised as alternative methods for forecasting inflation. The results indicate that news articles might serve as significant alternative data sources for the representations of NEEA IEs on near real-time data. Collecting near-real-time data on NEEA IEs will assist policymakers in improving their policies.

Regarding the investigation of central bank communication, Draghi (2014) emphasises that "Central Bank communication is right at the heart of monetary policy. It is actually a monetary policy tool in itself". This statement highlights the significance of central bank communication as a tool for implementing monetary policy. Central banks' communication disseminates information to the public, mainly through CBPRs of interest rate decisions. Literature has explored the direct impact of central bank communication on NEEA, as recorded by Coibion et al. (2018) and Lamla and Vinogradov (2019). On the other hand, research has also shown that CBPRs have an indirect influence, impacting through intermediary channels, particularly news articles (Lamla & Lein, 2010; Ehrman et al., 2017; Nimark & Pitschner, 2019). The indirect impact of the CBPRs can be ascribed to clarity (Haldane & McMahon, 2018), comprehensiveness (Dincer & Eichengreen, 2014), and consistency (Ehrman & Talmi, 2020). Given this reasoning, investigating how the CBPRs influence the NEEA IEs is crucial. The strategy should be focused on creating CBPRs that are easily understood, transparent, and consistent to improve understanding of monetary policy. Nevertheless, there is a lack of understanding regarding which features hold greater significance in shaping the NEEA IEs.

The research in Chapter 3 investigates the influence of specific features of CBPRs on NEEA IEs. The chapter aims to examine the transmission of CBPRs and the crucial role of its features on NEEA IEs in emerging economies. As far as we know, this study is the first to combine the impact of CBPRs' comprehensiveness, sentiment, and clarity features. We utilise the primary data sources of Bank Indonesia press releases between January 2009 and December 2018. This study applies Vector Autoregression with exogenous variables (VARX) to examine the correlation between the features of CBPRs, employed as the exogenous factors, and news articles, inflation, and IEs, which serve as the endogenous variables. We analyse the effects of the features of the CBPRs, including their comprehensiveness, clarity, and sentiment. We examine the CBPRs using three different windows: a three-day, a seven-day, and a one-month after the release. We also utilise the cosine similarity method to

examine the impact of the consistency of CBPRs on the similarity between the CBPRs and news articles. We discovered that the CBPRs indirectly influence NEEA IEs through news articles as an intermediary channel. The results show that the comprehensiveness and clarity of CBPRs are essential features that impact the quantity of news articles. We also found that maintaining consistency in the CBPRs is important for improving the similarity score between the CBPRs and news articles. By comprehensively examining the CBPRs from several perspectives in this study, we aim to improve our comprehension of their significance and provide constructive feedback to the central bank on constructing CBPRs effectively as one of the monetary policy tools.

The organisation of this thesis is as follows. Chapter 1, titled "Quantifying the Qualitative Data: Comparison Using Volatile Data," explains the effective methods for quantifying qualitative data of NEEA IEs and investigates the impact of socioeconomics variables on NEEA IEs. Chapter 2, titled "Understanding Non-Expert Economic Agents' Inflation Expectations Through Near Real-Time Data," thoroughly explores the most effective methods for representing NEEA IEs in near-real time and explores the alternative tools to predict inflation. Chapter 3, titled "Central Bank Press Releases: Effectiveness Through Intermediary Channels," explains the importance of CBPRs features and its impact on NEEA IEs. Finally, the last part is the Conclusion.

Chapter I

Quantifying the Qualitative Data: Comparison Using Volatile Data.

We investigate the most effective approach for quantifying qualitative data of non-expert economic agents' inflation expectations (NEEA IEs) in the volatile inflation condition, utilising Indonesian national and regional data. We discovered that the application of the Carlson-Parkin method with asymmetric threshold (AT) and regime-period unbiasedness (RPU) assumptions yields superior outcomes compared to alternative methods. AT acknowledges the potential existence of non-symmetrical lower and upper thresholds of NEEA IEs under relatively higher inflation. RPU indicates that economic agents in Indonesia have different thresholds in stable times and shock periods. To assess the impact of socioeconomic characteristics, we employ a regional cross-section using panel data analysis. We revealed that education and expenditure are essential variables influencing NEEA IEs.

1.1. Introduction

Given the important role of non-expert economic agents' (NEEA) inflation expectations (IEs), policymakers need to understand the NEEA IEs comprehensively. Consequently, policymakers need to have reliable and meaningful source data on IEs. Most of the data used to analyse NEEA IEs is obtained from consumer surveys, which typically include questions regarding the expectations on the future general price: whether it will increase, decrease, or stay the same. The main challenge is the qualitative nature of the survey's outcome, which presents the distribution of agents' responses, usually used to determine the direction of the IEs. In order to obtain the point forecast of the NEEA IEs, qualitative data needs to be transformed into a quantitative representation. The growing literature has examined the most effective approaches to quantifying qualitative data. However, most studies have primarily concentrated on data from developed countries, which are generally more stable and less prone to inflation fluctuations. Prior research has not addressed the unpredictable inflation circumstances in typical developing countries. Therefore, this study investigates the most effective techniques for quantifying qualitative data using data from developing countries. We also employ regional data and investigate the socioeconomic variables that impact the NEEA IEs, offering insights into the unique characteristics of different regions that impact the NEEA IEs in volatile inflationary environments.

Anderson (1952) pioneered converting qualitative data using the balancing statistics method (BS method hereafter). The method measures the qualitative data by subtracting the increased response from the decreased response. Nevertheless, this method is incapable of quantifying IEs, as it can solely determine the direction of IEs. To provide the quantitative representation of IEs, Batchelor (1986) developed the Balanced Approach (BA hereafter) as an extended version of the BS method. This method compares the technique with the actual inflation and assumes long-term unbiasedness[4]. Moreover, Carlson and Parkin (1975) constructed a theoretical framework utilising the probability method. The underlying premise of the Carlson-Parkin method (CP method hereafter) is that the reported answer generates a probability distribution either above or below a specific threshold, commonly known as the indifference threshold. The CP method made symmetric threshold[5], normal distributions[6] and long-term unbiasedness[7] assumptions. Literature also demonstrates an

[4] Please refer to footnote 2 for the explanation.

[5] Please refer to footnote 1 for the explanation.

[6] The CP method assumed that the NEEA have normally distributed expectations allowing to transform the "increase" and "decrease" proportions into the quantitative representations.

[7] Please refer to footnote 2 for the explanation.

alternative approach to quantifying qualitative data by employing a regression method, as Pesaran (1984) pioneered using this method. Under this method, actual inflation is considered a dependent variable, whereas the responses indicating increases and decreases in the survey are considered explanatory variables.

To date, numerous studies have investigated the methods of quantifying qualitative data. Nevertheless, the efficacy of this approach, particularly in making symmetric threshold and long-term unbiased assumptions, remains unclear in the context of a generally unpredictable and unstable inflation condition. Prior research has predominantly concentrated on data from developed nations, neglecting the data from developing countries. Due to relatively high inflation conditions in developing countries, the symmetric threshold assumption may not accurately capture economic agents' responses. This aligns with Breitung and Schmeling (2013) and Lahiri and Zhao (2015), who expressed disapproval of the symmetric threshold assumption in the CP method[8]. Therefore, it is essential to apply the asymmetric threshold (AT hereafter) assumption when quantifying qualitative data utilising data from developing countries to relax the symmetric threshold assumption. Moreover, due to its reliance on global economic conditions, the developing country's inflation is occasionally influenced by global variables, making it challenging to maintain a consistent policy regime. Incorporating regime-period unbiasedness (RPU hereafter) assumption with varying thresholds for normal and shock periods makes it possible to accurately represent the data from developing countries while relaxing the assumption of long-term unbiasedness, similar to Ranyard *et al.* (2008), who discovered that agents tend to adopt new standards of expectations and adjust their prior beliefs in response to an economic shock.

Developing countries also display considerable diversity, with a more pronounced regional imbalance than developed countries (Venables 2005; Piketty 2014; Permanyer & Smits 2020). The disparities in socioeconomic characteristics, such as education, expenditure, and geographical conditions, could contribute to the uniqueness of NEEA IEs' formation across regions. However, the literature has not addressed the inclusion of regional data to quantify the qualitative data of IEs. Therefore, using regional data to analyse different regions' unique characteristics and investigate the regional socioeconomic factors that have influenced NEEA IEs is valuable.

[8] The articles critique the assumption of a symmetric threshold, based on US survey data where proportions of increase and decrease data, as well as the point of forecasts data are collected. The studies found that the asymmetric threshold approach better represents the point of forecast from the survey.

This study fills a gap in the existing literature by examining the most effective strategies for quantifying qualitative data using data from a developing country. This study also aims to investigate the socioeconomic variables that could potentially impact the NEEA IEs. Gaining a comprehensive understanding of the most effective techniques for quantifying the qualitative data of NEEA IEs and discerning the unique characteristics of various regions will provide valuable insights for policymakers in formulating impactful policies.

This study provides three valuable contributions to the current body of literature. First, this research examined various methods for quantifying qualitative data, providing new perspectives on adopting effective methodologies for data in volatile and fluctuating inflationary contexts. Second, to our knowledge, this is the first study to utilise national and regional data in developing countries to quantify the qualitative data. Incorporating national and regional data will enrich the current body of literature by offering valuable insights into the unique characteristics of different regions that impact the NEEA IEs. Third, this study investigates the socioeconomic variables that impact the NEEA IEs. This approach can provide valuable perspectives and enhance our comprehension of how socioeconomic factors influence NEEA IEs in the developing country data.

The primary data obtained monthly from consumer surveys in Indonesia covers the period from January 2009 to December 2019. Indonesia has unique characteristics as the largest archipelagic nation, exhibits a wide range of geographical diversity, has disparities in socioeconomic conditions across different regions, and experiences volatile inflation rates. Therefore, the dataset utilised in this study comprises cross-sectional data from 18 regions in Indonesia, enabling the mapping and exploration of the region's socioeconomic uniqueness. This study employs various quantitative and qualitative data methods to compare national and regional data: the BA, CP, and regression methods. Given the investigation of this research in a country with relatively volatile and higher inflation conditions and susceptible to global conditions, we also applied the extended methods that relaxed the assumptions of symmetric threshold and long-term unbiasedness assumptions. Relaxing the symmetric threshold assumption and implementing the AT assumption allows us to acknowledge the potential existence of non-symmetrical lower and upper thresholds of NEEA IEs and better represent the economic agents' behaviour under relatively higher inflation. We relax the long-term unbiasedness assumptions and apply the RPU assumption, allowing us to consider the possibility that economic agents in Indonesia have different thresholds in stable times and shock periods, resulting in a better fit for the volatile data condition. To study the influence of socioeconomic characteristics on NEEA IEs across

different regions, we conduct a panel data analysis using inflation, education and expenditure data as representative socioeconomic variables. Education is considered a variable based on the assumption that consumers develop expectations based on their ability, which correspond to their education level, where expenditure plays an important part in influencing the supply and demand of goods and services.

This study demonstrated that the CP method outperformed the BA and regression methods. Specifically, the extended version of the CP method, incorporating AT and RPU assumptions, yielded the most satisfactory outcomes. Based on the regional comparison, the CP method with the AT-RPU assumptions is more suitable for regions with relatively unstable inflation. Conversely, the findings indicate that statistically, there is no difference between the original CP and extended CP with assumptions of AT-RPU methods in developed regions with low volatility. Regarding the inquiry into the socioeconomic variables, this study has shown that NEEA IEs are influenced by inflation, education level, and expenditure. The rise in inflation affects the increase of NEEA IEs. Unsurprisingly, an increased level of education and expenditure impacted decreasing NEEA IEs. These results indicate that socioeconomic variables play a role in the formation of NEEA IEs. The findings of this research enhance our understanding of the best methods for quantifying qualitative data and our understanding of the socioeconomic characteristics of various regions. This can be advantageous for policymakers in formulating and implementing effective policies.

This study has been structured as follows. Section two provides an exposition of the data utilised in the article. Section three describes the methodology of the research. The fourth section provides the empirical results. Lastly, the fifth section contains the discussion, while the sixth section presents the summary and conclusions.

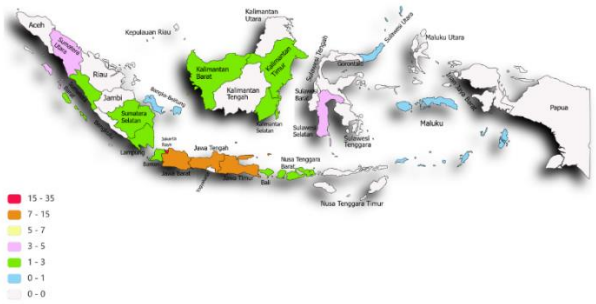
1.2. Data

The primary data for this study is obtained from the consumer survey in Indonesia, conducted monthly by Bank Indonesia, the central bank of Indonesia, from January 2009 to December 2019. The research analysis utilises both the aggregated national data and the data at the regional level. The consumer survey encompasses 18 out of the total 38 provinces in Indonesia, as depicted in Figure 1.1. These regions are Jakarta, Bandung, Semarang, Surabaya, Medan, Makassar, Bandar Lampung, Palembang, Banjarmasin, Padang, Pontianak, Samarinda, Manado, Denpasar, Mataram, Pangkalpinang, Ambon, and Banten.

One of the questions in this survey focuses on consumer IEs. The question captures consumer responses on IEs over six months. The survey requests respondents to report their expectations by answering the following questions:

"How do you see the general price expectation over the next six months? Increase, Decrease, or Stay the same."

Figure 1.1 Consumer Survey Coverage and Contribution for Inflation



This figure illustrates the region's contribution to inflation in Indonesia. The region's contribution is represented by a colour, with legends explaining the percentage. The colour area corresponds to the region encompassing the consumer Survey. The white region represents the portion that the consumer survey does not cover.

According to Figure 1.1, the regional area considered in the consumer surveys conducted for this research accounts for 88.26% of Indonesia's inflation weight. In Indonesia's inflation calculation, Jakarta holds the highest weight, 20.15%; Jakarta's surrounding territory contributes 34.87% to Indonesia's total inflation. In total, Java Island has the highest contribution to Indonesian inflation, accounting for 61.99% of the total inflation in Indonesia.

This study also analyses the inflation statistics, education levels, and expenditures obtained from the Statistical Bureau of Indonesia. The inflation rate data is the monthly actual inflation rate calculated on a year-on-year (YoY) basis. Education level is a measure of the average number of years of schooling completed by individuals who are 25 years old or older, serving as an indicator of their educational attainment. The per capita expenditure variable refers to the average amount of money spent per person.

1.3. Methodology

The following sections, 1.3.1 to 1.3.3, explain different methods for quantifying qualitative data. The methodology used to determine the factors influencing NEEA IEs using socioeconomic variables is explained in subsection 1.3.4.

1.3.1. The Nature of Qualitative Survey Data

The qualitative expectation data provides directional responses regarding future situations. Consider a scenario where, at time t, agents inquire about their IEs for time $t+k$ in qualitative survey data, with their responses consisting of A response answers. Let A consist of three choices: $A1$ represents an increase in response, $A2$ represents a decrease, and $A3$ represents the answer remains the same. This qualitative survey posits that respondents'

cognitive abilities and information processing contribute to creating a threshold in their thoughts. The response will be in the following format:

$A1_{t+k|t}$: Increase if: $x_{t+k|t} \geq \delta_{t+k|t}$ (1.1)

$A2_{t+k|t}$: Decrease if: $x_{t+k|t} \leq \beta_{t+k|t}$ (1.2)

$A3_{t+k|t}$: The same if: $\beta_{t+k|t} < x_{t+k|t} < \delta_{t+k|t}$ (1.3)

where $Ai_{t+k|t}$ represents the response at time t of the expected price for the period $t+k$; $x_{t+k|t}$ is the expected price for the period $t+k$; β_t represents the lower threshold of the price expectation at time t; and δ_t represents the upper threshold of the price expectation at time t.

From Equation (1.1), if the expected price exceeds the upper threshold, respondents will respond with an increase response. In contrast, as in Equation (1.2), respondents would indicate a decrease if the expectation falls below the threshold. In order to maintain the convenience of notation without compromising the significance of the forecast horizon, the equation simplifies the expectation for period $t+k$ by referencing time t, for instance, $x_{t+k|t}$ is defined as x_t.

From Equations (1.1), (1.2), and (1.3), the normal distribution of the respondents can be generated as follows:

$$P_t^{A1} = \Pr(x_t \geq \delta_t) = \int_{\delta_t}^{\infty} f(x)dx \tag{1.4}$$

$$P_t^{A2} = \Pr(x_t \leq \beta_t) = \int_{-\infty}^{\beta_t} f(x)dx \tag{1.5}$$

$$P_t^{A3} = \Pr(\beta_t < x_t < \delta_t) = \int_{\beta_t}^{\delta_t} f(x)dx \tag{1.6}$$

where P_t^{Ai}represents the proportion of respondents at time t; $f(x)$ represents the value of the density function of x; β_t and δ_t are defined in the Equations (1.14) and (1.18).

1.3.2. Quantification of the Qualitative Data Methods

In the subsequent part, we explain the methods for quantifying qualitative data.

1.3.2.1. Balanced Statistics

Anderson (1952) proposes the BS method for quantifying qualitative data. The formulation of this method is as follows:

$$p_{tBS}^e = P_t^{A1} - P_t^{A2} \tag{1.7}$$

Due to the lack of comparability between this approach's results and macroeconomic variables, such as inflation, Batchelor (1986) introduced an extended version of the BS method called the BA method. The expressions for IEs using this approach are:

$$p_{tBA}^{e} = \gamma(P_t^{A1} - P_t^{A2}) \tag{1.8}$$

where p_{tBA}^{e} represents the inflation expectation of the BA method; γ represents the parameter of the BA method.

In order to determine the value of γ, Batchelor assumed that the agents possess long-term unbiasedness. IEs can be formulated as a result of the assumption with the formula:

$$\sum_{t=1}^{T} p_{tBA}^{e} = \sum_{t=1}^{T} \pi_t \tag{1.9}$$

where π_t represents the actual inflation rate.

From Equations (1.8) and (1.9), we can get:

$$\hat{\gamma} = \frac{\sum_{t=1}^{T} \pi_t}{\sum_{t=1}^{T} (P_t^{A1} - P_t^{A2})} \tag{1.10}$$

1.3.2.2. The Carlson-Parkin Method

This sub-section will discuss the original CP method and its extended versions.

A. Original Carlson-Parkin Method

Carlson and Parkin (1975) developed the theoretical framework of the CP method to quantify qualitative data obtained from surveys using the probability approach. The CP method assumed normal distribution and performed a normalisation process that resulted in a mean of zero and a variance of one, which produced in the following manner:

$$n_t = \frac{x_t - p_t^{e}}{\sigma_t} \tag{1.11}$$

The normalisation form of Equations (1.4), (1.5), and (1.11) is represented as follows:

$$P_t^{A1} = \Pr(n_t \geq a_t) = \int_{a_t}^{\infty} f(n)dn \tag{1.12}$$

$$P_t^{A2} = \Pr(n_t \leq b_t) = \int_{-\infty}^{b_t} f(n)dn$$

(1.13)

where n_t represents the normalisation of zero mean and unit variance; σ_t denotes the standard deviation; p_t^e represents the inflation expectation at time t; a_t and b_t are defined in Equations (1.15) and (1.16); Equations (1.12) and (1.13), as illustrated in Figure 1.2.

CP method assumed a symmetric threshold when constructing the framework, meaning that the upper and lower thresholds are equidistant from zero. CP method also presupposes that economic agents exhibit long-term unbiasedness, meaning that their long-term IEs align, on average, with actual inflation. The assumptions are outlined as follows:

Symmetric Threshold.

The CP method assumes the presence of a symmetric threshold whereby:

$$\beta_t = -\delta_t \tag{1.14}$$

By symmetric assumption, we can rearrange Equations (1.11), (1.12), and (1.14) as follows:

$$a_t = \frac{\delta_t - p_t^e}{\sigma_t}$$

(1.15)

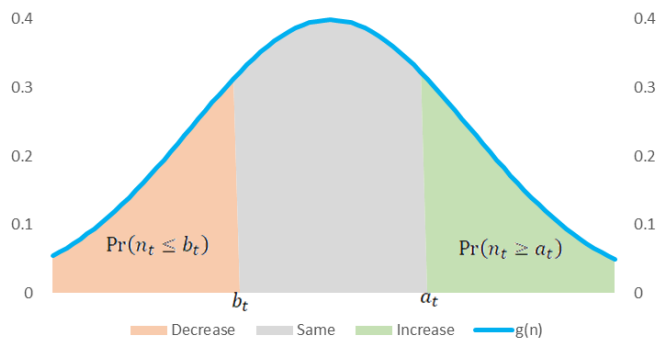
By utilising Equations (1.11), (1.14), and (1.15), we can express the following:

$$b_t = \frac{-\delta_t - p_t^e}{\sigma_t}$$

(1.16)

where a_t represents the upper threshold of the normalisation with zero mean and unit variance; b_t represents the lower threshold of the normalisation with zero mean and unit variance.

Figure 1.2 The Probability Density Function



This figure illustrates the Probability Density Function related to Equations (1.12) and (1.13). The orange area is the area of decreased answers, and the green area is the area of increased answers.

From Equations (1.15) and (1.16), the formula of p_t^e is:

$$p_t^e = -\delta_t \left(\frac{a_t + b_t}{b_t - a_t}\right) \tag{1.17}$$

As proposed by Carlson and Parkin (1975), in the event of a null response for either an "increase" or "decrease" answer, it is necessary to adjust at least one response. This is because, as shown in Equations (1.15) and (1.16), the values of a_t and b_t will approach infinity.

Long-Term Unbiasedness

The CP method assumed long-term unbiasedness, where the average IEs would equal the actual inflation rate in the long term. Given the assumption of unbiasedness among agents, where $E[p_t^e] = E[\pi_t]$, it is further assumed that δ_t remains constant and scales with p_t^e. The formula for $\hat{\delta}$ can be derived using the assumption of long-term unbiasedness as follows:

$$\hat{\delta} = \frac{\sum_{t=1}^{T} \pi_t}{\sum_{t=1}^{T} \left(\frac{a_t + b_t}{b_t - a_t}\right)} \tag{1.18}$$

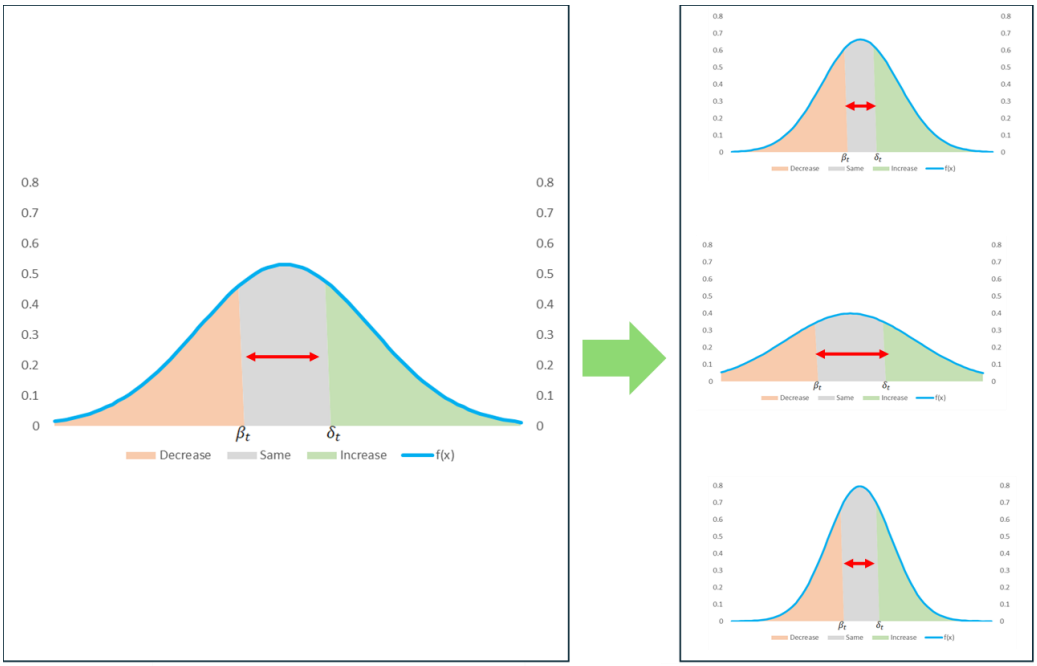
where π_t represents the inflation rate (Year on Year/YoY) at time t, it is calculated using the formula $\pi_t = \left(\frac{CPI_t - CPI_{t-12}}{CPI_{t-12}}\right) x100$.

B. Extension of Carlson Parkin Method

Relaxed Long-Term Unbiasedness Assumptions

The long-term unbiasedness assumption of the CP method, as stated in Equation (1.18), assumes that δ_t remains constant. This assumption can be a reliable approximation in a relatively stable inflationary environment. However, the underlying assumptions can lead to incorrect interpretations in unpredictable and volatile inflation conditions. Relaxing this assumption for the volatile inflation scenario, in which agents held different expectations during the shock, is valuable. Figure 1.3 illustrates that separating the sample into distinct periods during normal conditions and periods of shock makes it possible to accurately determine the optimal values for the lower and higher thresholds in both normal and shock periods.

Figure 1.3 The Illustration of Regime-Period Unbiasedness



This figure illustrates the long-term unbiasedness and regime-period unbiasedness assumptions. The orange area represents decreased responses, whereas the green region represents increased responses.

Therefore, this study employed an alternative time frame to establish δ and alleviate the assumption of long-term unbiasedness, namely by considering RPU. The process of dividing the sample when shocks occur can yield improved outcomes as the method employed by Thornton (2013) for splitting the sample in the presence of data shocks. In a study conducted by Ranyard *et al.* (2008), it was also discovered that consumers tend to adopt a new standard expectation and modify their prior beliefs when faced with unexpected circumstances. To demonstrate the technique of utilising different time frames, let us assume that a shock has taken place within the specified timeframe. The extended version of Equation (1.18) can be expressed as:

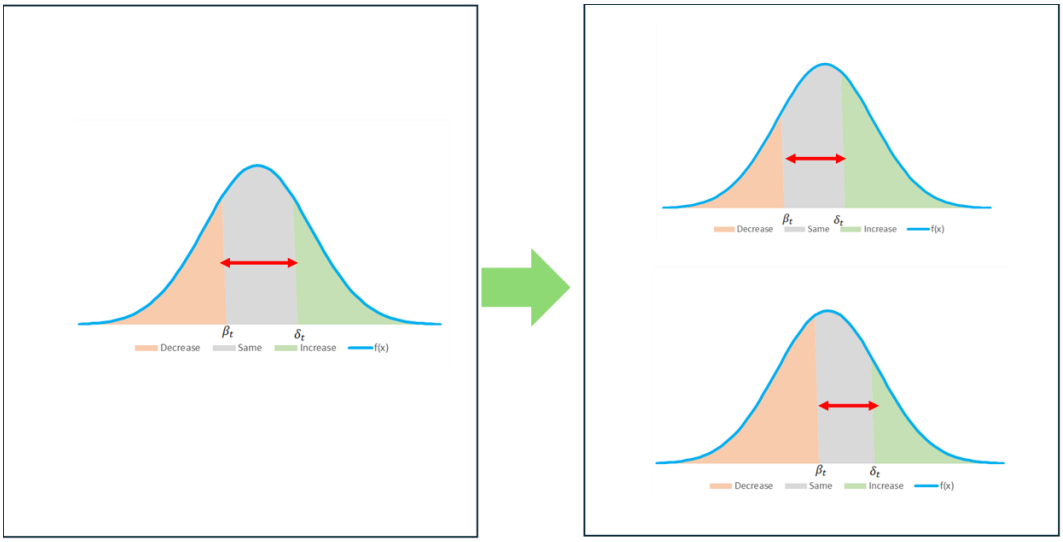
$$\hat{\delta}_1 = \frac{\sum_{t_1=1}^{T_1} \pi_{t_1}}{\sum_{t_1=1}^{T_1} \left(\frac{a_{t_1} + b_{t_1}}{b_{t_1} - a_{t_1}} \right)} \; ; \hat{\delta}_2 = \frac{\sum_{t_2=T_1+1}^{T_2} \pi_{t_2}}{\sum_{t_2=T_1+1}^{T_2} \left(\frac{a_{t_2} + b_{t_2}}{b_{t_2} - a_{t_2}} \right)} ; \hat{\delta}_3 = \frac{\sum_{t_3=T_2+1}^{T_3} \pi_{t_3}}{\sum_{t_3=T_2+1}^{T_3} \left(\frac{a_{t_3} + b_{t_3}}{b_{t_3} - a_{t_3}} \right)} \tag{1.19}$$

where $\hat{\delta}_1$ represents the parameter value from the time frame prior to the occurrence of the shock; $\hat{\delta}_2$ represents the parameter value at the time of the shock; $\hat{\delta}_3$ represents the parameter value from the time frame after the occurrence of the shock.

Relaxed Symmetric Threshold Assumptions

Equation (1.14) of the CP method assumes that the indifference threshold (-δ_t and δ_t) is symmetrically centred around zero. Nevertheless, this assumption fails to accurately depict the actual state of the volatile data condition. As illustrated in Figure 1.4, agents can possess varying thresholds for the upper and lower bounds in volatile inflation situations. In line with this, Berk (1999) and Breitung and Schmeling (2013) expanded the CP method by incorporating an AT, which enables differentiation between the upper and lower thresholds.

Figure 1.4 The Illustration of Asymmetric Threshold



This figure illustrates the symmetric and asymmetric threshold assumptions. The orange area represents decreased responses, whereas the green region represents increased responses.

This study aims to challenge the symmetric threshold assumption by introducing the asymmetric threshold set-up. By removing the requirement of symmetry, we can transform Equation (1.16) into the following form:

$$p_t^e = \beta_t - \sigma_t b_t \tag{1.20}$$

Equation (1.20) provides an alternative calculation for IEs. From Equation (1.15), we can obtain σ_t with the following formula:

$$\sigma_t = \frac{\delta_t - p_t^e}{a_t} \tag{1.21}$$

In order to modify the expression of IEs in Equation (1.20), which involves variables a_t and b_t representing respondents' probability answers, we can rearrange Equations (1.20) and (1.21) to obtain the formulation for IEs as:

$$p_t^e = \beta_t \left(\frac{a_t}{a_t - b_t}\right) + \delta_t \left(\frac{-b_t}{a_t - b_t}\right) \tag{1.22}$$

As outlined by Berk (1999) and Breitung and Schmeling (2013), the values of β_t and δ_t can be obtained by regression. The format is as follows:

$$\pi_t = \beta(c_t) + \delta(d_t) + \varepsilon_t \tag{1.23}$$

By using Equation (1.23), we can define $c_t = \frac{a_t}{a_t - b_t}$, and $d_t = \frac{-b_t}{a_t - b_t}$. With this equation, we can solve for β as the lower threshold and δ as the upper threshold. By relaxing the symmetry assumption, we can better capture the actual behaviour of economic agents, particularly in relatively volatile economies with limited experience periods of deflation. The upper threshold might be assigned a more substantial value by making an asymmetry assumption in a context of relatively high volatility and experiencing high inflation.

1.3.2.3. Regression Method

Pesaran (1984) proposes a regression technique to quantify qualitative data, employing the following formula:

$$p_{tR}^e = \vartheta A1_t + \rho A2_t \tag{1.24}$$

where p_{tR}^e represents the inflation expectation in the regression method; ϑ and ρ are the parameters of the regression method.

The underlying premise of this method is:

$$p_{tR}^e = \pi_t \tag{1.25}$$

By Equations (1.24) and (1.25), we can establish a formulation:

$$\pi_t = \vartheta A1_t + \rho A2_t + \varepsilon_t \tag{1.26}$$

1.3.3. Comparison Different Methods

The IEs results from different methods are compared with actual inflation statistics, as Batchelor (1981) and Löffler (1999). The comparative performance is evaluated using the Mean Absolute Error (MAE hereafter) and Root Mean Square Error (RMSE hereafter) to compare outcomes obtained from various methodologies. The expressions for MAE and RMSE are as follows (Greene 2003):

$$MAE = \sum_{t=1}^{T} \frac{|\pi_t - \pi_t^e|}{T} \tag{1.27}$$

$$RMSE = \sqrt{\sum_{t=1}^{T} \frac{(\pi_t - \pi_t^e)^2}{T}}$$

(1.28)

where MAE represents the Mean Absolute Error score, $RMSE$ represents the Root Mean Squared Error score, T represents the observation period.

The subsequent stage involved comparing the benchmark with alternative methods using the Diebold-Mariano test (Diebold & Mariano 1995). This test aims to determine if there are statistically significant differences between the benchmark and alternative methods. The Diebold-Mariano test (DM-test hereafter) is based on the following equation:

$$DM = \frac{\bar{d}}{\sqrt{\frac{[\hat{\gamma}_d(0) + 2\sum_{\tau=1}^{h-1} \hat{\gamma}_d(\tau)]}{T}}}$$

(1.29)

where DM represents the Diebold Mariano Test result; $\bar{d}$ represents the sample mean of loss differential series; $\hat{\gamma}_d(\tau)$ denotes as autocovariance at lag τ; h represents the maximum order of the lag used in the test.

1.3.4. The Determinants of Inflation Expectations

This study examines whether the inflation rate was the sole factor influencing NEEA IEs or if any socioeconomic variables also impacted NEEA IEs. The estimation employs panel data analysis, utilising the following formulation:

$$p_{it}^e = \zeta \pi_{it} + x'_{it}\eta + \theta_i + u_{it} \quad (1.30)$$

where p_{it}^e represents the IEs in region i and time t; π represents the inflation rate (YoY) in region i and time t; ζ measures the causal effect of inflation on IEs; x represents the socioeconomic variables that influence IEs; θ is a regional fixed-time effect represented as time-invariant dummy variable; u_{it} is an error term, where $E(u_{it}) = 0, \forall_i, \forall_t$.

1.3.5. Robustness Checks

This study employs the Harvey, Leybourne, and Newbold test (Harvey *et al.* 1997) as a robustness check to assess the reliability of the DM-test and ensure the consistency of the findings. The Harvey, Leybourne, and Newbold (HLN) test is formulated as follows:

$$HLN = DM \sqrt{\frac{[t + 1 - 2h + h(h-1)]}{T}}$$

(1.31)

where HLN refers to Harvey, Leybourne, and Newbold score; h denotes the maximum lag used in the test.

1.4. Empirical Result

This section analysed several methodologies for quantifying qualitative data using BA, CP, and regression methods. The study employed Indonesian national survey data in part 1.4.1 and data from 18 regions in section 1.4.2. In addition, we examine the factors that impact NEEA IEs by considering socioeconomic variables in subsection 1.4.3.

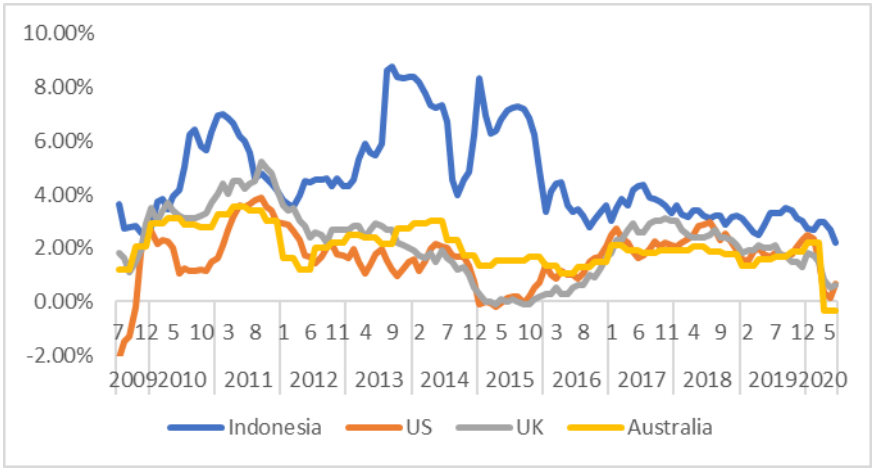
1.4.1 Indonesian Aggregate Data

In this sub-section, we present the results utilising Indonesian national statistics. In sub-section 1.4.1.1, we discuss the characteristics of Indonesian inflation conditions and the technique employed for the analysis before providing the results. In sub-section 1.4.1.2, we provide the results.

1.4.1.1. Indonesia Inflation Condition and Methodology Approach

Indonesia is a compelling subject of analysis for several reasons: the largest archipelagic nation, exhibits a wide range of geographical diversity; and the disparities in education and expenditure across different regions substantially affect its socioeconomic conditions; and likewise experiences volatile inflation rates. Figure 1.5 demonstrates that the average inflation rate in Indonesia, based on the data timeframe used in this study, is 4.63% (YoY) greater than the average inflation rates in the United States (US), United Kingdom (UK), and Australia, which are 1.66% (YoY), 2.16% (YoY), and 2.04% (YoY), respectively. The standard deviation of inflation in Indonesia (1.71%) is larger than the standard deviation of inflation in the US (1.01%), UK (1.24%), and Australia (0.75%).

Figure 1.5 Inflation Rate in Indonesia, the US, UK, and Australia

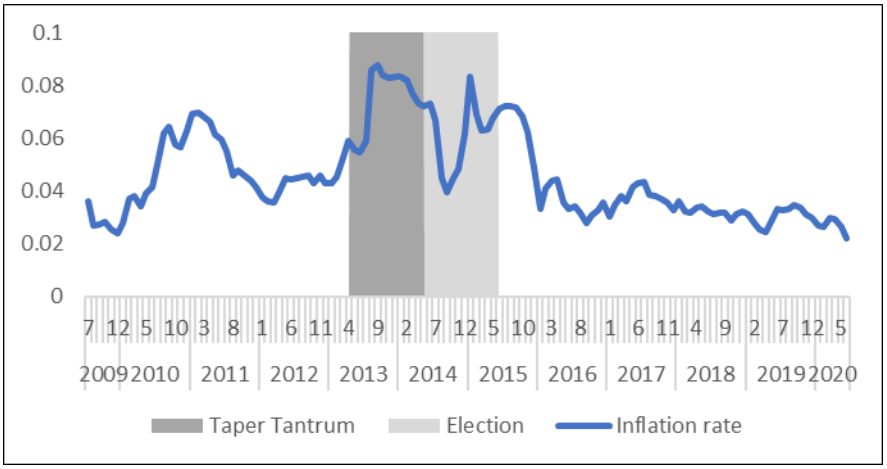


This figure compares the inflation rate in Indonesia, which represents developing countries, with the inflation rates in the US, UK, and Australia, which represent developed countries. The inflation rate is calculated using the Consumer Price Index (CPI) on a year-on-year (YoY) basis. The CPI is released monthly in Indonesia, the US, and the UK, whereas it is released quarterly in Australia.

The MAE and RMSE assess each method's accuracy, with the lowest score considered the most effective for quantifying qualitative data (Smith & McAleer 1995; Berk 1999; Sloman *et al.* 2018). To address the issue of a null response, this study addresses it by treating the null response as though it represents a single response. Furthermore, this research employed the DM-test (Diebold & Mariano 1995) to examine the statistical distinction between the benchmark and alternative models.

This study examined the function of unbiasedness in NEEA IEs by comparing three different unbiasedness horizons: short-term unbiasedness (STU hereafter), RPU, and long-term unbiasedness (LTU hereafter), where LTU is considered as the original assumptions of the approaches. This comparison seeks to determine the duration of unbiasedness that accurately reflects the perspective of economic agents. STU employs a rolling window and has characteristics that vary over time. Given the rapid increase in speed and extensive availability of information, it is valuable to apply time-varying parameters as a means of comparison to depict a continuous learning perspective, where consumers routinely update their information. Due to the higher volatility of Indonesia's inflation data compared to developed countries, relying on the assumptions of LTU can lead to incorrect perceptions, as Ranyard *et al.* (2008) discovered that NEEA tended to acquire a new standard expectation and adjust their previous views when to deal with economic shocks.

Figure 1.6 Inflation Rate and Event Analysis in Indonesia



This figure illustrates the event that influenced the inflation shock in Indonesia within the specified data period. The inflation rate from July 2009 to June 2020 aligns with the expected six-month consumer IEs survey. The analysis considers the taper tantrum era (dark grey) and the election period (light grey) as shock periods.

In implementing the RPU assumption, we divided the period into the normal and the shock periods. The shock period in this research was determined by an economic event, which identifies an exogenous event that caused a significant impact on inflation. Two notable events significantly impacted inflation, as Figure 1.6 illustrates a consistent rise in

the inflation rate from 2013 to 2015[9]. In May 2013, an external shock occurred due to the taper tantrum period, triggered by the US Federal Reserve's announcement of the conclusion of the quantitative easing programme. This announcement has substantially influenced Indonesia's economic condition, causing a depreciation of the exchange rate and a rise in the prices of imported commodities. The currency rate depreciation and the increase in global oil prices have intensified the government's need to reduce oil subsidies. Consequently, this exerted significant upward pressure on Indonesia's inflation rate during that era. The second economic event occurred in 2014 during the presidential and legislative elections held in July. Before election day, there is a campaign phase during which the amount of money in circulation in the market grows due to the extensive campaigning in all regions of Indonesia. These factors have led to an increase in demand for goods and services, affecting inflation. Given that this study utilises YoY data, the shocks are measured within a one-year timeframe (12 months) following their occurrence. This paper considered the period between May 2013 and May 2015 as the designated shock period. There are three alternative estimates of $\hat{\delta}$ as in Equation (19). $\hat{\delta}_1$represents the pre-shock period from January 2009 to April 2013, $\hat{\delta}_2$ represents the shock period from May 2013 to May 2015, and $\hat{\delta}_3$ represents the stable period after the shock from June 2015 to December 2019.

1.4.1.2. Quantification of Qualitative Data.

Our findings indicate that the CP method yields superior results to the BA and regression methods, mainly when the long-term unbiasedness and symmetric threshold assumptions are relaxed. The standard CP is chosen as the benchmark within the comparison methods, while the other method serves as an alternative. A negative sign on the DM-Test indicates that the benchmark method is superior, while a positive sign indicates that the alternative method is superior. Further exploration of this outcome is offered in the subsequent sub-section analysis.

Balanced Approach Method

This research explores three BA methods: Standard LTU (no.1), RPU (no.2), and STU (no.3). The BA method presented in Table 1.1 yields higher MAE and RMSE compared to the CP method in Table 1.2. The DM-test reveals a significant statistical difference between the standard BA method and the CP method used as a benchmark, where the standard BA method is comparatively weaker than the CP method.

[9] There is a noticeable spike between mid-2010 and mid-2011; however; no exogenous events can be identified during this period.

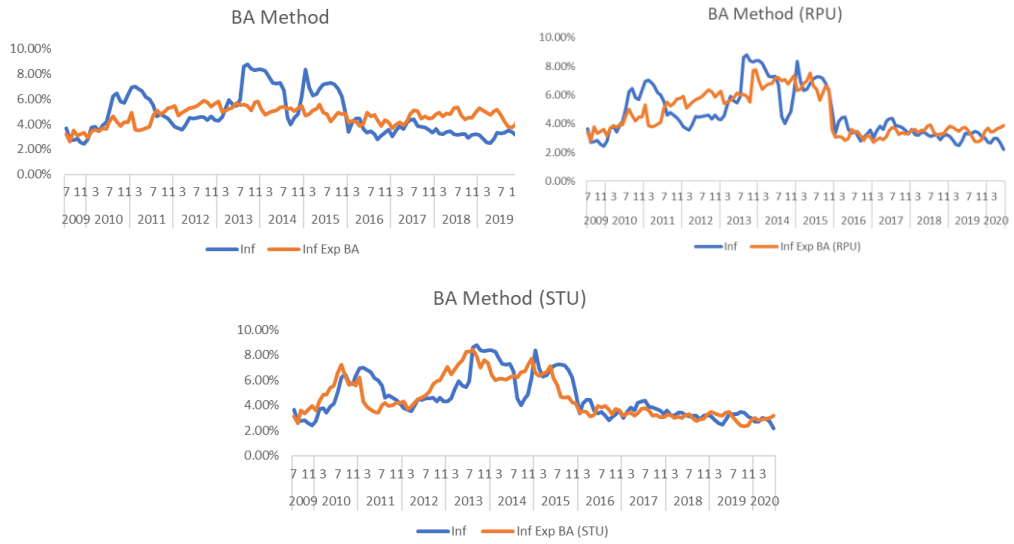
The IEs, represented by Figure 1.7, exhibit a significant disparity with the actual inflation rate, particularly when using the BA method with LTU assumptions. The RPU assumptions yield superior outcomes, particularly from 2015 to 2020. Nevertheless, this approach typically yields a comparatively inferior outcome compared to the CP method outlined in Table 1.2. Claveria *et al.* (2007) also showed that BA methods had a relatively weak outcome, possibly due to the simplicity of the procedure.

Table 1.1 Results of Balanced Approach Methods (National Data)

No	Methods	MAE	RMSE	DM-Test
1	BA Method	1.37	1.64	-4.11***
2	BA Method (RPU)	0.93	1.21	-1.14
3	BA Method (STU)	0.95	1.25	-1.04

This table compares quantifying qualitative data using BA methods and the actual inflation rate. BA is for the Balanced Approach; RPU refers to the regime-period unbiasedness; STU stands for short-term period unbiasedness. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test, the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Figure 1.7 Inflation Rate and IEs Utilising Balanced Approach Methods



This figure compares the quantification of qualitative data using BA methods and the actual inflation rate in Indonesia. BA stands for the Balanced Approach; RPU refers to the regime-period unbiasedness; STU stands for short-term period unbiasedness. Inf represents the inflation rate; Inf Exp denotes Inflation Expectations.

Carlson-Parkin Method

This paper employed five CP methods to compare the most effective techniques, including the original CP methods, CP method utilising STU, CP method utilising RPU, CP method utilising an AT, and CP method utilising RPU-AT. Table 1.2 demonstrates that loosening the

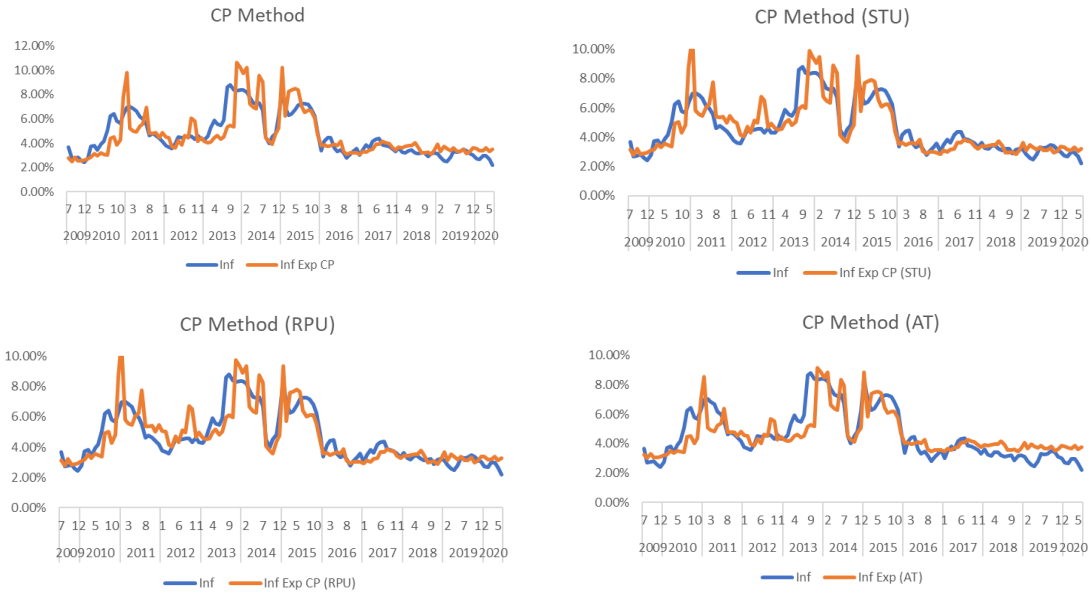
LTU assumption shows a notable improvement[10], particularly with the RPU assumption. The RPU approach exhibits a comparatively robust outcome compared to the STU method, similar to the results obtained by BA methods. The results improve by relaxing the symmetry threshold assumption. The extended CP methods, when compared to the original CP methods, yield superior MAE and RMSE scores. The utilisation of the CP method improves the accuracy of the results by relaxing the assumption of long-term unbiasedness and symmetric threshold. The MAE and RMSE of the CP RPU-AT method are reduced to 0.62 and 0.83, respectively. The DM-test in Table 1.2 indicates that the AT approach shows a statistically significant difference compared to the original CP method. The DM-test score for CP AT is 1.67, while for CP RPU-AT, it is 2.07.

Table 1.2 Results of Carlson-Parkin Methods (National Data)

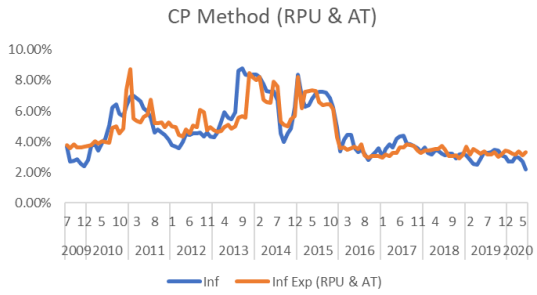
No	Methods	MAE	RMSE	DM-Test
1	CP Method	0.76	1.06	-
2	CP Method (STU)	0.69	0.99	1.31
3	CP Method (RPU)	0.71	0.96	1.09
4	CP Method (AT)	0.73	0.95	1.67*
5	CP Method (RPU & AT)	0.62	0.83	2.07**

This table compares quantifying qualitative data using the original and extended versions of the CP methods and the actual inflation. CP is for the Carlson-Parkin, RPU stands for regime period unbiasedness, STU is for short-term period unbiasedness; and AT stands for asymmetric threshold. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test, the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Figure 1.8 Inflation Rate and IEs Utilising Carlson-Parkin Methods



[10] In terms of the metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Diebold-Mariano Test (DM-Test).



This figure compares the quantification of qualitative data using the original and extended versions of the CP methods and the actual inflation rate in Indonesia. CP is for the Carlson-Parkin, RPU stands for regime period unbiasedness, STU is for short-term period unbiasedness; and AT stands for asymmetric threshold. Inf represents the inflation rate; Inf Exp denotes Inflation Expectations.

Figure 1.8 demonstrates that the IEs of the CP method surpass the performance of the BA method. In general, the NEEA IEs for 2009-2012 tended to align with the actual inflation rate. However, in the mid-2013 period, known as the taper tantrum, the IEs did not mirror the actual inflation situation. This shock also affected the tendency of NEEA IEs to overreact. Economic agents can foresee the second shock during this period since they are already aware of the upcoming significant event of Indonesia's presidential and legislative elections in mid-2014. Based on this information, this shock appears to resemble the sunspot shock[11].

Regression Method

The preceding two approaches demonstrate that RPU methods yield superior outcomes. Therefore, we examined the RPU and LTU assumptions in this regression method. The RPU yields superior results to LTU assumptions, as shown in Table 1.3, similar to the BA and CP methods. The RPU assumption yields a positive DM-test, although they do not exhibit statistical significance compared to the CP method. The LTU method is statistically distinct from the benchmark but yields a negative value, indicating that the benchmark is superior. Figure 1.9 illustrates that the regression method delivers unsatisfactory results, although the RPU method generates outcomes with a greater correlation to the actual inflation data after 2013.

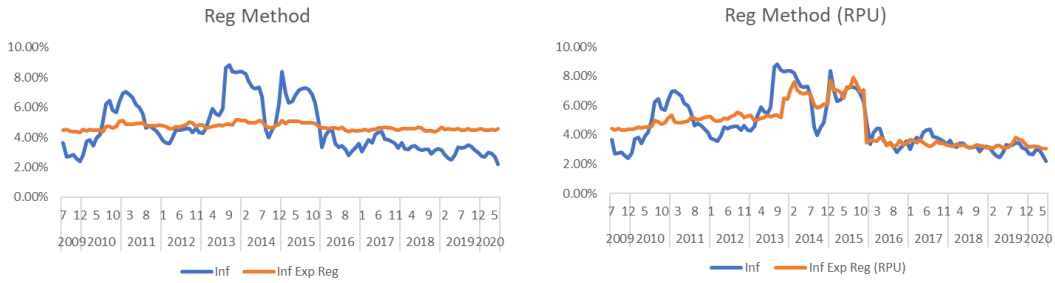
Table 1.3 Results of Regression Methods (National Data)

No	Methods	MAE	RMSE	DM-Test
1	Reg Method	0.84	1.30	-2.96***
2	Reg Method (RPU)	0.59	0.93	0.67

This table compares quantifying qualitative data and the actual inflation rate using regression methods. Reg is Regression; RPU stands for regime period unbiasedness. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test, the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

[11] The sunspot shock is an exogenous shock that influences the behavior of economic agents even before it occurs, as they adjust their actions in response of its potential likelihood.

Figure 1.9 Inflation Rate and IEs Utilising Regression Methods



This figure compares the quantification of qualitative data using regression methods and the actual inflation rate in Indonesia. Reg is Regression; RPU stands for regime period unbiasedness. Inf represents the inflation rate; Inf Exp denotes Inflation Expectations.

Overall, it has been discovered that the extended version of the CP method, incorporating an AT and RPU, yields the optimal outcome. Among the findings obtained from Tables 1.1, 1.2, and 1.3, the RPU assumption demonstrates superior performance. The outcome suggests that economic agents in Indonesia hold distinct perspectives on parameters during normal and shock conditions. The discovery of the superior outcome of RPU aligns with the assertion made by Ranyard *et al.* (2008) that a new expectation standard exists, prompting individuals to modify their beliefs on the original level of expectation in response to an economic shock. The unpredictable nature of Indonesian inflation during the timeframe indicated that economic agents change their expectations when an unexpected occurrence happens. As economic agents create their understanding of the situation, shocks modify people's cognitive processes and lead to either pessimistic or optimistic expectations (Sloman *et al.* 2018). The superior outcome of RPU compared to STU approaches may also suggest that economic agents do not consistently and periodically update the information. This finding aligns with Carroll's (2003) study, which observed that NEEA updated information infrequently. By relaxing the assumption of a symmetric threshold, the results for Indonesian data improve. This outcome can be attributed to Indonesia's consistent positive inflation rate, which affects economic agents with varying thresholds between the upper and lower bounds. The difference between the upper and zero is greater than the lower bound and exhibits differing sensitivities when the economy experiences a shock.

1.4.2 Indonesian Regional Data

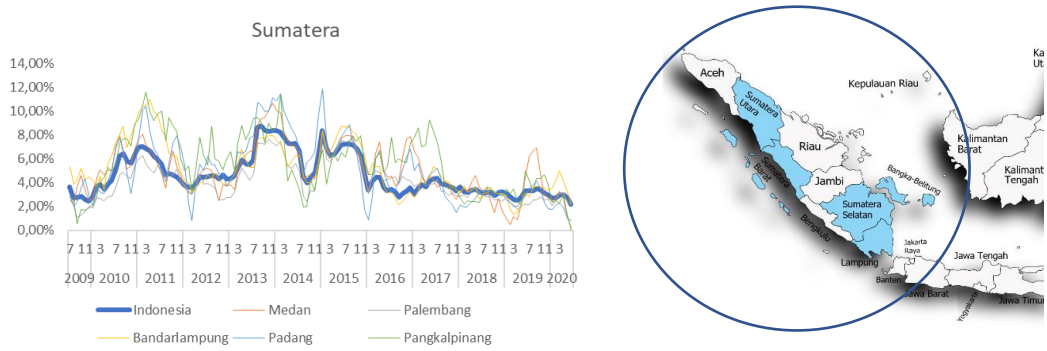
Indonesia presents a unique array of socioeconomic conditions unprecedented in the literature, making it intriguing to investigate the optimal techniques for quantifying qualitative data in greater detail using Indonesian regional data. Examining regional data might further elucidate the influence of the socioeconomic variables on regional Indonesia's NEEA IEs. The BA, CP, and regression methods are employed to quantify the qualitative data

for regional data, similar to the Indonesian aggregate data. The standard CP is selected as the benchmark within the comparison methods, whereas the other method is an alternative. Subsequently, the IEs derived from different methodologies compared to the regional inflation statistics[12]. In sub-section 1.4.2.1, we explain the characteristics of the regional inflation condition[13] before presenting the results of the regional data. In the subsequent sub-section, we provide the findings from the analysis of regional data.

1.4.2.1 Regional Inflation Condition

The regional data in Indonesia reveals a range of inflation rate conditions, which can be observed from Figure 1.10 to Figure 1.13. As depicted in Figure 1.10, the regional inflation condition in Sumatera[14] exhibits greater volatility than Indonesia's overall inflation condition. Medan serves as the primary economic hub for the Sumatera region and is among Indonesia's most developed regions, as seen in Figure 1.14.

Figure 1.10 Inflation Rate in Indonesia and Sumatera



This figure compares the actual inflation rate in Indonesia and the Sumatera regions.

Figure 1.11 illustrates that the level of volatility in regional inflation on Java island[15] is the lowest compared to other islands. The inflation in Java Island is closely aligned with the overall inflation condition of Indonesia, as Java Island contributes the highest inflation weight among all the other islands. The Java region is renowned as Indonesia's most advanced and

[12] All the 18 regions in Indonesia have regional inflation data, which have different weights to contribute to Indonesian inflation. The weight of every area depends on the regional consumption basket compared to the total national consumption basket.

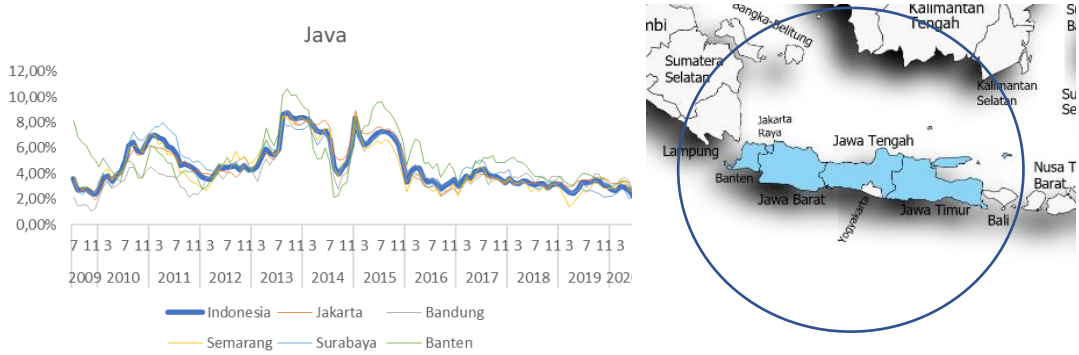
[13] Explicate four distinct regional areas: Sumatera Island, Java Island; Borneo, Bali and Nusa Tenggara; and east Indonesia

[14] Out of the nine provinces, five provinces are included in the consumer survey coverage. Medan serves as the capital of Sumatera Utara (North Sumatera), Palembang as the capital of Sumatera Selatan (South Sumatera), Bandar Lampung as the capital of Lampung, Padang as the capital of Sumatera Barat (West Sumatera), and Pangkalpinang as the capital of Bangka-Belitung.

[15] Out of the six provinces, five provinces are included in the consumer survey coverage. Jakarta serves as the capital city of Indonesia and the capital of Jakarta Special Region, Bandung as the capital city of Jawa Barat (West Java), Semarang as the capital city of Jawa Tengah (Central Java), Surabaya as the capital city of Jawa Timur (East Java), and Banten serves as the capital city of Banten.

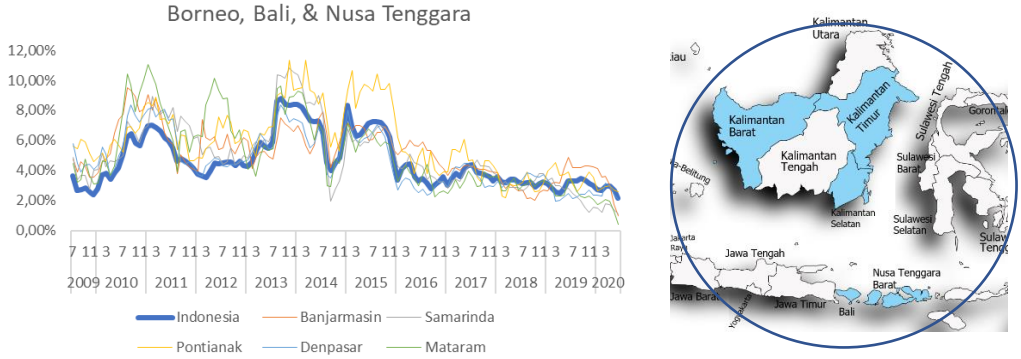
developed area, as depicted in Figure 1.14. The abnormal condition in Java Island is exclusively observed in Banten, the most economically disadvantaged province in Java Island.

Figure 1.11 Inflation Rate in Indonesia and Java



This figure compares the actual inflation rate for Indonesia and the Java regions.

Figure 1.12 Inflation Rate in Indonesia and Borneo, Bali, Nusa Tenggara



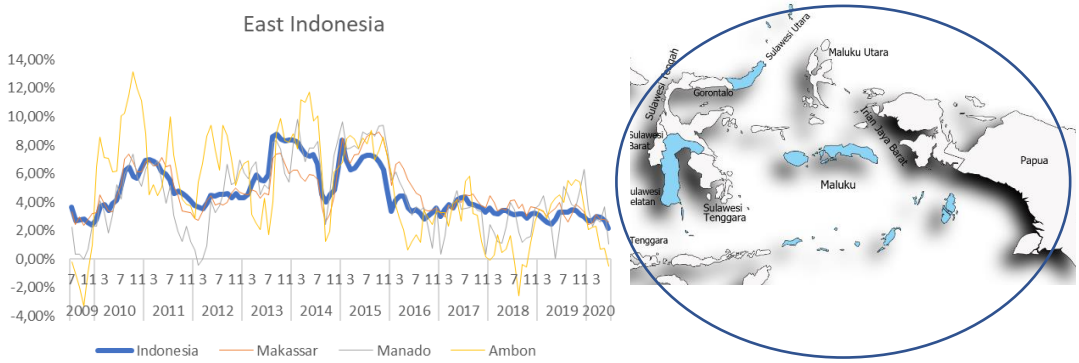
This figure compares the actual inflation rate for Indonesia and the Borneo, Bali, and Nusa Tenggara regions.

The volatility of inflation in Borneo, Bali, and Nusa Tenggara[16] (as depicted in Figure 1.12) is significantly higher compared to the regional inflation in Java and Sumatera. The level of volatility in the eastern area of Indonesia[17] fluctuates more than in other regions, as depicted in Figure 1.13. Makassar is the only city with a relatively lower inflation rate, primarily due to its role as the East Indonesia region's economic hub and the region's most developed area, as depicted in Figure 1.14. The volatility in this region stems from the comparatively more significant transportation costs compared to other regions. The supply of goods in this area remains reliant on other places, particularly Java.

[16] Out of the eight provinces, five are included in the consumer survey coverage. Banjarmasin serves as the capital of Kalimantan Selatan (South Borneo); Samarinda as the capital of Kalimantan Timur (East Borneo); Pontianak as the capital of Kalimantan Barat (West Borneo); Denpasar as the capital of Bali; and Mataram serve as the capital of Nusa Tenggara Barat (West Nusa Tenggara).

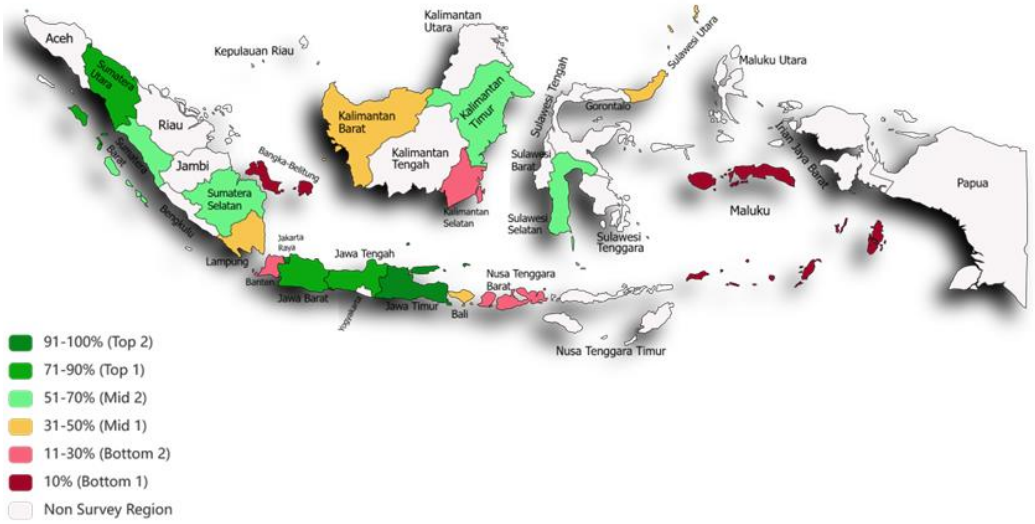
[17] Out of the total of fifteen provinces, three provinces are included in the consumer survey coverage. Makassar serves as the capital of Sulawesi Selatan (South Sulawesi); Manado as the capital of Sulawesi Utara (North Sulawesi); and Ambon as the capital of Maluku (Mollucas).

Figure 1.13 Inflation Rate in Indonesia and East Indonesia



This figure compares Indonesia's and East Indonesia's actual inflation rates.

Figure 1.14 The Ranking of Developed Regions in Indonesia



This figure illustrates the provinces' ranking of regional GDP. Out of 38 provinces, 18 were included in the survey data. Dark green represents the top of developed regions, with Jakarta and Surabaya ranking in the top 10%. Dark red represents the least developed regions, with Pangkalpinang and Ambon at the bottom 10%. The white areas are the unsurveyed regions.

1.4.2.2 Quantification of Qualitative Data.

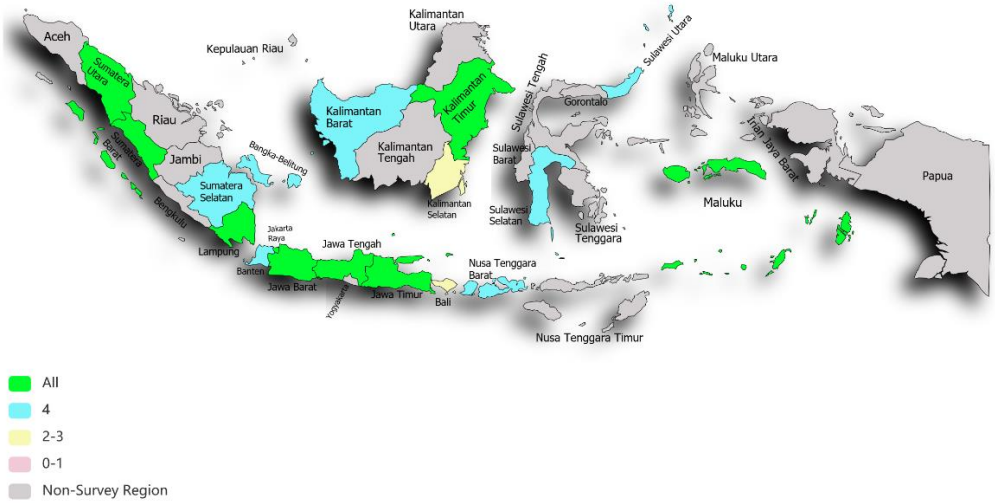
This subsection presents the quantification of qualitative data results from 18 regions in Indonesia. Similar to the national data, our findings indicate that the CP method is the most effective compared to other approaches, particularly with the AT and RPU assumptions. The discussion of these findings is provided in the subsequent sub-section.

Comparison of the methods.

The analysis of regional data indicated that the CP methods yield superior results compared to the BA and regression methods. The method's comparison is depicted in Figure 1.15. This

figure compares five alternative BA and regression methods[18], using the CP method as the benchmark. Figure 1.15 demonstrates that, overall, the CP method consistently yields superior results across the majority of regions. The CP method demonstrates supremacy in nine places, where all benchmark methods outperform the five alternative methods in terms of BA and regression methods (shown by the green colour). Interestingly, the outcome reveals that the majority of the area encompassed by the green list colour corresponds to developed regions. The four developed regions in Java island that play a crucial role in contributing to Indonesian growth are Jakarta, Bandung, Semarang, and Surabaya. However, Banten, the least developed region in Java, is not included on the green list. In addition, Medan and Samarinda, which are the most advanced regions in Sumatera and Borneo, respectively, are also part of the green list.

Figure 1.15 Comparison Result of the Methods (Regional Data)



This figure illustrates the contrast between the CP with BA and regression methods. The green indicates that the CP method yield superior results to all five alternative methods. Using the blue colour signifies the superiority of the CP method over the four alternatives in producing more accurate outcomes. The yellow indicates that the CP method yields superior outcomes in two to three compared to alternative methods. The colour grey represents the non-survey region.

When considering the Indonesian national data result, the combination of AT and RPU assumptions, as shown in Table 1.2, yields the most favourable among all the methods. Nevertheless, according to Table 1.4, the DM-test indicates that the values for Jakarta, Bandung, Semarang, Pangkalpinang, and Ambon are not substantially different from zero. Interestingly, the outcome in this table reveals that the region yielding negligible findings can be divided into two distinct groups.

[18] Three BA methods (Standard LTU, RPU, and STU) and two regression method (Standard LTU and RPU) used as comparison.

The first cluster, comprising Jakarta, Bandung, and Semarang, are regarded as some of the most advanced regions in Indonesia. This region exhibits a higher-than-normal regional GDP and lower inflation volatility than other regions. The standard deviation of inflation for the data period is 1.93%, 1.82%, and 1.98%, respectively, whereas the average standard deviation is 2.29%.

The second cluster comprises Pangkalpinang and Ambon. These regions share at least two common conditions that could explain the result. Both regions are remote regions (island provinces) and face challenges in supplying the demand for goods and services. The condition of the remote regions of Pangkalpinang and Ambon significantly influences the fluctuation of inflation in these regions. The inflation standard deviation in Ambon and Pangkalpinang is 3.50% and 2.77%, respectively, making them the highest and second-highest among the 18 regions surveyed. Figure 1.14 highlights that these regions are the red-coloured areas, representing the lowest 10% of the least developed regions in terms of regional GDP.

Table 1.4 Results of the CP (RPU & AT) Method (Regional Data)

CP Method (RPU & AT)				
No	**Region**	**MAE**	**RMSE**	**DM-Test**
1	Jakarta	0,510	0,823	1,187
2	Bandung	0,499	0,715	0,693
3	Semarang	0,862	1,098	-1,224
4	Surabaya	0,548	0,723	2,002**
5	Medan	0,983	1,247	1,685*
6	Palembang	0,656	0,868	2,004**
7	Banjarmasin	0,806	1,051	4,327***
8	Bandarlampung	0,821	1,103	2,352**
9	Makassar	0,716	0,943	2,222**
10	Samarinda	0,755	1,045	3,236***
11	Denpasar	0,696	0,856	2.996***
12	Padang	0,982	1,251	1,952*
13	Pontianak	0,839	1,043	3,702***
14	Manado	1,304	1,621	1,747*
15	Mataram	0,787	1,004	2,949***
16	Pangkalpinang	1,353	1,622	1,477
17	Ambon	1,478	1,848	1,565
18	Banten	0,862	1,098	4,114***

This table compares quantifying the qualitative data using extended versions of the CP method with AT and RPU assumptions and actual inflation rate. CP is for the Carlson-Parkin, RPU stands for regime period unbiasedness, and AT stands for asymmetric threshold. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test, the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Based on the results of the regional data, we may infer that the CP methods outperforms other approaches, which aligns with the findings from the national data. When comparing the CP with AT and RPU assumptions as alternative and original CP methods as a benchmark, we identified several regions with non-significant results of the DM-test. The developed regions with steady inflation demonstrate no substantial deviation from the benchmark method. Further, applying AT and RPU assumptions in locations with high inflation volatility, particularly in the least developed areas, is ineffective. Overall, when used with AT-RPU assumptions, the CP method yields the most favourable outcomes for the Indonesian regional inflation data.

1.4.3 The Determinants of Inflation Expectations

Works of literature often assert that consumers develop expectations based on their ability, which is closely tied to their level of education (Branch 2004; Patton & Timmermann 2010). Research suggests that higher levels of education can lead to reduced NEEA IEs. Conversely, agents with lower levels of education tend to have higher IEs (Bryan & Venkatu 2001; Pfajfar & Santoro 2008; Bruine de Bruin *et al.* 2010). Further investigation of the impact of expenditure is also essential. This variable significantly influences the supply and demand of goods and services, affecting inflation and IEs (Ruge-Murcia 1999). Therefore, it is intriguing to investigate the education level and expenditure serving as indicators of the socioeconomic variables in this study.

This study specifically investigated the determinants of IEs through panel data analysis, utilising 132 time series observations across 18 regions for its observationsThe IEs data used in this analysis was derived from the CP methods, which has been found to yield superior findings compared to other methods. Two CP methods are employed: the original CP and the extended version with AT and RPU methods. The analysis utilises three explanatory variables: inflation, average years of schooling (educ), and per capita expenditure (expen). We conduct fixed-effect testing for all alternative approaches[19] using the Hausman test (Hausman 1978)[20].

[19] We also employed time fixed-effects, yielding results that are generally consistent with those obtained from the fixed-effect model presented in Table 1.5.

[20] The Hausman test is a statistical test used to determine the appropriate estimation method in panel data analysis. It assesses the unobserved effects are correlated with the independent variables in the model. In the null hypothesis the preferred model is the random effects, while the alternative hypothesis supports the application of fixed effect.

Table 1.5 The Determinant of IEs – Panel Data Analysis

CP	(1)	(2)	(3)	(4)
Inflation	0.3218***	0.2745***	0.2665***	0.2664***
Educ		-0.7551**		-0.2060
Expen			-0.0004**	-0.0003
R-squared	0.1415	0.1526	0.1539	0.1540
Hausman	0.0000	0.0000	0.0000	0.0000
CP AT&RPU	(5)	(6)	(7)	(8)
Inflation	0.3276***	0.2123***	0.2048***	0.2041***
Educ		-1.8419***		-1.2893
Expen			-0.0009***	-0.0003
R-squared	0.2072	0.3022	0.2951	0.3043
Hausman	0.0000	0.0000	0.0000	0.0000

This table displays the IEs determinant using two distinct alternative approaches, CP and CP, with assumptions of AT and RPU. CP is for the Carlson-Parkin, RPU stands for regime period unbiasedness, and AT stands for asymmetric threshold. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. In models 1 through 4 the standard CP method was utilized, while models 5 through 8 employed the CP method with assumptions of AT and RPU. In column 1 (models 1 and 5), the variable used is the inflation rate. In column 2 (models 2 and 6), the variables used are the Inflation and Educ. In column 3 (models 3 and 7), the variables used are Inflation and Expen. In column 4 (models 4 and 8), the variables used are Inflation, Educ, and Expen. Educ is Education; Expen refers to expenditure.

Based on the results from Table 1.5, from models 1 and 5, it is evident that the increase in inflation has a statistically significant effect on increasing IEs in all methods when no other variables are included in the equation. Including education variables in the equation demonstrates that inflation continues to have a statistically significant effect on IEs. However, this effect decreases in both the CP method (model 2) and its extended version (model 6). In both methods, it is observed that increasing education leads to a decrease in IEs. When inflation and per capita expenditure are included in the equation, as in models 3 and 7, inflation continues to have a similar influence. Increasing per capita expenditure had a statistically significant effect on decreasing IEs. When examining the equation that includes inflation, education, and expenditure as independent variables, as in models 4 and 8, it is evident that increased inflation statistically significantly affects rising IEs. Individually, education and expenditure were statistically insignificant, but they jointly significantly impacted IEs[21]. The potential reason for the outcome is a multicollinearity issue, which suggests a correlation between the education and expenditure variables.

Overall, the findings demonstrate that increasing inflation statistically impacts increasing NEEA IEs. This aligns with previous studies with similar results (Lyziak 2003; Mestre 2007). Increasing the education level tends to decrease IEs; as the education level rises,

[21] The education and expenditure are jointly significant at a 95% confidence level using original CP method (model 4 of Table 1.5) and jointly significant at a 99.9% level of confidence using extended version of CP method with AT & RPU assumptions (model 8 of Table 1.5).

economic agents' literacy will improve, leading to a greater understanding of economic concepts and an enhanced ability to make accurate predictions, resulting in decreased IEs. Higher levels of education will also lead to increased production and innovation. This circumstance will affect efficiency and increase the supply of goods and services, leading to a decrease in prices and impacting the decreasing IEs. The impact of education on IEs is similar to the findings of Bryan and Venkatu (2001), Pfajfar and Santoro (2008), and Bruine de Bruin *et al.* (2010). This condition could account for the phenomenon where regions with a relatively greater level of education tend to have relatively lower IEs. Similarly, increasing per capita expenditure has an impact on decreased IEs. The possible explanation for this could be that an increase in per capita expenditure impacts the infrastructure condition, increasing the supply of goods and services. Raising per capita expenditure also has the potential to enhance production capacity and improve production efficiency. As the supply of products and services increases, prices generally decrease, affecting a decrease in IEs. The results also highlight the correlation between regions with higher per capita expenditure and lower IEs. However, there is a collinearity between the education and expenditure variables[22], meaning that as the education level increases, there is a high association with an increase in expenditure. The explanation may be attributed to the positive correlation between higher education levels and the potential to attain higher income. Higher income is likely to result in an increase in the spending pattern. This can help interpret the correlation between regions with higher education levels and per capita expenditure.

1.4.4 Robustness Checks

Harvey, Leybourne, and Newbold (HLN) Test

In addition to the DM-test, this work employs the Harvey, Leybourne, and Newbold test (Harvey *et al.* 1997) as a robustness check. This alternative approach to the DM-test is used to assess the reliability and consistency of the test results.

Table 1.6 demonstrates that the Harvey, Leybourne, and Newbold test (HLN-test hereafter) outcome aligns with the DM-test outcome, with the CP with AT and RPU approach yielding the most favourable result. We find that the DM-test result is more conservative than the HLN-test.

[22] The correlation coefficient between education and expenditure variables is 0.61.

Table 1.6 Comparison of DM and HLN test (National Data)

No	Methods	DM-Test	HLN-Test
1	BA Method	-4.11***	-4.39***
2	BA Method (RPU)	-1.14	-1.21
3	BA Method (STU)	-1.04	-1.11
4	CP Method (STU)	1.31	1.40
5	CP Method (RPU)	1.09	1.17
6	CP Method (AT)	1.67*	1.78*
7	CP Method (RPU & AT)	2.07**	2.21**
8	Reg Method	-2.96***	-3.17***
9	Reg Method (RPU)	0.67	0.72

This table presents the comparative outcome of the DM and HLN tests. Nine alternative methods are used alongside the CP method as the benchmark. BA stands for Balanced Approach; CP is for the Carlson-Parkin; Reg is Regression; RPU stands for regime period unbiasedness; STU stands for short-term period unbiasedness; and AT stands for asymmetric threshold. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test; HLN-test is the Harvey, Leybourne, and Newbold test; the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Different Period of Regime-Period Unbiasedness.

In terms of robustness checks, this subsection additionally attempted to utilise different periods of RPU, prolonging the shock period to the conclusion of 2015. Upon analysing the outcomes over an extended duration, as specified in Table 1.7, there is no significant discrepancy in the conclusion compared to the earlier periods, as shown in Table 1.2.

Table 1.7 Results of the CP RPU (extended) method (National Data)

No	Methods	MAE	RMSE	DM-Test
1	CP Method (RPU)	0.71	0.97	1.07
2	CP Method (RPU & AT)	0.61	0.83	2.09**

This table compares quantifying the qualitative data using the extended versions of the CP method, employing RPU assumptions, with the actual inflation rate. CP is for the Carlson-Parkin; RPU stands for regime period unbiasedness; AT stands for asymmetric threshold. Three stars (***) = P<0.01, two stars (**) = P<0.05, and one star (*) = P<0.1. The DM-Test is the Diebold-Mariano test, the standard CP is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable. The robustness evaluations utilising more extended shock periods are exclusively conducted using national data.

1.5. Discussions

The study's primary objective was to investigate the most effective methods for quantifying qualitative data using national and regional data from developing countries with volatile inflation conditions. Various methodological approaches were used to quantify qualitative data. This study also examined the factors that influence IEs from a socioeconomic standpoint using panel data analysis incorporating socioeconomic variables. We employed the national and 18 regional datasets from the consumer survey in Indonesia conducted by Bank Indonesia, the central bank of Indonesia, from January 2009 to December 2019.

This study found that the CP methods outperform BA and regression methods, where the extended version of CP with AT and RPU assumptions yielded superior outcomes. The regional comparison indicates that the CP with AT and RPU give satisfactory outcomes for most regions in Indonesia. In the developed region with low volatility, statistically, there is no difference between the standard CP and CP with AT and RPU assumptions. In regards to gaining a deeper understanding of the determinants of IEs using socioeconomic factors, the study incorporates inflation, education, and expenditure variables as explanatory variables to identify the determinants of the IEs. We found that education and expenditure influence NEEA IEs. However, when these two variables are combined, the results appear insignificant, suggesting a collinearity between the education and expenditure variables.

The quantification of qualitative data using national and regional data shows that Indonesia's economic agents better fit the CP methods with AT and RPU assumptions. The result indicates that Indonesia's economic agents have a separate parameter view between normal and shock conditions. An explanation for this might be Indonesia's volatile nature, making economic agents shift their expectations when a shock occurs. This result is in line with Sloman *et al.* (2018), who stated that the shocks' condition changes the way of thinking since economic agents frame their understanding of the situation. The better fit with the RPU also indicates that economic agents do not update the information regularly, similar to the findings of Carroll (2003).

While this paper has made positive contributions, there is still room for improvement for future research. Utilising a microdata survey could be advantageous for analysing the behaviour of individual economic agents. The least-developed regions with relatively higher volatility showed that the CP method with AT and RPU assumptions is not statistically superior to the original CP method; exploring the best method in this region could be relevant for future research.

Based on this study's results, it is generally determined that using the CP method with the assumptions of AT and RPU can be advantageous for quantifying qualitative data in the context of relatively volatile inflation data. The findings of this study could be advantageous for policymakers in determining effective strategies for assessing NEEA IEs using qualitative survey data to enhance their policies' effectiveness.

1.6. Summary and Conclusion

IEs are a crucial factor for policymakers, serving as a significant component in their policy decisions. Most NEEA IEs data were obtained via the survey that provided qualitative information. Therefore, it is valuable to obtain a quantitative representation of this data.

Given the significance of this subject and the existing lack of research, particularly regarding the volatile inflation situation, the main aim of this study was to investigate the most effective methods for quantifying qualitative data in volatile conditions. Furthermore, we examined the determinants of the NEEA IEs by incorporating the socioeconomic variables. The study found that utilising the CP method, incorporating AT and RPU assumptions, is the most effective approach for quantifying qualitative data in a dataset that exhibits significant volatility. This study also discovered that socioeconomic variables are crucial in shaping NEEA IEs.

The results of this study suggest that the method used to quantify qualitative data effectively depends on the data's characteristics. Economic agents in the context of relatively volatile inflation exhibit distinct perspectives under stable and shock periods. There is still room for improvement in future research; further enhancements can be made to examine the utilisation of microdata and explore the methods in the least-developed regions with relatively higher volatility. The results of this study provide policymakers with a more comprehensive grasp of the NEEA IEs. The study contributes to our comprehension of the process of selecting the most effective methods for quantifying qualitative data, which is contingent upon the specific characteristics of the data. This study examined regional data, contributing to comprehending how socioeconomic variables affect IEs across regions. Enhancing the education level is crucial for boosting economic literacy, resulting in decreasing NEEA IEs. Together, the results of this study give valuable insight to policymakers that could be beneficial in implementing effective policies.

Chapter II

Understanding Non-Expert Economic Agents' Inflation Expectations Through Near Real-Time Data

We examine news articles as an alternative data source for measuring non-expert economic agents' inflation expectations (NEEA IEs) and as alternative tools to predict inflation using news articles written in Bahasa Indonesia. We utilise news articles to mimic consumer surveys and measure NEEA IEs. We apply supervised and semi-supervised learning of Natural Language Processing (NLP) to explore the value of information included in news articles. The Support Vector Classifier in supervised learning and a bespoke dictionary with fewer and more essential words in semi-supervised learning yielded superior outcomes. To achieve the optimal transformation of NLP outcomes, we employ a variety of comparison approaches, including keyword analysis, examination of article titles and bodies, and consideration of forecast horizons. We discover that news articles can provide substantial information that can be used as an alternative source of traditional NEEA IEs data and inflation forecasts, particularly for the combination of 75% keyword inflation and 25% keyword price, 25% title and 75% body of articles, and a 6-month forecast horizon.

2.1 Introduction

Prior studies have emphasised the importance of inflation expectations (IEs hereafter) in macroeconomics (Mankiw & Reis 2002; Carroll 2003). The primary method employed in academic research to measure economic agents' IEs, particularly non-expert economic agents (NEEA hereafter), is through survey data. Regrettably, the survey data are constrained due to their high cost and require significant collection time. Increasingly vast quantities of unstructured data, such as text, are generated and can be a relatively new opportunity to access in near real-time that also encompasses valuable information regarding NEEA IEs. However, this unstructured data has not been extensively employed to understand NEEA IEs. The expansion of machine learning and big data analytics enables the extraction of extremely valuable IEs from unstructured data. Varian (2014), Gentzkow *et al.* (2019), and Jarmin (2019) highlight the significance of text as an unstructured data source for obtaining information. According to Carroll (2003), news articles significantly impact the NEEA IEs and serve as a critical source of information. Hence, employing a specific methodology to convert the news articles to acquire essential data regarding IEs is vital. Nevertheless, limited research has been conducted on news articles regarding IEs. With this objective in mind, this study seeks to extract valuable data from news articles to mimic consumer surveys, serving as a proxy and representation NEEA IEs.

Natural Language Processing (NLP hereafter) is a technique that may convert textual information from news articles into valuable insights. NLP is a branch of machine learning that uses computational methods to effectively collect and analyse unstructured data from textual sources to manage natural language (Greene 2008; Collobert *et al.* 2011). The three primary learning methods used to evaluate information in textual data in NLP are supervised, unsupervised, and semi-supervised. Supervised learning requires researchers to label each desired output manually. Unsupervised learning is a method that detects textual characteristics without using labels. Semi-supervised learning is a method that involves some limited manual labelling in the process. The Support Vector Classifier (SVC hereafter) and Naive Bayes are commonly used models in supervised learning, topic modelling in unsupervised learning, and a dictionary-based method in semi-supervised learning. The research purpose determines the various learning strategies used in the literature (Jurafsky & Martin 2009).

NLP has had limited application in economics compared to its potential, but it is a growing research area. The study by Hansen *et al.* (2018) is the inaugural economic publication that employs topic modelling to analyse the effects of the Federal Open Market

Committee (FOMC). Similarly, Gentzkow *et al.* (2019) analysed the speeches made by members of the US Congress in order to gauge the issues that Congress is focused on, employing topic modelling. Larsen and Thorsrud (2019) analyse the subject matter of news in Norway in order to create a comprehensive news index. Jiao *et al.* (2020) researched economic agents' actions by analysing news and social media sentiment. Although an increasing number of studies in economics have incorporated NLP into their approach, there has been limited focus on converting it into economic agents' IEs that can serve as valuable inputs for policymakers. Within the scarce body of literature, Angelico *et al.* (2022) conducted a study that examined the economic agents' IEs using NLP. They employed Italian tweets to apply a dictionary-based method with topic modelling to identify the economic agents' IEs. The study discovered that textual data from Twitter could serve as an alternate means of representing the economic agents' IEs. While the previous study incorporated NLP to analyse textual data to represent economic agents' IEs, there is still a lack of understanding regarding the efficacy of news articles on these expectations. As noted by Conrad *et al.* (2022) and Gardt *et al.* (2022), NEEA continue to rely on conventional media, such as news articles, for information concerning inflation. For this reason, it is imperative to use news articles to measure NEEA IEs.

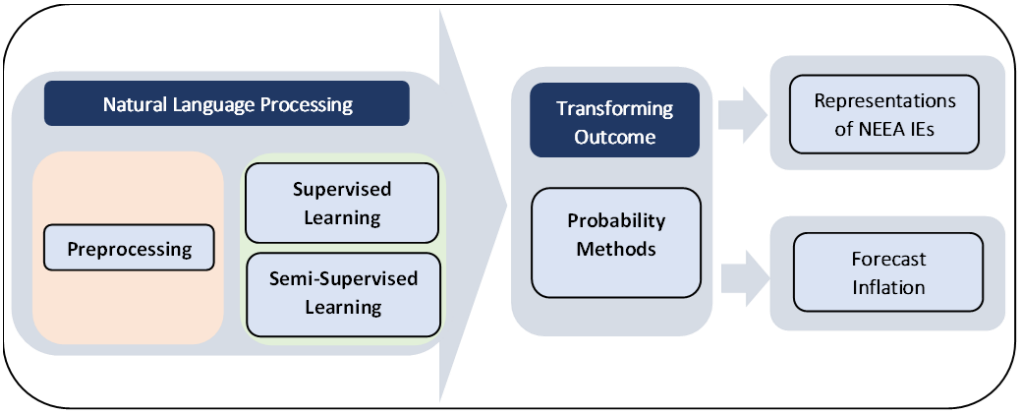
Since there is a gap in the literature, this study seeks to address three main objectives. The first objective is to determine the most effective techniques for collecting useful information from news articles. The second objective is to transform this information to measure NEEA IEs. The third objective is to investigate the influence of the various components of news articles, including the title, body, and keywords.

This paper makes five valuable contributions to the existing body of literature. First, to our knowledge, this is the first study to employ news articles to model NEEA IEs using supervised learning. Second, this study examines the optimal approach to collecting valuable information from news articles using four supervised learning and two semi-supervised learning, as similar works to investigate this remain limited. Third, by using the dictionary-based method as one of the approaches, this study adds to the body of literature by developing a dictionary that can be used to represent NEEA IEs. Fourth, this research evaluates the relative importance of news article titles and bodies and the NEEA IEs' associate keywords. This analysis's results help clarify the roles played by the title, body, and main keywords in news articles, as well as in measuring NEEA IEs and forecasting inflation. Fifth, this study uses the extracted information to predict inflation across four forecast horizons: one-month, three-months, six-months, and twelve-months. This investigation can

augment the current literature by offering an alternative approach to predicting inflation using near real-time data and provide a more comprehensive grasp of the most representative forecast horizons.

The primary dataset to address the study objectives consists of published news articles written in Bahasa Indonesia from January 2009 to December 2018. This study utilises the primary keywords "*inflasi*" (inflation) and "*harga*" (price) to refine the relevant data related to IEs[23]. Once we have the required data, as depicted in Figure 2.1, we apply NLP techniques and utilise the probability method to transform the outcome.

Figure 2.1 General Framework



This figure illustrates the general framework processes of the research. The study's primary approach involves applying NLP and data transformation.

In the initial stage, we use preprocessing techniques to ensure high-quality and optimal data representations via feature selection. The preprocessing procedures for feature selection are normalisation, removal of stop words, and Term Frequency-Inverse Document Frequency (TF-IDF hereafter). The NLP methods used in the study are supervised learning and semi-supervised learning. Supervised learning requires an analyst to label news articles based on specific categories needed for the study. The chosen number of classes corresponds to the consumer survey in Indonesia, which are: increase, stay the same, and decrease classifications. This study explores four supervised learning models: SVC, Naive Bayes, K-Nearest Neighbors (KNN hereafter), and Decision Trees, to provide an effective approach and achieve optimal outcomes from supervised learning. The model that is employed for semi-supervised learning is dictionary-based. We compare two dictionaries and construct the bespoke dictionary in the dictionary-based method. Subsequently, we analyse the impact of information on NEEA IEs by independently examining the title and body of articles. In order to get the representations of NEEA IEs data, this research applies the

[23] The main keywords to filter the news articles is "*inflasi*" (inflation). The remaining news articles that do not contain the main keyword are filtered using the keyword "*harga*" (price).

probability method of the Carlson-Parkin (CP hereafter) method and its extended version to modify the NLP results[24]. We apply a comparative analysis of four different forecast horizons: one month, three months, six months, and twelve months.

We can extract valuable information from news articles regarding NEEA IEs. The NLP analysis reveals that the SVC in supervised learning outperforms the other models in terms of the commonly used metrics: accuracy and F1 score[25]. The implementation of the semi-supervised learning of the dictionary-based method showed that the bespoke dictionary with fewer words is more effective in revealing the signal of information from news articles, probably due to this dictionary's focus on essential words. The application of the transformation of NLP results shows that the extended version of the CP methods yields the most optimal results in terms of forecasting. The results also indicate that optimal performance is achieved when 25% of the weight is given to the title and 75% to the bodies of the news articles. The research outcomes also indicate that both keywords utilised in this study demonstrate encouraging outcomes, particularly the combination of 75% of the keyword "*inflasi*" (inflation) and 25% of the keyword "*harga*" (price). The news articles with the keyword "*inflasi*" (inflation) may also include the keyword "*harga*" (price), but not vice versa, which could make the keyword "*inflasi*" (inflation) more complete information. Applying the transformation of CP methods with the extended version demonstrates that the six-month forecast horizons yield the most optimal results. The study demonstrated that news articles can represent NEEA IEs in near real-time and serve as an alternative tool for predicting inflation. While the consumer survey demonstrated a slightly superior performance in predicting inflation, the findings of the forecast-encompassing test indicated that the consumer survey does not encompass the NLP forecast results, indicating that the NLP result can provide information on top of the survey results. Accordingly, we believe this research will provide innovative insights and enhance the conceptual understanding of various approaches to analysing IEs. Capturing near real-time data of NEEA IEs will support policymakers in enhancing the input for their policies.

This study has been organized in the following way. Section two explores the literature. Section three presents the data used in the paper. Then, Section four explains the methodology used for this study. The fifth and sixth sections provide the empirical results

[24] The further explanation in subsection 1.3.2.2.

[25] The performance metrics consists of accuracy and F1 score. Accurracy is a measure of the correct prediction from all the samples used, while F1 score is a measure of the harmonic mean between the precision (output that are predicted as positive) and recall (output that are actually positive).

and discussion of the research analysis, respectively. Finally, the summary and conclusion of this study are presented in Section seven.

2.2 Literature Review

The data on the NEEA IEs is primarily obtained through a survey. Unfortunately, conducting a survey as a primary source of NEEA IEs has several limitations. One of the survey's drawbacks is the limited data collection frequency. Another challenging problem in conducting a survey is its high cost since it requires many human resources to support it (Cavallo & Rigobon 2016). Traditional surveys also have nonresponse challenges (Groves 2011). Given these, alternative methods for identifying NEEA IEs are worth exploring. Regrettably, the literature has not considered using an alternative data source sufficiently. On the other hand, increasing amounts of unstructured data generated and accessible in near real-time offer a relatively new opportunity as an alternative data source for NEEA IEs.

As unstructured data, text can serve as a valuable alternative source for investigating NEEA IEs in the current digital age. The text's main advantage as an alternative data source lies in its ability to encompass a wide range of extensive, varied, and generated data regularly. This vast volume of textual data also includes valuable information about NEEA IEs that may be analysed in near real-time. Varian (2014), Gentzkow *et al.* (2019), and Jarmin (2019) highlight the significance of the text as a valuable information source in the digital age.

The literature also pays particular attention to the correlation between IEs and the information derived from the text. Carroll (2003) conducted a study using surveys and the quantity of inflation news to examine how information from news articles affects NEEA IEs. The study found that the news articles impacted NEEA IEs. Similarly, Ehrmann et al. (2017) underscored the significance of providing information on IEs through disseminating news relevant to inflation. They found that those who lack knowledge of economics tend to make high inflation forecasts. According to Baumeister *et al.* (2001), individuals tend to have stronger emotional responses to negative news than positive news, which aligns with the findings of Kahneman and Tversky's (1979) prospect theory. This is explained by the occurrence of an economic shock, which then leads to an upsurge in the dissemination of adverse news through various media channels. Angelico *et al.* (2022) found that using text data from Twitter can serve as an alternative way to portray the economic agents' IEs. All of the studies provided here recognise that information impacts IEs. However, the researchers are still limited in exploring the textual content of news articles for analysing IEs. Given the

significance of news articles as a valuable data source, converting them to extract valuable information regarding IEs is essential.

Advancements in computer science and big data analytics have enabled text data to provide nearly real-time analysis through the application of NLP. NLP is a machine-learning technique involving analysing and understanding human language. It combines computer science, linguistics, and mathematics to achieve this goal (Jurafsky & Martin 2009). According to Collobert *et al.* (2011) and Green (2012), employing NLP as a methodology allows for examining textual data patterns to assess the content of useful information, including investigating IEs. As computer science progresses, a growing body of literature implements NLP as an approach and develops various learning methods.

In NLP, the common approaches for analysing textual data information are supervised, unsupervised, and semi-supervised. In supervised learning, it is necessary to provide manual labels for each desired output by the researcher. Conversely, the unsupervised learning technique classifies textual features without explicitly assigning labels to them; instead, labelling is done based on the topic created by the model. This technique detects concealed functional patterns within extensive textual data (Evans & Aceves 2016). In addition, semi-supervised learning is a technique that limits manual labelling in the process. The selection of the learning approach is contingent upon the objective of the research (Jurafsky & Martin 2009).

In the context of supervised learning, researchers commonly used a range of techniques, with Naive Bayes and SVC being the most commonly applied methods (Lee *et al.* 2018). The Naive Bayes method utilises probability-based techniques and incorporates the naive conditional assumption, which assumes that all features in the model are independent. Vapnik (1998) introduced the SVC model, which is well-suited for data where a margin classifier can effectively distinguish the dataset based on the desired categorisation. Margin classifiers attempt to separate the categories in the dataset by drawing a boundary line. The margin classifier is the dividing boundary that maximises the distance between groups. This technique can nevertheless generate exceptional results in datasets with a large number of features, even in cases where the data is not evenly distributed. SVC has demonstrated encouraging outcomes in text classification, as evidenced by studies conducted by Joachims (2012) and Aletras *et al.* (2016). In addition, KNN and Decision Trees are commonly employed models in supervised learning of NLP. KNN is a classification model that categorises data by identifying the nearest point to the test data. It was first introduced by Fix and Hodges (1989). The KNN model exhibits strong learning capabilities when dealing with data that has highly

flexible boundaries and can adapt seamlessly to new data. However, when working with higher dimensional data, the KNN model's complexity increases, resulting in longer processing times. Decision trees utilise classification labels as leaves and features as branches for clustered datasets. This approach was pioneered by Morgan and Sonquist (1963). Decision trees possess adaptability when dealing with datasets that exhibit nonlinear properties (Varian 2014). Nevertheless, employing this method in datasets with a large number of dimensions can result in overfitting. Supervised learning encompasses a diverse range of models with their benefits and drawbacks. Grimmer and Stewart (2013) state that no all-encompassing model can accurately accommodate various datasets. Consequently, researchers often assess numerous supervised learning models in NLP during their studies. Out of all the models previously discussed, the classification of textual data with a large number of features and unbalanced data is likely to yield good results when employing SVC, as discovered by Joachims (2012), Bajari *et al.* (2015), and Aletras *et al.* (2016). Therefore, in order to identify the optimal model, this study will utilise the SVC model as a benchmark and compare it to other models.

Unsupervised learning commonly uses topic modelling as the learning model, as demonstrated by Hansen *et al.* (2018), Gentzkow *et al.* (2019), and Larsen and Thorsrud (2019). Researchers have determined the specific number of topics they want to investigate using this method. Topic modelling categorises themes by considering the number of topics and the frequently occurring terms within each category. Labelling is performed on the topic groups created by the model in this technique. The Latent Dirichlet Allocation (LDA) method, introduced by Blei *et al.* (2003), is a widely used tool for topic modelling. Unsupervised learning provides a valuable perspective for categorising topics and uncovering unknown data. However, these learning methods are not particularly useful when the researcher already has a predetermined number of classification categories since it could generate ambiguous and overlapped topics (Jurafsky & Martin 2009).

Moreover, most studies on semi-supervised learning have conducted sentiment analysis using the dictionary-based method. This strategy initially collects essential words that are represented in the categorisation category. Furthermore, a score is assigned to each word in the collection of words, leading to a cumulative sentiment score for each dataset. The approach was first introduced by Stone *et al.* (1966), and its use has subsequently expanded (Evans & Aceves 2016). For instance, it is employed to classify the sentiment in news articles, as demonstrated by the work of Eshbaugh-Soha (2010), Baker *et al.* (2016), and Calomiris and Mamaysky (2019). Sentiment analysis is a prevalent technique used in

semi-supervised learning methods. It effectively categorises data by assigning sentiment scores, enabling automated documents into different categories.

The utilisation of NLP analysis has grown in numerous fields due to the progress in computer science and the enhancement of learning models in recent years. Within the field of economics, an increasing number of studies have employed NLP as a methodology. The study by Hansen *et al.* (2018) is the inaugural economic publication that employed topic modelling to investigate the impact of the Federal Open Market Committee (FOMC). Gentzkow *et al.* (2019) employed topic modelling to analyse the discourse in the US Congress in order to ascertain the main concerns of Congress. Larsen and Thorsrud (2019) utilised unsupervised learning to examine the news themes in Norway and generate a comprehensive news index. Jiao *et al.* (2020) utilised sentiment analysis of news and social media to investigate the actions of economic agents. Angelico *et al.* (2022) performed a study that investigated the economic agents' IEs using NLP. The study used Italian tweets to implement a dictionary-based method with topic modelling to identify the economic agents' IEs. They found that using text data from Twitter might be used as an alternative way to portray the economic agents' IEs. Nevertheless, the application of NLP in investigating IEs utilising news articles remains limited.

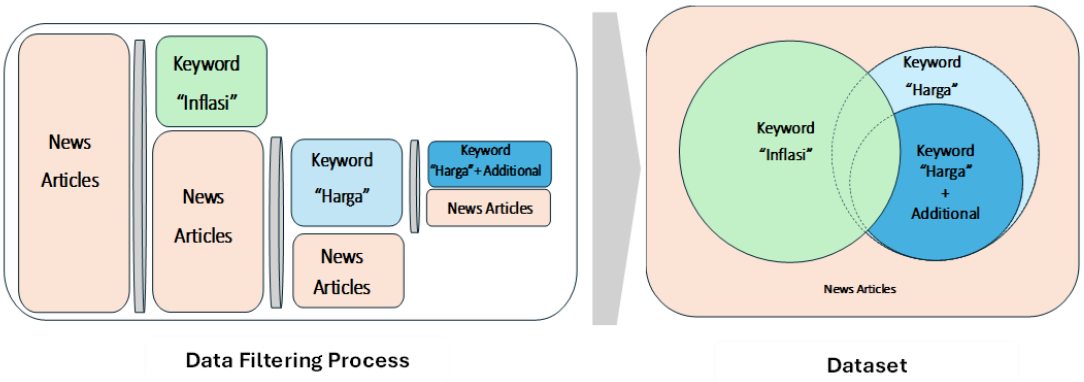
In summary, it has been shown from this review that with the rise of textual data from news articles and the advancement of computer science, it is more important than ever to investigate the predictive potential of news articles to analyse NEEA IEs. Thus, this study aims to contribute to the existing literature by examining NEEA IEs through news articles using NLP techniques. Utilising NLP approaches to analyse news articles offers clear benefits in terms of cost, availability, and frequency compared to traditional surveys. This research examines NEEA IEs by employing various models in supervised learning and sentiment analysis of dictionary-based. The data utilised in this investigation is from news articles written in Bahasa Indonesia. This study employs Bahasa Indonesia, as Indonesia has unique characteristics, and the literature on this language is limited despite its widespread usage among hundreds of millions of economic agents (Hirschberg & Manning 2015). The result can serve as an alternative method for evaluating the NEEA IEs. It can provide critical information for policymakers to produce effective decision-making processes based on near real-time data.

2.3 Data

We employ Indonesian economic news articles from the BI Cyberlibrary archives written in Bahasa Indonesia from January 2009 to December 2018. The published news articles are

obtained from ten reputable Indonesian news outlets, all of which have extensive national coverage and cover economic news, amongst other things. A filtering process was employed to identify articles that reflect IEs using specific keywords to narrow down from 224,747 news articles. The initial filter employs the main keyword "*inflasi*" (inflation). After applying the initial filter, we found that 3,797 articles include the keyword "*inflasi*" (inflation) in their titles, and 20,900 articles contain it in their body, as shown by the green colour in Figure 2.2. To create an alternative dataset, a second filter is applied to the remaining news articles that do not contain the main keyword "*inflasi*" (inflation). This filter uses the keyword "*harga*" (price) in the title to narrow the selection further. After implementing this filter, 46,702 articles were found, as indicated by the light blue colour in Figure 2.2. For the third filter, we implemented an additional keyword for "*harga*" (price) because a single word or unigram may have a broad meaning and can appear in articles unrelated to IEs. The extra keywords[26] we have introduced for this step include: *minyak/gas/BBM/listrik* (oil/gas/fuel/electricity); *emas* (gold); *beras* (rice); *sayuran* (vegetable); *rumah* (house); *gula* (sugar); *daging* (beef); *cabai* (chilli); *bawang* (onion); *pangan/sembako/kebutuhan pokok/bahan pokok* (food/staples food). After applying the third filtering, the resulting output consists of 10,593 articles; the dark blue colour in Figure 2.2 represents this.

Figure 2.2 Data Filtering Process



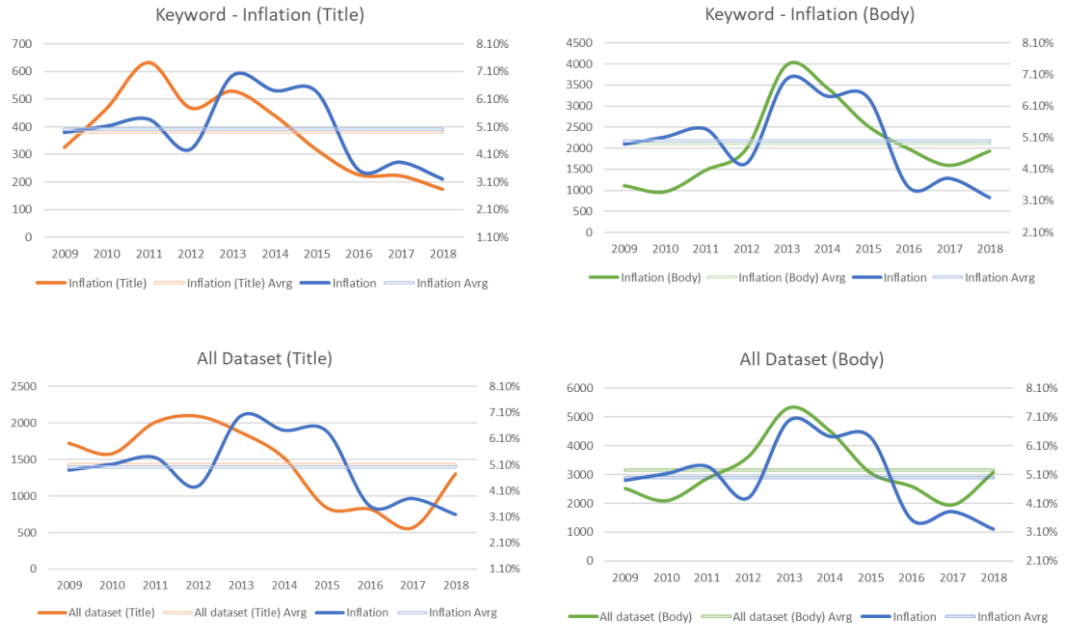
This figure illustrates the process of data filtering. The colour grey represents the filtering procedure, which involves three data filtering steps in this study. The green colour represents the dataset obtained from the first filter. The light blue colour represents the dataset resulting from the second filtering phase. The dark blue colour represents the dataset from the third filter. The dataset utilised in this study consists of two datasets. The first dataset, represented by green, consists of the main keyword "*inflasi*". The second dataset, represented by the dark blue colour, is associated with the keyword "*harga*" along with additional keywords.

In the annual data in Figure 2.3, the combined count of inflation articles (including both body and title) in 2013 and 2014 exceeded the average. During that period, the quantity

[26] We employed these keywords due to the significant contribution of the commodities they represent to the inflation rate in Indonesia.

of articles shadowed Indonesia's actual inflation rate. The Indonesian inflation rate over those years can be attributed to two major events: the taper tantrum and the Indonesian election. The correlation between the quantity of articles about inflation (in the title and body) and the actual inflation rate are 0.64 and 0.62, respectively. When we compute the correlation between all datasets and actual inflation, the correlation of the title declines to 0.33, while the correlation of the body remains reasonably consistent at 0.64.

Figure 2.3 Yearly Data Distribution



This figure displays the annual distribution of the datasets employed in this study in relation to the annual inflation rate. The annual mean values for the aggregate news articles on inflation (title), inflation (body), all dataset (title) and all dataset (body) are 380, 2102,1433, and 3155, respectively. The average inflation rate is 5.00%.

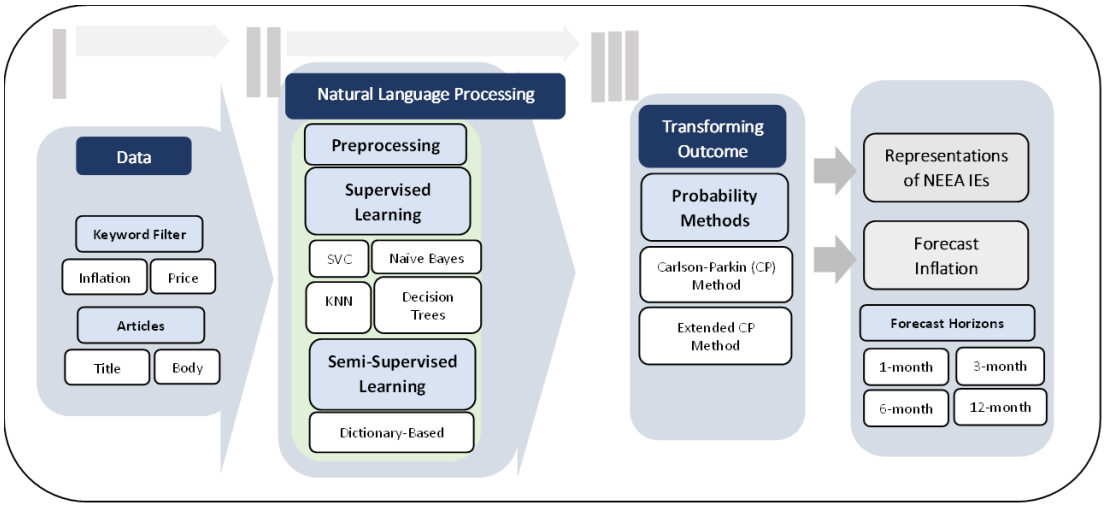
This research also examined Indonesia's inflation and consumer survey data from January 2019 to December 2018. The inflation rate data is the monthly actual inflation rate on a year-on-year (YoY) obtained from the Statistical Bureau of Indonesia. The consumer survey in Indonesia, conducted monthly, was obtained by Bank Indonesia, the central bank of Indonesia.

2.4 Methodology

We employ a series of phases, including applying NLP techniques and transforming these outcomes into NEEA IEs. Figure 2.4 illustrates the research framework, which utilises multiple steps to accomplish the study's objectives. The initial phase involves selecting articles that are linked using the keywords "*inflasi*" (inflation) and "*harga*" (price) as a filter. Subsequently, we generate datasets that include the keywords in the title and the body of the news articles.

The subsequent phase involves the application of NLP to convert textual data into valuable information about NEEA IEs[27]. To ensure high data quality and lower computing costs, it is essential to decrease the dimensionality of features and obtain an appropriate data representation during the preprocessing stage. This preprocessing includes normalisation, removing stop words, and TF-IDF.

Figure 2.4 The Framework of The Research



This figure depicts the procedural phases involved in the research.

As a next step, this research employs four widely used supervised learning models: SVC, Naïve Bayes, KNN, and Decision Trees; and semi-supervised learning using dictionary-based methods. The last step is transforming NLP by mimicking consumer surveys into IEs using two probability of CP methods: the original CP method and the extended version. We compare the outcomes with actual inflation data utilising four distinct horizons, 1, 3, 6, and 12 months ahead, as also implemented by Boero and Lampis (2017). The transformation outcome is important in representing the NEEA IEs data and forecasting inflation.

This section will provide a more detailed explanation of the approach used in NLP and the methods used to transform the outcomes of NLP.

2.4.1 Natural Language Processing

2.4.1.1 Pre-processing

The preprocessing step seeks to enhance the performance of the data by removing extraneous aspects and transforming the text into a legible format. This study will employ

[27] Survey data is the main source data used in academic research to collect NEEA IEs. Unfortunately, the survey data is limited because of its high cost and require significant time to collect.

several preprocessing techniques to reduce the word list, including normalisation, stop word removal, and implementing TF-IDF[28].

The initial preprocessing stage[29] is normalisation, which entails converting capital letters to lowercase, eliminating hyphens, and removing punctuation marks, decreasing the dimensionality of features in the dataset. Next, we eliminate stop words, commonly used for inconsequential terms in the corpus that do not provide relevant information for IEs. For instance, the words "*bagi*" (for), "*lalu*" (then), and "*kalau*" (if) are included in the stop word lists. The subsequent procedure employed to alter the vector involves TF-IDF, which calculates a word's informativeness score (Singhal 2001; Blei & Lafferty 2009; Hansen *et al.* 2018). TF-IDF is computed by multiplying two statistical measures of the feature, namely TF (Term Frequency) and IDF (Inverse Document Frequency). TF is a term frequently used in a text to highlight the significance of a certain word. DF measures whether a common term is used in numerous documents and hence lacks document substance (Singhal 2001). A high TF-IDF score signifies that the words significantly contribute, enhancing the model's classification capability. Conversely, a low score indicates that the word does not make a meaningful impact in distinguishing the model, and this low score is derived from either a low term frequency (TF) or inverse document frequency (IDF) score. The low term frequency (TF) score indicates that the word with the smallest occurrence has a negligible impact on the model. The low IDF score suggests that the word is commonly used across multiple articles. Therefore, adjusting the vector using TF-IDF is done in order to identify significant features, with the formula as follows:

$$tfidf = tf_j \; x \; df_j \tag{2.1}$$

$$tf_j = n_j \tag{2.2}$$

$$df_j = \log\left(\frac{A}{A_j}\right) \tag{2.3}$$

where n_j is the number of term j in the articles , $\sum_{j=1}^{m} w_{ij}$; A is the total number of articles, $\sum_{i=1}^{n} x_i$; A_j is total articles where term j appears, $\sum_{i=1}^{n} I\,(w_{ij} > 0)$.

[28] Although advanced techniques such as embeddings are available, this research did not apply them, opting instead for the method used in this study due to several advantages. Specifically relatively easy to implement, widely used in the literature, and faster to process without requiring special hardware. While state-of-the-art methodologies like embeddings are indeed powerful, the implementation was beyond the scope of this research due to the resource constraint. Their application could offer valuable insights and should be considered in future studies.

[29] In the preprocessing stage, we reduced the dimensionality of the features within the dataset. For instance, during the normalisation process, the terms “Inflation” (with capital letter), “inflation” (lowercase), and “inflation.” (followed by a punctuation mark) would be treated as three distinct features. Trough normalisation, the variations can be standardised into single term “inflation”, consolidating them into one feature.

The preprocessing step provides representative data for implementation using NLP. After preprocessing steps, this study utilises two learning methodologies: supervised and semi-supervised.

2.4.1.2 Supervised Learning

This research employs four supervised learning models: SVC, Naïve Bayes, KNN, and Decision Trees. In order to optimise the outcomes of the comparison approaches, we employ multiple performance indicators to determine the most suitable supervised learning approach to introduce with the given datasets. In the context of NLP, supervised learning refers to the methodology of leveraging labelled features extracted from training data to make predictions on labels using test data. The supervised learning approach consists of several essential steps (Grimmer & Stewart, 2013). Initially, the dataset will be constructed by manually annotating data. Next, the training data will be used to train the supervised learning model, creating a prediction model that is subsequently applied to the test data. The next step is to verify the accuracy of the model's output. The minimal number of documents required for supervised learning is not universally agreed upon, while Hopkins *et al.* (2010) suggest that a minimum of five hundred is acceptable[30].

To ensure the comprehensiveness of the outcome analysis, we conducted a separate examination of the title and body of the news articles. By doing a distinct analysis of the title and body of the articles, we can gain valuable insights into the main factors to measure NEEA IEs. A news article typically comprises a title and body, which can be represented as:

$$x_i = \{t_i, b_i\} \tag{2.4}$$

where t_i is the title of the article x_i; b_i is the body of the article x_i, the analysis of IEs from the news articles in this research will compare the analysis of the t_i and b_i separately, to help clarify the roles played by the title and body.

Furthermore, each article possesses a distinct classification pertaining to IEs. In the context of supervised learning, the process of classifying articles involves manual labelling. The procedure of assigning labels to articles is conducted by researchers who utilise their opinions and judgements to select the appropriate category for each article[31]. Human manual labelling reflects the cognitive expectations of agents when reading a news article. The categorisation can be expressed in the following manner:

$$Y = \{y_1, y_2, \dots, y_k\} \tag{2.5}$$

[30] The training data utilised in this research significantly exceeds the minimum requirement. The dataset for the keyword "*inflasi*" (inflation) in the title is 2,531; keyword "*inflasi*" (inflation) in the body is 13,933; and keyword "*harga*" (price) is 7,062.

[31] The manual labelling in this study was conducted by the author. A detailed explanation of the process provided in the appendix B.2.

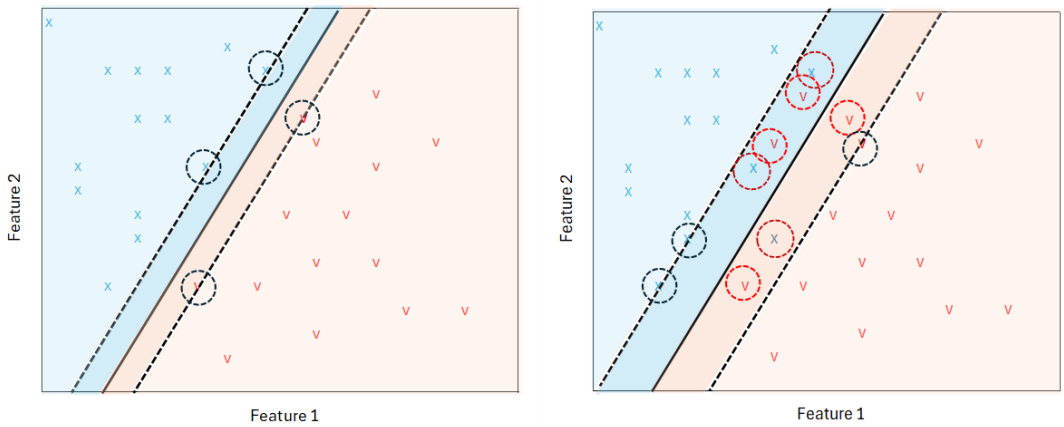
where Y is the classification in the research; y_k is the number of classifications used in the research; $t_i \in \{y_1, y_2, \dots, y_k\}$; $b_i \in \{y_1, y_2, \dots, y_k\}$: classification of t_i and b_i could be different.

Once the classification is completed, we can partition X, which represents the n articles in the dataset, into $\bar{X}$, which represents the p articles in the training dataset and $\grave{X}$, which represents the q articles in the test dataset, where n is equal to the sum of p and q. Following the completion of the labelling procedure, a total of p train-labeled documents were identified in the titles of the articles ($\bar{T} = \overline{t_1}, \overline{t_2}, \dots, \overline{t_p}$) and the body of the articles ($\bar{B} = \overline{b_1}, \overline{b_2}, \dots, \overline{b_p}$).

Support Vector Classifier (SVC)

This study's benchmark model for NLP is the SVC (Vapnik 1998). SVC is a classifier model that employs the maximisation of the margin classifier to classify datasets. The margin classifier attempts to partition the data into distinct classes by utilising a boundary line. This margin refers to the distance between the solid and dashed lines shown in Figure 2.5. In this model, the data points nearest the margin classifier are referred to as support vectors, as depicted by the dashed blue circle in Figure 2.5. Due to potential misclassification in the actual data, as indicated by the dashed red circle on the right side of Figure 2.5, this model exhibits a tolerance for misclassification beyond the margin. The regularisation parameter cost (C) controls the trade-off between allowing misclassification and the model's flexibility. The purpose of tolerating misclassification in the model is to mitigate the risk of the model being excessively complex, which can lead to an overfitting issue. Hence, in the SVC model, the variable C represents the margin cost, allowing error tolerance. Grid Search is a strategy to optimise the hyperparameter of C by examining multiple possibilities of C for comparison (Pedregosa *et al.* 2011).

Figure 2.5 The Illustration of Support Vector Classifier



This figure illustrates the SVC used to classify two classifications within a dataset containing two features. The picture on the left represents an SVC without misclassification, whereas the one on the right depicts an SVC that allows misclassification.

Naïve Bayes Classifier

The naïve Bayes classifier constructs the model using the probability derived from the Bayes theorem, a product of the conditional probability technique. The strategy was initially developed by Maron and Kuhns (1960). The equation of the naïve Bayes model which is expressed as follows:

$$Pr(y_k|w_1, \dots, w_m) = Pr(y_k) \prod_{j=1}^{m} \Pr(w_j|y_k) \tag{2.6}$$

where $Pr(y_k|w_1, \dots, w_m)$ is the posterior; $Pr(y_k)$ is the prior; $Pr(w_j|y_k)$ is the likelihood.

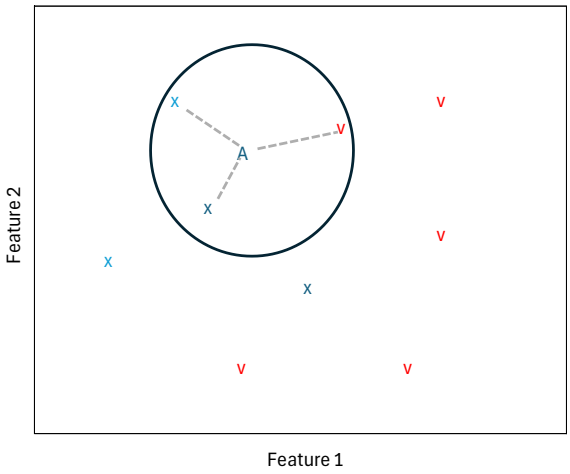
The naïve Bayes approach has the benefit of rapid processing time because of its naïve independent conditional assumption. The naïve Bayes model assumes that each feature is independent of all other features. The naïve Bayes classifier attempted to compute the model based on the prior probability of each classification. In this methodology, the preceding outcome will yield a score determined by the proportion of classifications within the training dataset. The outcome then computes the likelihood derived from the collective impact of each feature inside the model. Nevertheless, the naïve Bayes algorithm is ineffective when applied to an imbalanced dataset, as the prior score will result in a higher score for the more significant fraction of the classification in the training dataset.

K-Nearest Neighbors (KNN)

The KNN model is a supervised model that utilises a clustering technique pioneered by Fix and Hodges (1989). This classifier model determines the predicted classification by finding the nearest K-point in the training data. The nearest K-point neighbors are calculated using the Euclidean distance, as shown in the grey dashed line in Figure 2.6. The model attempts to predict the categorization by considering the most common classification among the K nearest neighbors. In the case of the illustration in Figure 2.6, the three nearest neighbors will be used to predict point A as a blue (x). Suppose there is a tie in the number of nearest neighbors, when multiple classes have equal frequency. In that case, the model will prioritise the classification of the nearest neighbor among the tied points classification. The classification of the KNN approach is contingent upon the number of K-points utilised in the model and the distinct classification derived from the training data. A small number of K-

points will give rise to overfitting issues, while a larger number of K-points can result in underfitting issues.

Figure 2.6 The Illustration of K-Nearest Neighbors

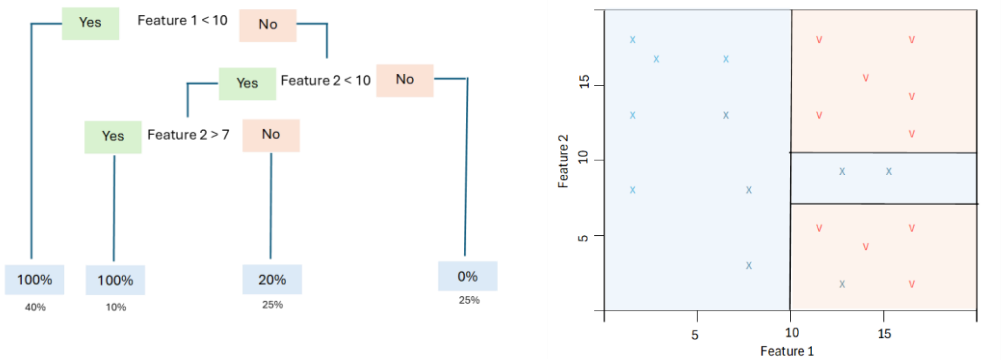


This figure illustrates the KNN with three nearest neighbors, which is employed to classify two classifications within a dataset that contains two features. The circle illustrates the process of predicting the classification of point A based on the three nearest neighbours, such that point A will be classified as a blue (x).

Decision Trees Classifier

The decision trees classifier was first introduced by Morgan and Sonquist (1963). The decision trees classifier model attempted to forecast the label by dividing and splitting the space of the training data into multiple regions of output variables belonging to the same class, as shown in Figure 2.7. The segmentation procedure will generate a result resembling a branching structure called a tree-like model. The decision trees model divides the space into high-dimensional rectangles. This model recursively splits the training data of $\bar{X}$ into M regions. The forecast of the test observation in regions $(R_1, R_2, \dots, R_m)$ is determined based on the minimum error score of each classification. The decision trees can effectively filter down the complex dataset and predict the classification of each region. Nevertheless, a limitation of this strategy is its inclination to overfit the training data due to the model's division of the dataset into smaller parts. Furthermore, this method necessitates additional time for processing due to its greedy nature, which involves repeating steps in multiple lower branches of the trees and following specific sequences in the process.

Figure 2.7 The Illustration of Decision Trees



This figure illustrates the decision trees model to classify two classifications within a dataset that contains two features. The left side depicts the procedural steps of the decision trees model, while the right side represents the area of classification prediction.

Performance Metrics of NLP Methods

Multiple metrics are utilised to assess the model's performance in predicting the classification label using test data. An approach to quantify the error rate of the classification labelling (y_k) is as follows:

$$\varepsilon_{y_k} = \frac{1}{n}\sum_{i=1}^{n} I\left(x_i \neq \hat{x}_i\right) \tag{2.7}$$

where ε_{y_k} is the error rate of the classification labelling (y_k); $I(x_i \neq \hat{x}_i)$ is an indicator variable; $I(x_i \neq \hat{x}_i) = 0 \rightarrow x_i = \hat{x}_i \rightarrow TP \vee TN$, the result of the prediction is the same as the actual classification label, which is also called True Positive (TP hereafter) or True Negative (TN hereafter); $I(x_i \neq \hat{x}_i) = 1 \rightarrow x_i \neq \hat{x}_i \rightarrow FP \vee FN$ or the prediction result is different from the actual classification label, also called False Positive (FP hereafter) or False Negative (FN hereafter).

This research employs various performance indicators derived from Equation (2.7) that are based on the error rate. The performance metrics consist of accuracy, precision, recall, and F1 measure, which are calculated using the following equation:

$$A = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{2.8}$$

$$P = \frac{TP}{(TP + FP)} \tag{2.9}$$

$$R = \frac{TP}{(TP + FN)}$$

(2.10)

$$F1 = 2 * \frac{(P * R)}{(P + R)}$$

(2.11)

where A is accuracy as the representation of the correct prediction from all the samples used; P is precision as the representation of true positive that are predicted as positive; R is recall as the representation of true positive that are actually positive; F1 is F-measure as the representation of the harmonic mean of precision and recall.

Accuracy is a measure of how well the model accurately predicts outcomes. Nevertheless, accuracy solely evaluates the overall effectiveness of the model and does not consider the performance of each classification. When evaluating the model's performance, particularly in the case of an imbalanced dataset, it is crucial to use many performance metrics such as F1-score, precision, and recall. This will ensure a comprehensive examination of the model's optimal performance. Following the characteristics of the dataset utilised in the study, several performance metrics are employed in this research.

2.4.1.3 Semi-Supervised Learning

The second model utilised in this study is the dictionary-based method. This model employed linguistic characteristics and compared the input word with the lexicon in the dictionary to differentiate its classification. The initial stage of this method is to choose a list of substantial words for the specific category. Each word in the dictionary is assigned a score that quantifies the tone of the document. The score will be assigned to the word linked to the category in the dictionary. For instance, if there are two categories, the words in the dictionary assigned to the first category have a sentiment score of 1 ($s_r = 1$), whereas words in the dictionary of the other category have a sentiment score of -1 ($s_r = -1$). Additionally, the approach is standardised by considering the total quantity of words, similar to the methodology used by Manela and Moreira (2017). The dictionary-based model will measure the document score belonging to a particular classification. For instance, in the study, if there are three categories, the equation used to classify each document into its respective category is as follows:

$$T(x_i) = \begin{cases} y_1, & if \quad \sum_{r=1}^{R} \frac{s_r}{W_i} > th_1 \\ y_3, & if \quad \sum_{r=1}^{R} \frac{s_r}{W_i} < th_3 \\ y_2, & if \quad otherwise \end{cases}$$

(2.12)

where $T(x_i)$ is the tone of document i; s_r is the sentiment score of the word r; W_i is the number of words in the document i; th_1 is the threshold for y_1; th_3 is the threshold for y_3.

2.4.2 Transforming NLP Outcome

This study uses the outcomes of NLP to mimic consumer surveys and transform them into IEs employing the CP method and its extended version. We explore various measures for robust analysis: distinct supervised and semi-supervised learning techniques, varying keyword inflation and price in the article, utilising different forecast horizons, and conducting multiple combination analyses of the title and body of the articles. This study employs Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Diebold-Mariano Test (DM-test), and Forecast-Encompassing test to assess the accuracy of IEs in relation to inflation data.

The Carlson-Parkin Methods.

Carlson and Parkin (1975) developed the theoretical framework of the CP method to quantitatively analyse qualitative data obtained from surveys using the probability approach. The equation of CP methods[32] is:

$$p_t^e = -\delta_t \left(\frac{a_t + b_t}{b_t - a_t} \right)$$

(2.13)

where p_t^e is the inflation expectation at time t; a_t is the upper threshold of the normalisation of zero mean and unit variance; b_t is the lower threshold of the normalisation of zero mean and unit variance.

Moreover, Figure 2.3 displays stable and shock periods; as a consequence, we address this by employing an extended version of the CP method with the formulation[33]:

[32] The further explanation in subsection 1.3.2.2 point A.

[33] The further explanation in subsection 1.3.2.2 point B.

$$p_t^e = \beta\left(\frac{a_t}{a_t - b_t}\right) + \delta\left(\frac{-b_t}{a_t - b_t}\right) \tag{2.14}$$

where β as the lower threshold; δ as the upper threshold

Outcome Performances

This study optimises the transformation of CP methods results by comparing them with actual inflation data using MAE and RMSE as Equations (1.28) and (1.29) in Chapter 1.

The subsequent procedure will involve comparing the benchmark and alternative methods utilising the Diebold-Mariano test (Diebold & Mariano 1995). This test aims to determine if there are statistically significant differences between the benchmark and alternative models, as in Equation (1.30) in Chapter 1.

In addition, we use the forecast-encompassing test developed by Chong and Hendry (1986) to test the accuracy and reliability of the benchmark with alternative methods. The equation for the forecast-encompassing test is as follows:

$$e_{1t} = \delta_2 f_{2t} + v_{1t}$$
$$e_{2t} = \delta_1 f_{1t} + v_{2t} \tag{2.15}$$

where e_{it} is the error of f_i to explain y_t; f_{it} is the result of the forecast i; δ_i is the coefficient of f_{it}.

In their study, Chong and Hendry (1986) investigated the forecast encompassing by utilising the significance of δ_i, as described in Equation (2.15). For instance, if in Equation (2.15), $\delta_1 = 0$ and $\delta_2 \neq 0$, it signifies that f_{2t} is a forecast encompassing f_{1t}. The significance δ_i represents the measure of a forecast's ability to explain the error of another forecast.

2.5 Empirical Result

This section provides the research findings. In sub-sections 2.5.1 and 2.5.3, we explore various techniques for extracting valuable data from news articles employing supervised and semi-supervised learning. In sub-sections 2.5.2, we focus on the transformation of supervised NLP outcomes into the representation of NEEA IEs. In sub-sections 2.5.4, we explore the transformation of NLP results to investigate the potential of using news articles as NEEA IEs and employ them to forecast inflation. We use the transformation of the keyword inflation in the title using CP methods as the benchmark for comparing the performance. The comprehensive findings are reported in this section.

2.5.1. Supervised Learning

We follow the classification employed in the Indonesian consumer survey, comprising three categories of labels, following Equations (2.5), $Y = \{y_1, y_2, y_3\}$ where: y_1 is increase as the first classification; y_2 is stay the same (neutral) as the second classification; and y_3 is decrease as the third classification. In order to decrease the dimensionality of the data, we carried out the pre-processing stage. Initially, we executed the normalisation as part of the pre-processing phase. Next, we eliminate the stop words, which consist of 754 words on our list[34]. Then, we utilised TF-IDF to modify the vector representation of the dataset.

In order to divide the training and test datasets, we attempted to implement five cross-validation (CV hereafter) methods: random splitting (with a 66.67% allocation to the training set and 33.33% to the test set), 5-fold, stratified 5-fold, 10-fold, and stratified 10-fold[35]. The five distinct CV results indicate that the random splitting slightly has better accuracy (results in the appendix). Consequently, we selected the random splitting method that divided the data into a training set comprising 66.67% and a test set comprising 33.33%.

Furthermore, this study conducted a comparison of four models in supervised learning in order to determine the optimal outcome: SVC, Naïve Bayes, KNN, and Decision Trees. The model utilises a linear SVC, as Varian (2014) recommended, to mitigate the overfitting issue. Prior to adopting the linear SVC model, we also attempted to utilise the nonlinear SVC model for analysing articles related to the keyword "*inflasi*" (inflation). The analysis reveals that the linear SVC model has marginally superior performance compared to the nonlinear SVC model, achieving accuracy ratings of 0.85 and 0.84, respectively (not displayed in the table).

Following pre-processing, we applied supervised learning and acquired the results documented in Table 2.1 through Table 2.4. Table 2.1 compares the results generated from the supervised learning model using the title of the keyword "*inflasi*" (inflation) articles. The dataset exhibits an imbalance, with category 1 (the classification representing an increase) accounting for 63.16% of the dataset, category 2 (the classification representing stay the same) accounting for 26.95%, and category 3 (the classification representing a decrease) accounting for 9.89%. The table demonstrates that the SVC model achieves the highest performance for the keyword "*inflasi*" (inflation) in the title. It attains an accuracy of 0.85 and F1-Scores of 0.90, 0.72, and 0.82 for the classifications 1, 2, and 3, respectively. Table 2.1 shows that the accuracy level of the four different models yields satisfactory outcomes.

[34] The list provided is an alternative version of the stop words in Bahasa Indonesia from NLTK (Bird *et al.* 2009) that has been modified to align with the specific objectives of the research. The list can be obtained upon request.
[35] The stratified K-fold approach ensure that each fold has the same class distribution as the label distribution.

Table 2.1 Comparison of Supervised Learning, Keyword *Inflasi* (Inflation) – Title

Classification	Category	Precision	Recall	F1-Score	Accuracy
SVC	1	0.89	0.91	0.9	0.85
	2	0.75	0.7	0.72	
	3	0.82	0.9	0.85	
NB	1	0.79	0.96	0.87	0.79
	2	0.76	0.57	0.65	
	3	0.95	0.3	0.45	
KNN	1	0.8	0.92	0.86	0.78
	2	0.71	0.58	0.64	
	3	0.77	0.43	0.55	
DT	1	0.88	0.87	0.87	0.82
	2	0.68	0.69	0.68	
	3	0.82	0.86	0.84	

This table displays the comparative outcome of the supervised learning model when utilising the keyword "*inflasi*" (inflation) in the titles of articles. SVC stands for Support Vector Classifier, NB stands for Naïve Bayes, KNN stands for K-Nearest Neighbors, and DT stands for Decision Trees. Category 1 represents the "increase" category; category 2 corresponds to the "stay the same" category, and category 3 denotes the "decrease" category.

Table 2.2 displays the outcomes of supervised learning on the body of the articles using the keyword "*inflasi*" (inflation). The percentage composition for the increase classification is 57.17%, while the composition for the stay the same and decrease classification is 29.96% and 12.88%, respectively. According to the data in Table 2.2, the SVC yields the most favourable result for the keyword "*inflasi*" (inflation) in the body, with an accuracy rate of 0.85. Upon careful examination of Table 2.2, it is evident that the naïve Bayes receives the lowest accuracy and F1-Score.

Table 2.2 Comparison of Supervised Learning, Keyword *Inflasi* (Inflation) – Body

Classification	Category	Precision	Recall	F1-Score	Accuracy
SVC	1	0.87	0.90	0.89	0.85
	2	0.79	0.76	0.77	
	3	0.85	0.78	0.81	
NB	1	0.58	1.00	0.73	0.58
	2	0.96	0.02	0.04	
	3	0.00	0.00	0.00	
KNN	1	0.76	0.86	0.81	0.73
	2	0.68	0.53	0.60	
	3	0.66	0.61	0.64	
DT	1	0.73	0.74	0.73	0.64
	2	0.5	0.5	0.5	
	3	0.58	0.56	0.57	

This table displays the comparative outcome of the supervised learning model when utilising the keyword "*inflasi*" (inflation) in the body of articles. SVC stands for Support Vector Classifier, NB stands for Naïve Bayes, KNN stands for K-Nearest Neighbors, and DT stands for Decision Trees. Category 1 represents the "increase" category; category 2 corresponds to the "stay the same" category, and category 3 denotes the "decrease" category.

Table 2.3 illustrates the outcome of the title on the keyword "*harga*" (price). The dataset comprises a 23.05% increase, 71.02% stay the same, and a 5.92% decrease in classifications for each category. In Table 2.3, the SVC achieves a greater accuracy of 0.90. The intriguing findings from Table 2.3 further indicate that the four distinct models exhibit satisfactory accuracy performance. Despite satisfactory accuracy, the naïve Bayes model in the small proportion category, category 3, has a poor F1-Score.

Table 2.3 Comparison of Supervised Learning, Keyword *Harga* (Price) – Title

Classification	Category	Precision	Recall	F1-Score	Accuracy
SVC	1	0.86	0.77	0.81	0.90
	2	0.91	0.95	0.93	
	3	0.85	0.73	0.79	
NB	1	0.87	0.29	0.44	0.77
	2	0.76	0.99	0.86	
	3	0.00	0.00	0.00	
KNN	1	0.64	0.67	0.65	0.80
	2	0.86	0.87	0.86	
	3	0.68	0.50	0.58	
DT	1	0.83	0.83	0.83	0.89
	2	0.92	0.92	0.92	
	3	0.69	0.71	0.70	

This table displays the comparative outcome of the supervised learning model when utilising the keyword "*harga*" (price) in the titles of articles. SVC stands for Support Vector Classifier, NB stands for Naïve Bayes, KNN stands for K-Nearest Neighbors, and DT stands for Decision Trees. Category 1 represents the “increase” category; category 2 corresponds to the “stay the same” category, and category 3 denotes the “decrease” category.

Table 2.4 shows the outcome obtained by analysing the body content associated with the keyword "*harga*" (price). The dataset exhibits a 32.78% increase classification, 60.67% for the stay the same and 6.55% for decrease classification. Similar to the findings of the preceding table, Table 2.4 shows that the SVC outperforms other models for the keyword "*harga*" (price) in the body.

Table 2.4 Comparison of Supervised Learning, Keyword *Harga* (Price) – Body

Classification	Category	Precision	Recall	F1-Score	Accuracy
SVC	1	0.81	0.77	0.79	0.83
	2	0.85	0.91	0.88	
	3	0.74	0.43	0.55	
NB	1	0.79	0.19	0.31	0.66
	2	0.64	0.98	0.78	
	3	0.00	0.00	0.00	
KNN	1	0.66	0.64	0.65	0.73
	2	0.78	0.82	0.80	
	3	0.50	0.28	0.36	
DT	1	0.68	0.65	0.66	0.72
	2	0.78	0.81	0.79	
	3	0.33	0.28	0.30	

This table displays the comparative outcome of the supervised learning model when utilising the keyword "*harga*" (price) in the articles' bodies. SVC stands for Support Vector Classifier, NB stands for Naïve Bayes, KNN stands for K-Nearest Neighbors, and DT stands for Decision Trees. Category 1 represents the “increase” category; category 2 corresponds to the “stay the same” category, and category 3 denotes the “decrease” category.

Based on the findings in this sub-section, we observed that the title's result, yields generally positive outcomes for all the comparison models, in contrast to the results obtained from the body of the articles. The potential explanation derived from the findings is that the title employs a comparatively limited number of words compared to the number of words utilised in the body of the article. Due to the word constraint, the choice of terms in the title effectively differentiates between categories of increase, stay the same, and decrease. The words employed in each category must possess sufficient potency to effectively indicate the article's standpoint to the reader. For instance, when there is a significant increase in the general price level, the title's chosen word should reflect this. As a result, the limited number and selective employment of terms in the title will enhance the model's predictability. The outcomes of the supervised learning model for the terms "*inflasi*" (inflation) and "*harga*" (price) in the title and body of the articles, as presented in Tables 2.1 to 2.4, demonstrate that the SVC performs better than other models. These results confirm that SVC is suitable for datasets with many features and imbalanced characteristics, similar to the dataset used in this study. This aligns with the findings reported by Bajari *et al.* (2015) and Aletras *et al.* (2016). Furthermore, the properties of the SVC model, enable misclassification within the model while preventing excessive complexity that might lead to the overfitting problem addressed in Varian (2014). In general, the naïve Bayes classifier yielded the lowest accuracy score. The issue can be attributed to unbalanced composition, as the prior condition of the naïve Bayes model yields optimal outcomes for high proportion categories and poor for low proportion. The KNN result is comparatively weaker than the

SVC result. This can be attributed to the sensitivity of KNN to mislabelled data and the probability of the presence of several majority groups, which ultimately hampers the model's performance. The subpar performance of the decision trees model can be attributed to its tendency to overfit the data (Varian 2014). Thus, this model is suitable for datasets with fewer characteristics, as indicated by the results in the titles of the articles. Nevertheless, implementing this model within the body produces a trained model that utilises an excessively intricate tree structure, impacting the performance.

2.5.2. Transforming Supervised NLP Outcome

Based on the outcomes of the NLP models, it is evident that the SVC exhibits the best performance. Therefore, we utilise the SVC outcome to mimic consumer surveys and transform them into the NEEA IEs. Initially, we conducted a comparison between the outcomes of the keywords "*inflasi*" (inflation) and "*harga*" (price). A comparison is also made between the title and body of the news article. We utilise the transformation of the keyword "*inflasi*" (inflation) in the title using CP methods as the performance benchmark. This study also examines and contrasts four distinct forecast horizons: one month, three months, six months, and twelve months, as well as the probability of the CP method and its extended version.

Keyword *Inflasi* (Inflation)

We initially compared the forecast horizons and probability methods, as shown in Table 2.5. This table presents a comparison of four distinct forecast horizons: 1-month (1m), 3-months (3m), 6-months (6m), and 12-months (12m). The approach employed for comparison is the CP method, as described by Equation (2.13), and the extended CP method, as described by Equation (2.14). Table 2.5 displays four distinct horizons, with the six-month horizon yielding the lowest scores for MAE and RMSE.

Table 2.5 demonstrates that the extended version of the CP method, which incorporates asymmetric threshold and regime period-unbiasedness, outperforms the original CP method across all forecast horizons. Applying the CP method to the news article's title as the benchmark method reveals that the MAE, RMSE, and DM-test score for the six-month forecast horizon exhibits significant improvement in forecast performance, where the six-month forecast horizon is similar to the forecast horizon of the consumer survey. This suggests that the alternative methods yield superior and statistically significant results compared to the benchmark method.

Table 2.5 Comparison of Forecast Horizons, Keyword *Inflasi* (Inflation)

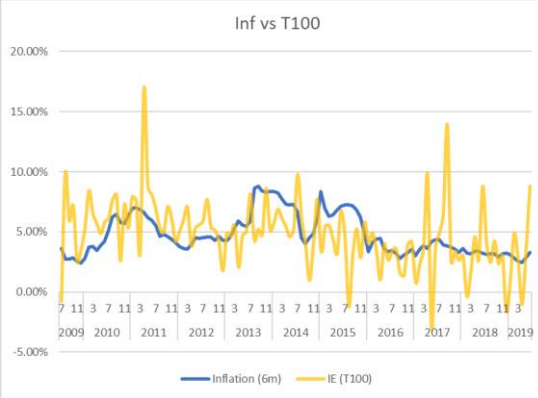
Article	Horizons	Model	MAE	RMSE	DM
Title	**1m**	**CP**	2.32	3.16	
		Ext-CP	1.23	1.55	0.45
	3m	**CP**	2.18	2.98	
		Ext-CP	1.05	1.36	5.33***
	6m	**CP**	2.08	2.87	
		Ext-CP	1.00	1.32	4.08***
	12m	**CP**	2.10	2.92	
		Ext-CP	1.15	1.42	3.65***
Body	**1m**	**CP**	2.06	2.68	0.19
		Ext-CP	1.08	1.35	1.28
	3m	**CP**	1.77	2.27	2.07**
		Ext-CP	0.89	1.13	5.06***
	6m	**CP**	1.69	2.06	2.29**
		Ext-CP	0.84	1.08	4.44***
	12m	**CP**	2.03	2.45	1.15
		Ext-CP	1.08	1.30	3.61***

This table displays the comparative outcomes of transforming IEs from NLP using the probability methods with the keyword "*inflasi*" (inflation). CP is for Carlson-Parkin, Ext-CP stands for extended version of CP method with regime period unbiasedness and asymmetric threshold assumptions. 1m refers to one month, 3m is three months, 6m indicates 6 months, and 12m represents 12 months. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

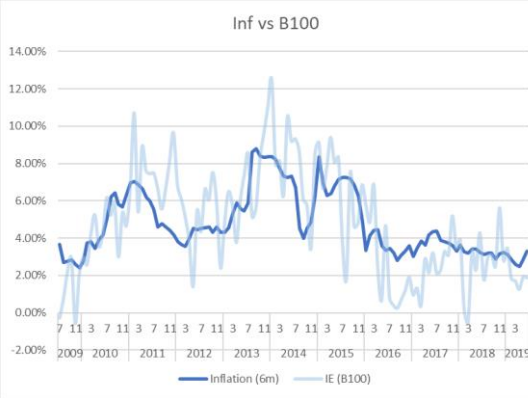
Due to the superior performance of the forecast horizons for the six-month horizon compared to other time horizons, we attempted to represent them visually in Figure 2.8. Figure 2.8 demonstrates a consistent moving pattern between IEs and actual inflations. There is a notable difference in the results between the performance of the extended version of the CP method in the title (Figure 2.8.3) and the body (Figure 2.8.4) of the news articles, particularly during the initial period from 2009-2013. This variation arises from the relatively similar volatility conditions observed in the titles of the articles during this period, as illustrated in Figure 2.8.1. When the regime-period unbiasedness assumption is applied, it reduces volatility and degrades the accuracy of the results in comparison to actual inflation. Conversely, in the body of the news articles, as in Figure 2.8.2, where volatility with a discernible trend is present in the data, the application of the regime-period unbiasedness assumption reduces volatility, but the fluctuation persists in alignment with the actual inflation data.

Figure 2.8 Inflation Rate and IEs, Keyword *Inflasi* (Inflation)

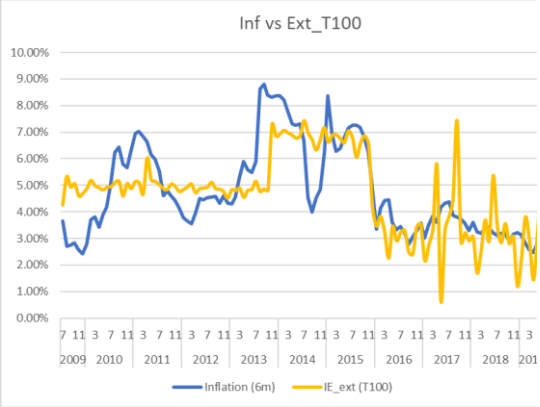
2.8.1. Title, CP Method



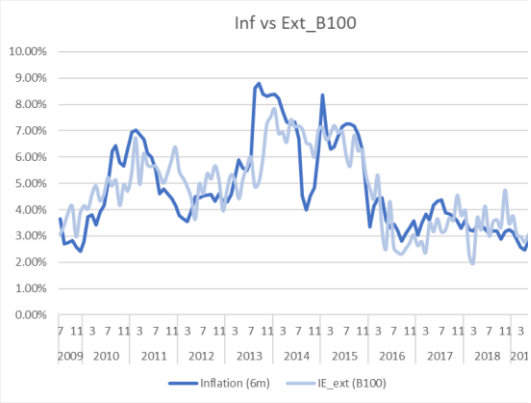
2.8.2. Body, CP Method



2.8.3. Title, Ext-CP Method



2.8.4. Body, Ext-CP Method



This figure compares the transformation of IEs containing the keyword "*inflasi*" (inflation) in both the title and body, and the inflation rate in Indonesia. This figure represents the inflation rate from July 2009 to June 2019 compared to the expected six months ahead of the IEs. CP stands for Carlson-Parkin, Ext-CP stands for the extended version of the CP method with regime period unbiasedness and asymmetric threshold assumptions.

Furthermore, as the extended version of the CP method demonstrates superior performance, we investigated the combinations of title and body using this method. Table 2.6 presents a comparison of three different combinations utilising the extended CP method: T75_B25 represents a weighting scheme where the title carries 75% of the weight, and the body carries 25% of the weight. T50_B50 represents a weighting scheme where the title and body carry 50% of the weight. T25_B75 represents a weighting scheme where the title carries 25% of the weight, and the body carries 75%. According to the data presented in Table 2.6, assigning 25% weight to the title and 75% weight to the body when employing the keyword "*inflasi*" (inflation) yields the most optimal outcome.

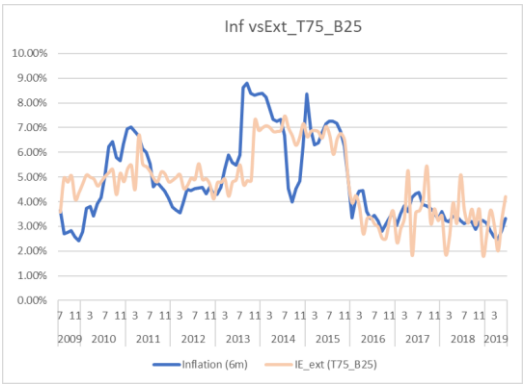
Table 2.6 Comparison Results of Keyword *Inflasi* (Inflation) – Combination

	MAE	RMSE	DM
T75_B25	0.88	1.19	4.51***
T50_B50	0.84	1.12	4.48***
T25_B75	0.83	1.08	4.47***

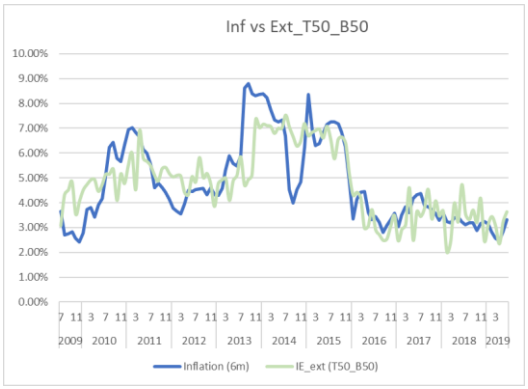
This table presents the comparative outcomes of transforming IEs from NLP using the extended CP-method, specifically focusing on the keyword "*inflasi*" (inflation) in both the title and body of the articles. T75_B25 represents 75% of the title, and 25% of the body; T50_B50 represents the title and body carry 50% of the weight; T25_B75 represents the title carries 25%, and the body carries 75%. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Figure 2.9 Inflation Rate and IEs, Keyword *Inflasi* (Inflation) – Combination

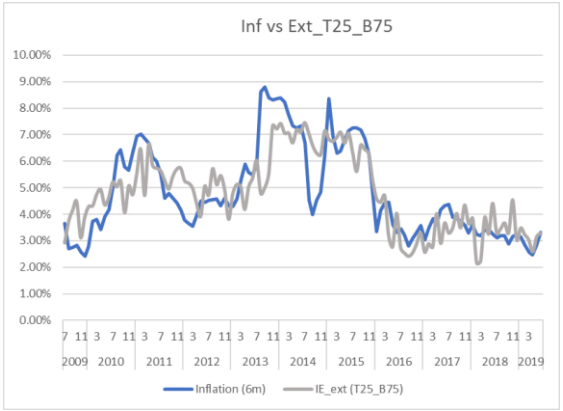
2.9.1. Title (75%) – Body (25%), Ext-CP



2.9.2. Title (50%) – Body (50%), Ext-CP



2.9.3. Title (25%) – Body (75%), Ext-CP



This figure illustrates the comparison between the transformation of IEs using the keyword "*inflasi*" (inflation) in both the title and body of thearticles, and the actual inflation rate in Indonesia. This figure represents the inflation rate from July 2009 to June 2019 in comparison with the expected six months ahead of the IEs. This figure utilises the extended version of the CP method. Ext-CP stands for the extended version of the CP method with regime period unbiasedness and asymmetric threshold assumptions.

Figure 2.9 demonstrates that the combined effect of the title and body of the keyword "*inflasi*" (inflation) yielded superior results. The data showed a similar trend in movement between IEs and the actual inflation rate, with the optimal outcome achieved by

using 25% of the title and 75% of the body. This suggests that NEEA not only prioritised the titles of the articles[36] but also paid attention to the substance of the articles.

Keyword Harga (Price)

By utilising the keyword "*harga*" (price), we applied the same comparisons as we did for the keyword "*inflasi*" (inflation). We employed several forecast horizons, probability methods, and the combination of title and body. Table 2.7 demonstrates that the title of the news articles related to the keyword "*harga*" (price) does not yield a good outcome when compared to the article's title for the keyword "*inflasi*" (inflation). Furthermore, Table 2.7 demonstrates that the most favourable outcome is achieved by utilising the keyword "*harga*" (price) for the upcoming six months.

Table 2.7 Comparison of Forecast Horizons, Keyword *Harga* (Price)

Article	Horizons	Method	MAE	RMSE	DM
Title	**1m**	**CP**	3.64	4.82	-5.53
		Ext-CP	1.07	1.38	1.04
	3m	**CP**	3.33	4.44	-2.56
		Ext-CP	0.95	1.24	4.84***
	6m	**CP**	3.08	4.13	-2.3
		Ext-CP	0.91	1.20	4.33***
	12m	**CP**	3.08	4.02	-2
		Ext-CP	0.98	1.25	3.59***
Body	**1m**	**CP**	1.95	2.44	-4.09
		Ext-CP	1.05	1.34	1.22
	3m	**CP**	1.76	2.12	2.67***
		Ext-CP	0.94	1.22	4.88***
	6m	**CP**	1.50	1.86	2.88***
		Ext-CP	0.88	1.14	4.52***
	12m	**CP**	1.44	1.85	2.45**
		Ext-CP	0.90	1.16	3.76***

This table displays the comparative outcomes of transforming IEs from NLP using the probability methods with the keyword "*harga*" (price). CP is for Carlson-Parkin, Ext-CP stands for the extended version of the CP method with regime period unbiasedness and asymmetric threshold assumptions. 1m refers to one month, 3m is three months, 6m indicates 6 months, and 12m represents 12 months. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

[36] The fact that the number of features in the title relative to the body in the corpus is just 1.39% indicates the significant influence of the title in the articles.

Table 2.8 Comparison Results of Keyword *Harga* (Price) – Combination

	MAE	RMSE	DM
T75_B25	0.90	1.18	4.35***
T50_B50	0.89	1.17	4.39***
T25_B75	0.88	1.15	4.45***

This table presents the comparative outcomes of transforming IEs from NLP using the extended CP method, specifically focusing on the keyword "*harga*" (price) in both the title and body of the articles. T75_B25 represents 75% of the title, and 25% of the body; T50_B50 represents the title and body carry 50% of the weight; T25_B75 represents the title carries 25%, and the body carries 75%. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

As part of the filtering process, we also attempted to assign a weight to both the title and the body. Table 2.8 presents a comparison of three distinct combinations utilising the extended CP approach. Table 2.8 demonstrates that the optimal score for the extended CP method is achieved using a combination of 25% title weight and 75% body weight. This particular combination of weights also yielded the most favourable result for the keyword "*inflasi*" (inflation).

Combination Keyword *Inflasi* (Inflation) – *Harga* (Price)

In this sub-section, we combined the two keywords utilised in this research to obtain optimal outcomes as a measure of NEEA IEs. In the preceding sub-section, we employed the optimal combination of keywords, consisting of a carries 25% of the weight on the title and a carries 75% of the weight on the body. The transformation method employed for this combination is the extended version of the CP method, as it exhibited superior performance in the preceding sub-sections.

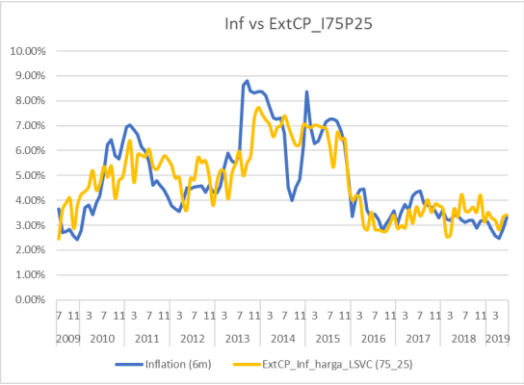
Table 2.9 Comparison Results of Combination Keywords

	MAE	RMSE	DM
I75_P25	0.79	1.05	4.53***
I50_P50	0.80	1.05	4.55***
I25_P75	0.83	1.14	4.52***

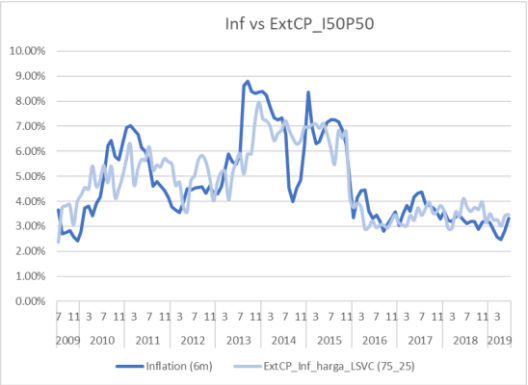
This table displays the comparative outcomes of transforming IEs results from NLP using the extended CP-method. The transformation is performed using the keywords "*inflasi*" (inflation) and "*harga*" (price), with a combination of 25% from the title and 75% from the body of the articles. I75_P25 represents 75% of the keyword inflation, and 25% of the keyword price; I50_P50 represents the keywords inflation and price carry 50% of the weight; I25_P75 represents the keyword inflation carries 25%, and the keyword price carries 75%. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Figure 2.10 Inflation Rate and IEs, Combination Keyword

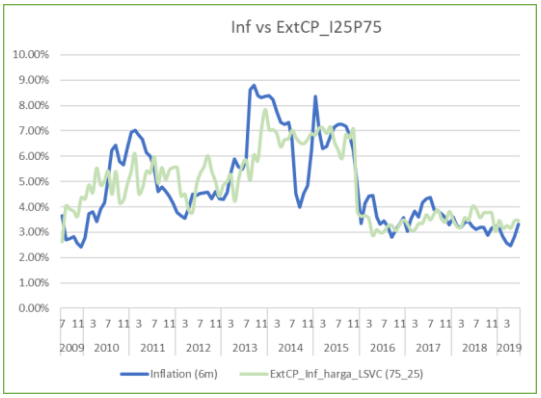
2.10.1. Inf (75%) – Prc (25%), Ext-CP



2.10.2. Inf (50%) – Prc (50%), Ext-CP



2.10.3. Inf (25%) – Prc (75%), Ext-CP



This figure illustrates the transformation of IEs by utilising the keywords "*inflasi*" (inflation) and "*harga*" (price), with a combination of 25% from the title and 75% from the body. This figure represents the inflation rate from July 2009 to June 2019 in comparison with the expected six months ahead of the IEs. This figure employs the extended version of the CP method. Ext-CP stands for the extended version of the CP method with regime period unbiasedness and asymmetric threshold assumptions.

Table 2.9 presents a comparison of three different combinations using the extended CP method. The combination labelled I75_P25 assigns a weight of 75% to "*inflasi*" (inflation) and 25% to "*harga*" (price). The combination labelled I50_P50 assigns a weight of 50% to "*inflasi*" (inflation) and 50% to "*harga*" (price). The combination labelled I25_P75 assigns a weight of 25% to "*inflasi*" (inflation) and 75% to "*harga*" (price). Additionally, we illustrate this comparison in Figure 2.10. The results are improved by combining the keywords, as demonstrated in Table 2.9 and Figure 2.10. According to the outcomes in Table 2.9, utilising a combination of I75_P25, which represents 75% keyword "*inflasi*" (inflation) and 25% keyword "*harga*" (price), yields superior results compared to employing a single keyword.

The analysis of supervised NLP outcomes transformation indicates a substantial increase in IEs from early 2011 to mid-2011. This trend appears to be driven by the

government's intention to reduce the fuel subsidy in Indonesia during that time[37]. The peak also occurred from mid-2013 to mid-2014, corresponding with the taper tantrum and election in Indonesia. There has been a rise in the quantity of news articles related to these events, which could impact NEEA IEs. According to the research conducted by Ehrmann *et al.* (2017), this can result in pessimism among economic agents and impact the increase of their IEs. An intriguing aspect of the title's keyword "*inflasi*" (inflation) transformation is the presence of volatility starting from 2016, as depicted in Figures 2.8.1 and 2.8.3. However, the actual inflation rates only exhibit minor changes. This phenomenon arises due to the comparatively limited number of headlines pertaining to inflation compared to other periods. Due to the relatively small size of the news articles during that period, the weight proportion of an individual article in relation to the total number of articles in a specific month will be larger. This will have an impact on the volatility of that period. Conversely, the condition shown in the body of the article (as seen by Figures 2.8.2 and 2.8.4) had comparatively lower levels of volatility following the year 2015. The circumstance is characterised by the more extensive number of articles in the body datasets compared to the title datasets. Furthermore, the decrease in the number of articles pertaining to inflation compared to other periods can be attributed to Indonesia's relatively stable inflation and economic situation during that time.

Overall, the extended version of the CP method yields the most favourable outcome for both keywords in the title and body, as demonstrated in this sub-section on transforming supervised learning outcomes. Upon merging the outcome of the title and body, it became evident that the optimal representation of IEs was achieved by combining 25% of the title and 75% of the body. This finding suggests that economic agents in Indonesia not only prioritised the titles of the articles but also paid attention to the information presented in the body of the articles. When the keywords "*inflasi*" (inflation) and "*harga*" (price) are utilised together, the keyword "*inflasi*" (inflation) carries greater significance than the keyword "*harga*" (price). This result suggests that economic agents give greater importance to news articles that include the keyword "*inflasi*" (inflation) in their IEs. The possibility of this result is that the news article containing the keyword "*inflasi*" (inflation) may also include the keyword "harga" (price); however, the news articles with the keyword "harga" (price) do not include "*inflasi*" (inflation). This could enhance the comprehensiveness of the information related to the keyword "*inflasi*" (inflation). On the other hand, not all news articles with the keyword "harga" (price) may be directly associated with inflation. The article

[37] As evidenced by the increase in the number of news articles covering inflation-related topics during that period.

with the keyword "*harga*" (price) may have different commonly used words compared to the keyword "*inflasi*" (inflation). Articles on the topic of inflation typically exhibit consistent features and target audiences. Conversely, the keyword "*harga*" (price) possesses distinct attributes and caters to specific target audience segments. The term "*harga + minyak*" (price + oil) and "*harga + beras*" (price + rice) might target various audiences and have distinct word characteristics. The media offers numerous types of information to cater to different segments, confirming an economic theory of democracy by Downs (1957). Due to the consistent correlation between the inflation information and articles with the keyword "*inflasi*" (inflation), as well as the broad meaning of the keyword "*harga*" (price), economic agents may prioritise news articles that contain the keyword "*inflasi*" (inflation).

2.5.3. Semi-supervised Learning

In this sub-section, we explored the practical application of the dictionary-based method in semi-supervised learning. This study constructs its dictionary in accordance with the recommendation of Loughran and McDonald (2011), Hansen and McMahon (2016), and Gardner *et al.* (2022), who emphasised the importance of developing a dictionary-based method that aligns with the specific research context. Loughran and McDonald's dictionary is widely used in the literature, particularly in the field of finance. However, it is important to note that Loughran and McDonald's dictionary does not include the terms inflation and deflation, which are essential for this research. Given the restricted availability of research with a similar setting, it was essential to construct the dictionary in this study. The dictionary classifies word representations into two distinct dictionaries: the "increase" wordlist dictionary and the "decrease" dictionary[38].

Two different versions of dictionaries were used for comparison. In the initial version, we construct a dictionary based on the most frequently occurring word in the dataset. This dictionary comprises words that are semantically relevant to the study topic. This dictionary includes 405 words related to an "increase" and 287 terms associated with a "decrease" (the dictionary can be obtained upon request). In the second version, we tried to minimise the dictionary's size by eliminating potentially unnecessary terms. This was done since there was a chance that an irrelevant word would have been included, hence diminishing the model's ability to classify accurately. In the second version of the dictionary-based model, we implemented the reduction of the dictionary from the first version,

[38] By employing separate dictionaries for the “increase” and “decrease” categories, we also account for contrasting terms that represent the concept within these dictionaries, including negation words, which may be inadequately addressed when using single dictionary.

resulting in a more robust and meaningful association with the chosen dictionary group. Furthermore, we adjusted the composition of "decrease" words in the dictionary followed by the composition of decreased classification of the body of news articles using the keyword "*inflasi*" (inflation), which constituted the largest dataset in this research, accounting for around 13% of the total. As a result, in the second version of the dictionary-based model, we incorporated 244 "increase" and 36 "decrease" words in the dictionary (see the appendix).

Table 2.10 Comparison Results of Dictionary Based V.1

Article	Horizons	Model	MAE	RMSE	DM
Title	**1m**	**Inf**	2.17	2.84	-3.96***
		Harga	29.48	39.96	-4.55***
	3m	**Inf**	2.15	2.82	0.38
		Harga	29.04	39.33	-4.61***
	6m	**Inf**	2.06	2.76	0.24
		Harga	28.41	38.45	-4.6***
	12m	**Inf**	2.16	2.90	0.04
		Harga	28.28	38.50	-4.59***
Body	**1m**	**Inf**	8.28	11.64	-2.47**
		Harga	4.13	5.64	-2.54**
	3m	**Inf**	8.01	11.33	-2.31**
		Harga	4.13	5.55	-2.06**
	6m	**Inf**	7.75	11.02	-2.31**
		Harga	4.07	5.43	-2.29**
	12m	**Inf**	7.70	11.19	-2.16**
		Harga	4.12	5.55	-2.38**

This table displays the comparative outcomes of the transformation results of the IEs using the dictionary-based method. Utilisation of the Carlson-Parkin Method (CP) for transformation method. 1m refers to one month, 3m is three months, 6m indicates 6 months, and 12m represents 12 months. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

The outcome of the initial version of the dictionary-based method is displayed in Table 2.10. The dataset was the same as the one used for the supervised learning: the article titles and bodies contained the keywords "*inflasi*" (inflation) and "*harga*" (price). The table employs the CP method for transformation and compares four forecast horizons: 1-month (1m), 3-months (3m), 6-months (6m), and 12-months (12m). The DM-test used the CP method of supervised learning with keyword inflation in the title of the articles as the benchmark for comparing the performance of other articles. As seen in Table 2.10, the dictionary-based methods generally showed inferior performance compared to supervised learning models. However, regarding the keyword "*inflasi*" (inflation), the article's title displays a positive DM-test score, even though the difference is not statistically significant.

Table 2.11 Comparison Results of Dictionary-Based V.2

Article	Horizons	Model	MAE	RMSE	DM
Title	**1m**	**Inf**	3.96	7.28	-2.11**
		Harga	2.52	3.24	-6.19***
	3m	**Inf**	3.92	7.16	-1.91*
		Harga	2.30	2.96	-0.02
	6m	**Inf**	3.92	7.08	-1.96*
		Harga	2.16	2.79	0.23
	12m	**Inf**	4.04	7.25	-2.05**
		Harga	2.30	2.80	0.08
Body	**1m**	**Inf**	1.63	2.02	-1.59
		Harga	2.10	2.86	-3.36***
	3m	**Inf**	1.48	1.88	3.10***
		Harga	1.97	2.66	0.73
	6m	**Inf**	1.42	1.82	2.73***
		Harga	1.78	2.48	0.84
	12m	**Inf**	1.53	1.94	2.62***
		Harga	1.78	2.37	0.98

This table displays the comparative outcomes of the transformation results of the IEs using the dictionary-based method with the reduction dictionary version (V.2). Utilisation of the Carlson-Parkin Method (CP) for transformation techniques. 1m refers to one month, 3m is three months, 6m indicates 6 months, and 12m represents 12 months. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Table 2.11 displays the second version of the dictionary-based method. For this analysis, we employed the CP method as the transformation approach. We then proceeded to evaluate four different forecast horizons: 1-month (1m), 3-months (3m), 6-months (6m), and 12-months (12m). The adoption of the second version of the dictionary-based method demonstrates enhanced overall outcomes. A closer look at Table 2.11 reveals that 6-month forecast horizons produce superior results, particularly for the body of the articles with the keyword "*inflasi*" (inflation).

Table 2.12 Comparison Results of Dictionary-Based V.2, Combination

Keyword	Method	MAE	RMSE	DM
Inflation	**CP**	1.39	1.81	2.80**
	Ext-CP	0.90	1.17	4.39***
Price	**CP**	1.53	2.08	0.56
	Ext-CP	0.87	1.17	4.40***

This table displays the comparative outcomes of the transformation results of the IEs using the dictionary-based method with the reduction dictionary version (V.2). CP is for Carlson-Parkin, Ext-CP stands for extended version of CP method with regime period unbiasedness and asymmetric threshold assumptions. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

In addition, we applied the same proportions of 25% title and 75% body in Table 2.12, which yielded the best results for supervised learning in Tables 2.6 and 2.8. The transformation method employed in Table 2.12 consists of the CP method and its extended version (Ext-CP). Table 2.12 demonstrates that assigning 25% weight to the title and 75% weight to the body yields a favourable outcome when using the extended CP method. Based on the DM-test score, this method greatly outperforms the benchmark method.

Combination Keyword *Inflasi* (Inflation) – *Harga* (Price)

Due to the satisfactory performance of the second version of the dictionary-based method, we further incorporated the combination of the terms "*inflasi*" (inflation) and "*harga*" (price) in the second version of the dictionary. In line with supervised learning, we utilised a combination of the terms "*inflasi*" (inflation) and "*harga*" (price) from 25% of the title and 75% of the body. The extended CP method was used to compare three different combinations in Table 2.13. These combinations include I75_P25, I50_P50, and I25_P75. According to Table 2.13, the combination of both keywords leads to lower MAE and RMSE scores compared to the results in Table 2.12, although the improvement is relatively small compared to solely using the keyword "*harga*" (price). However, given that the keyword "*inflasi*" (inflation) is the main keyword and contains important information on NEEA IEs, the results from combining keywords are preferable.

Table 2.13 Comparison Results of Dictionary-Based, Combination Keywords

	MAE	RMSE	DM
I75_P25	0.88	1.15	4.37***
I50_P50	0.87	1.16	4.37***
I25_P75	0.87	1.17	4.39***

This table displays the comparative outcomes of transforming IEs results from NLP (semi-supervised learning) using the extended CP method. The transformation is performed using the keywords "*inflasi*" (inflation) and "*harga*" (price), with a combination of 25% from the title and 75% from the body of the articles. I75_P25 represents 75% of the keyword inflation, and 25% of the keyword price; I50_P50 represents the keywords inflation and price carry 50% of the weight; I25_P75 represents the keyword inflation carries 25%, and the keyword price carries 75%. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the standard CP (1m) is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Overall, the implementation of the second or reduced version of the dictionary resulted in an improvement in the performance of the dictionary-based method. One potential hypothesis for the results is that the initial version of the dictionary-based method included insignificant words since removing the inconsequential word in dictionary version 2 demonstrated enhancement performance. This finding suggests that the dictionary-based

method may serve as a substitute for other NLP models with longer processing times. The dictionary-based method performs relatively well, as indicated by its MAE and RMSE scores.

2.5.4. The Effectiveness of NLP Results

Forecast Ability Comparison

The preceding subsection demonstrated that transforming the NLP output yielded a relatively good prediction outcome for the actual inflation rate, with the 6-month forecast horizon producing the most favourable outcome. Table 2.14 presents the prediction performance of the NLP model by comparing it with the random walk model. The random walk will be considered as a benchmark model, while the combination of 75% "*inflasi*" (inflation) weight and 25% "*harga*" price weight will serve as a comparison model. In this comparison, we utilised this particular combination due to its reasonably strong performance in both the supervised (Table 2.9) and semi-supervised (Table 2.13) transformations. Table 2.14 demonstrates that the supervised and semi-supervised learning approaches get superior scores for MAE and RMSE. Both NLP outputs have a positive DM score that is notably better than the benchmark approach.

Table 2.14 Comparison Model of NLP and Randow Walk

	MAE	RMSE	DM
R_W	1.40	1.88	-
Sup_I75_P25	0.79	1.05	2.39**
SemSup_I75_P25	0.88	1.15	2.42**
Survey	0.64	0.86	2.63***

This table displays the comparative outcomes of transforming IEs results from NLP (supervised and semi-supervised learning) using the extended CP method with the Random Walk Model and Survey. The transformation is performed using the keywords "*inflasi*" (inflation) and "*harga*" (price), with a combination of 25% from the title and 75% from the body of the articles. R_W stands for Random Walk Model; Sup refers to the supervised learning model; SemSup refers to the semi-supervised learning (dictionary-based V.2). I75_P25 represents 75% of the keyword inflation and 25% of the keyword price. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. The DM-Test is the Diebold-Mariano test, the random walk model is chosen as the benchmark within the comparison methods; A negative sign indicates that the benchmark method is preferable, while a positive sign indicates that the alternative method is preferable.

Comparison with Consumer Survey

This subsection assesses the feasibility of using NLP as an alternative to the traditional survey method. Hence, we also compared the outcomes of NLP with the same probability methods used in a consumer survey conducted in Indonesia. According to the data presented in Table 2.14, the MAE and RMSE scores for the NLP model are marginally higher than those obtained from the survey transformation. In addition, we conducted a forecast-encompassing test, as proposed by Chong and Hendry (1986), to compare the findings obtained from the survey

and NLP. Table 2.15 indicates that the NLP result has the potential to provide information on top of the survey results. Figure 2.11 of the comparison between the survey and NLP results provides additional information that suggests a strong resemblance between the survey and NLP results and the actual inflation rate.

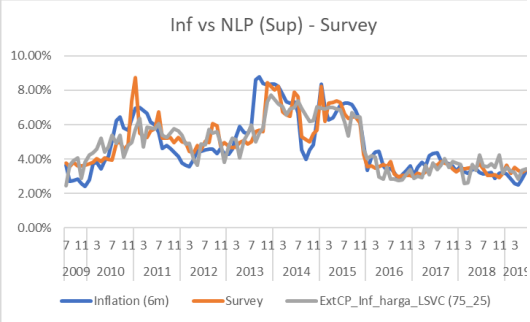
Table 2.15 Forecast Encompassing Test

Comparison		Variable	Coef	S.E	P-Value
1	eq.1	Sup_I75_P25	0.003	0.016	0.832
	eq.2	Survey	0.016	0.019	0.387
2	eq.1	SemSup_I75_P25	-0.002	0.016	0.900
	eq.2	Survey	0.022	0.021	0.293

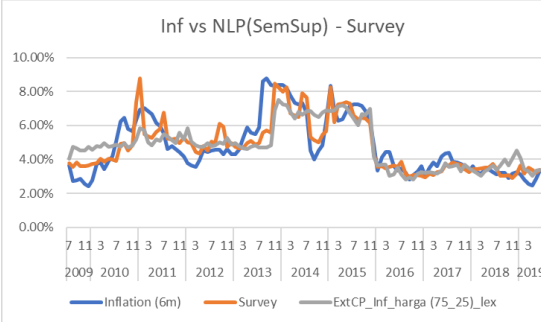
This table presents the forecast encompassing test of the IEs transformation outcomes derived from the survey and NLP (supervised and semi-supervised learning), utilising the extended CP method. Comparison 1 involves analysing the outcomes of surveys and supervised learning, whereas Comparison 2 focuses on comparing surveys with semi-supervised learning. Sup refers to the supervised learning model; SemSup refers to the semi-supervised learning (dictionary-based V.2). I75_P25 represents 75% of the keyword inflation, and 25% of the keyword price.

Figure 2.11 Inflation Rate and IEs, Comparison of NLP and Survey

2.11.1. Survey vs Supervised



2.11.2. Survey vs Semi-Supervised



This figure illustrates the comparison of the transformation of IEs using three different methods: the survey, NLP (utilising the keywords inflation (75%) & price (25%) and the combination of 25% title & 75% body), and the actual inflation rate in Indonesia. This figure represents the inflation rate from July 2009 to June 2019, with the expected six months ahead of the inflation expectation. This figure utilises the extended version of the CP method. The figure illustrates a comparison between survey and supervised learning using SVC (2.11.1) and survey and semi-supervised learning using the dictionary-based model V.2 (2.11.2).

The findings of this sub-section indicate that the supervised and semi-supervised NLP models achieved good predictive performance. These models can be considered viable options for predicting the inflation rate, as shown in Table 2.14. In comparison, the survey performed somewhat better than the NLP result, whether through supervised or semi-supervised learning. However, the forecast-encompassing test showed that the survey result does not forecast encompass the NLP outcome. The satisfactory performance of the NLP transformation outcome demonstrates the possibility of NLP as an alternate approach for acquiring information on NEEA IEs. The NLP approach offers numerous benefits in comparison to the survey results. For instance, the NLP outcomes from news articles can

efficiently retrieve data in near real-time while providing a comprehensive narrative background of the event. The NLP approach is also cost-effective and requires minimal resources.

2.6 Discussion

The study examined the best approach to extract valuable information from news articles. We assessed the feasibility of transforming news articles into NEEA IEs. Furthermore, we examined the application of news articles as an alternative tool for forecasting inflation. We utilised published news articles written in Bahasa Indonesia from 2009 to 2018 to address the study objectives.

This study employed supervised and semi-supervised learning of NLP. By employing supervised learning in NLP, this study determined that the model exhibited satisfactory accuracy in predicting the tone or signal of the articles. The SVC has superior performance compared to other models in predicting information signals. Furthermore, upon comparing the two versions of dictionaries, we found that the one with a smaller number of terms yielded greater outcomes. This study utilised NLP results that were transformed utilising the CP methods. In order to obtain optimal results, we employed a variety of comparison approaches, including keyword analysis, examination of article titles and bodies, and consideration of forecast horizons. We found that the extended version of the CP method yields the most optimal outcomes. Upon comparing the keywords "*inflasi*" (inflation) and "*harga*" (price), it was found that utilising both keywords with a 75% weight on "*inflasi*" (inflation) and a 25% weight on "*harga*" (price) yielded superior results compared to using only one keyword. Moreover, a 25% title and 75% body composition yield optimal outcomes when comparing the title and body. The study also found that the 6-month forecast horizon yields the best results for supervised and semi-supervised learning, outperforming the 1, 3, and 12-month forecast horizons. The analysis of the consumer survey and NLP demonstrated that both supervised and semi-supervised learning yielded satisfactory outcomes. The consumer survey demonstrated a slightly superior performance in predicting inflation. Nevertheless, the findings of the forecast-encompassing test proposed by Chong and Hendry (1986) indicated that the consumer survey does not encompass the NLP forecast results.

This study discovered that the results of NLP of supervised and semi-supervised learning could predict the classification of news articles with a relatively satisfactory outcome. This finding indicates that the information conveyed in the news articles gives a good signal to predict the tendency information related to inflation, whether it is increase, decrease or stay the same signal information to a mimicking consumer survey. It was found

that the results of NLP using both supervised and semi-supervised learning showed a somewhat similar picture with the transforming outcome of the consumer survey. While the consumer survey results were slightly better, the forecast-encompassing test indicated that the consumer survey does not forecast encompass the NLP outcomes, indicating that the NLP result can provide information on top of the survey results. The findings indicate that NLP outcomes have the potential to serve as an alternative approach for measuring the NEEA IEs. The NLP forecast outcomes are quite accurate and might potentially be used as an alternate method for predicting inflation. NLP offers the benefits of efficiently collecting data in near real-time and the depth of the event's narrative context. The NLP approach is cost-effective and requires minimal human resources. The NLP outcomes can also be applied as a near real-time monitor of NEEA IEs throughout the period between surveys.

While this study has made positive contributions, there is still scope for improvement. The NLP transformation yields slightly lower scores compared to the consumer survey. Even though the forecast-encompassing test shows that the consumer survey does not forecast encompass the NLP outcomes, this presents an opportunity for future studies to discover results that yield superior outcomes compared to the consumer survey. One effective strategy is to enhance the scope of supervised learning by adding more than three categories, while also integrating additional methods such as embeddings. Furthermore, the methodologies employed in this research could be expanded and implemented to analyse data from other macroeconomic variables.

According to the findings of this study, news articles can measure NEEA IEs, as Carroll (2003) and Tetlock *et al.* (2008) found. The findings of this study provide new insights into the usefulness of non-traditional data, such as news articles data, which could provide important feedback to policymakers in near real-time data. This study also found that news articles can give meaningful information about NEEA IEs and be used as an alternative tool for predicting inflation. This discovery highlights the significance of investigating the abundance of information in textual data for other macroeconomic data.

2.7 Summary and Conclusion

Amidst the expansion of digital technology, textual data can serve as an alternate means for policymakers to understand the NEEA IEs. Given this subject's significance and the existing literature gap, the study aimed to investigate the valuable information in news articles concerning NEEA IEs. Then, our objective was to explore the potential of news articles as an alternative data source for studying NEEA IEs and for developing tools to predict inflation. This research discovered that news articles in Indonesia could provide valuable information.

Furthermore, NLP outcomes can be an alternative source of traditional data for IEs since research has shown that NLP results perform well. The study also discovered that the NLP transformation yielded satisfactory prediction outcomes for inflation, especially for the 6-month forecast horizon.

These findings suggest that news articles can measure NEEA IEs, as observed in previous studies by Carroll (2003) and Tetlock *et al.* (2008). Furthermore, the results presented in this study provide fresh insights into the significance of non-traditional data, such as news articles data, which can offer useful feedback to policymakers. The study establishes the foundation for future research in analysing textual data to uncover significant insights that can enhance our comprehension of economic agents. While this study has made positive contributions, there is still scope for improvement. Investigating other methods in NLP and expanding the methodologies to analyse data from other macroeconomic variables would be a productive focus for future research. Nevertheless, the study undeniably contributes to our comprehension of how news articles can serve as a valuable source of information, enabling policymakers to access near real-time information. The conclusions of this study also acknowledge and comprehend the significance of unstructured data sources such as news articles. The results of this study can be applied to monitor NEEA IEs throughout the period between surveys. News articles also offer narrative material regarding the events, bolstering comprehensive understanding for policymakers on the narrative of inflationary events. The findings of this research will provide policymakers with an alternative source of information on NEEA IEs in near-real time. Finally, the valuable information from the news articles could give signals and provide valuable insights to the economic agents in forming their IEs, which we will explore further in the following chapter.

Chapter. III

Central Bank Press Releases: Effectiveness Through Intermediary Channels

We examine Central Bank Press Releases' (CBPRs) comprehensiveness, clarity, and sentiment features concerning their influence on non-expert economic agents' inflation expectations (NEEA IEs), specifically investigating whether there are direct or through intermediary channels utilising Indonesian data. Using several windows analyses, we apply Vector Autoregression with exogenous variables (VARX) to investigate the dynamic relationship between CBPRs features and news articles, inflation, and IEs. We also investigate how CBPRs consistency affects the similarity between CBPRs and news articles. We discovered that CBPRs indirectly impact NEEA IEs via news articles as an intermediary channel. The features of CBPRs are important in influencing news articles as an intermediary channel, particularly clarity and comprehensiveness. The study found that CBPRs consistency affects news articles and CBPRs similarities, particularly in the inflation paragraph.

3.1. Introduction

The management of inflation expectations (IEs hereafter) by central banks is a crucial tool in monetary policy (Bernanke 2007). By comprehending the factors behind IEs, central banks can influence them in pursuit of their objectives of maintaining inflation within the desired range set by their target (Woodford & Walsh 2005; Binder 2017). When IEs increase above the central bank's target, it can lead to a self-fulfilling prophecy of an actual inflation increase. To effectively manage non-expert economic agents' IEs (NEEA IEs hereafter), central banks employ communication strategies to align the NEEA IEs with the central bank's inflation target (Woodford 2001). This alignment is crucial for successfully implementing monetary policy (Binder 2017; Hayo & Neuenkirch 2018; Blinder *et al.* 2022).

Central banks' communication, mainly through press releases (PRs hereafter) of interest rate decisions (Ehrmann & Talmi 2020), disseminates information to the public and can significantly influence NEEA IEs, as Blinder *et al.* (2008) highlight. Multiple studies have examined the direct influence of central bank communication on NEEA, as documented by Lamla and Vinogradov (2019) and Coibion *et al.* (2022). Several researchers examined the influence through intermediary channels (Binder 2017; Ehrmann *et al.* 2017; Hayo & Neuenkirch 2018). Nevertheless, there is a lack of consensus regarding the precise processes through which central bank information is conveyed to NEEA (Dräger *et al.* 2016). Hence, it is crucial to investigate the channels through which central bank PRs (CBPRs hereafter) are communicated to economic agents (Picault *et al.* 2022). Research on this topic is particularly limited for economic agents in developing nations, as the attention has primarily been on developed countries (Conrad *et al.* 2022). Understanding central bank communication in developing countries is essential to comprehending its effects. This is particularly important because developing countries often experience more unstable inflation than developed countries. Following this, this study aim to investigate the transmission channel of CBPRs, especially for the NEEA in the developing country.

Several studies identified the transmission of CBPRs through intermediary channels, especially news articles (Lamla & Lein 2010; Ehrmann *et al.* 2017; Nimark & Pitschner 2019). These studies indicated that CBPRs have an indirect influence that depends on the level of clarity (Haldane & McMahon 2018), comprehensiveness (Dincer & Eichengreen 2013), and consistency (Ehrmann & Talmi 2020) of the CBPRs. In light of this rationale, it is imperative to formulate a communication strategy to shape NEEA IEs. This strategy should prioritise enhancing the clarity, comprehensiveness, and consistency of CBPRs, which might facilitate NEEA in obtaining a more perceptive understanding of monetary policy information.

Enhancing clarity within the PRs will result in a higher level of comprehension of the conveyed information. Providing comprehensive information allows NEEA to acquire knowledge about the policy's context and grasp the present economic situation. Moreover, maintaining consistency in the message facilitates comprehension for NEEA, as repeated exposure to the information enhances their level of understanding. However, there is a lack of knowledge regarding which features are of more significant importance for NEEA.

Since there is a gap in the literature, this study has three objectives related to assessing the impact of CBPRs. Firstly, it examines the impact of CBPRs on NEEA IEs, specifically investigating whether it is direct or through intermediary channels. Secondly, it investigates the features of CBPRs that substantially influence the NEEA IEs. Thirdly, it investigates how the consistency of CBPRs affects the similarity between the CBPRs and news articles.

This research offers five valuable contributions to the existing literature. First, this study provides a better understanding of the transmission of CBPRs to the NEEA IEs in developing countries with relatively volatile inflation conditions, as research on this topic in the context of developing countries remains scarce. Second, this research improves the understanding of the valuable features of CBPRs. To our knowledge, it is the first study to integrate the CBPRs' comprehensiveness, sentiment, and clarity. This investigation could provide insight for the central bank, which can be utilised as an alternative policy tool. Third, this study utilises Vector Autoregression with exogenous variables (VARX hereafter) to examine the impact of the CBPRs features. As far as we know, this is the first study that employs VARX to analyse the impact of CBPRs features by examining the dynamic relationship between variables. Fourth, this research investigates the influence of the time frames of CBPRs on various time windows and the effects of utilising the quantity (number of articles) and sentiment (language used or tones) of the news articles. Understanding the time window effect of CBPRs features can provide insight into the duration of their impact. Fifth, it contributes to comprehending the importance of CBPRs consistency and its impact on news articles in developing countries.

The primary data consists of the Bank Indonesia PRs and news articles written in Bahasa Indonesia from January 2009 to December 2018. The variables utilised in this study encompass CBPRs features, news articles, inflation, and IEs. This study applies VARX analysis to investigate the relationship between the abovementioned variables and the features of CBPRs, which were treated as exogenous variables. We examine the impact of the CBPRs features: comprehensiveness, clarity, and sentiment. The comprehensiveness is obtained

from the quantity of information disclosed in the PRs, as reflected in the number of words and topics. The clarity score is obtained from the Flesch-Kincaid score, and the sentiment score is derived from the dictionary-based method. Our study compares effects over a three-day window (Window 1), a seven-day window (Window 2), and a one-month window following the release (Window 3). Our research also examines the impact of CBPRs on the quantity and the sentiment expressed in the news articles. We utilise the cosine similarity approach to investigate the consistency and similarity of the CBPRs and news articles. The investigation also examines the degree of similarity between the CBPRs and the news using N-gram analysis. The analysis measures how the content of CBPRs is directly quoted by the news articles as a reliable source of undistorted information to economic agents.

The research discovered that the CBPRs influence NEEA IEs through news articles as an intermediary channel. Our study indicated that comprehensiveness and clarity are the key features of CBPRs that affect the quantity of news articles as an intermediary channel, which in turn influences NEEA IEs. The comprehensiveness of the PRs has a statistically significant impact on Window 3, whereas the clarity score on Windows 2 and 3. The sentiment expressed in the CBPRs also plays a significant role in shaping the sentiment of news articles. Furthermore, we discovered that the consistency of the CBPRs is key to enhancing the similarity score between the CBPRs and news articles. Our investigation into the effect of consistency on the media's direct quotation of information from CBPRs indicated that news articles also directly mentioned the content frequently provided by the CBPRs. The direct quote could incorporate the forward guidance and policy actions, which are essential for effectively influencing NEEA IEs.

This study has been organized in the following way. Section two explores the literature review. Then, Sections three and four explain the data and methodology used for this study. The fifth and sixth sections provide the empirical results and discussion of the research analysis, respectively. Finally, the summary and conclusion of this study are presented in Section seven.

3.2. Literature Review

The communication strategies employed by central banks are transitioning from a period of "constructive ambiguity", as exemplified by Alan Greenspan (Woodward 2001), to a more explicit and transparent approach (Issing 2019), as they aim to establish and stabilise the expectations of economic agents (Blinder *et al.* 2008). Recognizing the significance of central bank communication has sparked considerable research on the topic. The significance of central bank communication has been extensively examined in developed countries, but

research on this topic in emerging countries is still sparse. The existing studies were examined with a particular focus on the communication strategies of the Federal Reserve (Lamla & Vinogradov 2019; Coibion *et al.* 2020; Gardner *et al.* 2022), the European Central Bank (Hayo & Neuenkirch 2018; Conrad *et al.* 2022; Gardt *et al.* 2022), the Bank of England (Haldane & McMahon 2018), and the Bank of Canada (Ehrmann & Talmi 2020).

The significance of central bank communication has prompted numerous studies to investigate its influence on NEEA IEs. This aligns with the assertion made by Blinder *et al.* (2008) and Haldane *et al.* (2020) that effective central bank communication influences NEEA. In their study, Dräger *et al.* (2016) examined the impact of central bank communication on the comprehension of monetary policy, and they found its influence on NEEA IEs. According to Carvalho and Nechio (2014), the significance of central bank communication lies in its impact on the level of comprehension about implementing monetary policy. Their research revealed that NEEA exhibit heightened attention towards monetary policy during economic instability. In a study conducted by Coibion *et al.* (2022), a sample of 20,000 NEEA in the United States was utilised to examine the influence of reading the Federal Open Market Committee (FOMC) announcement and its impact on NEEA IEs. In their study, Lamla and Vinogradov (2019) analysed a dataset of 15,000 customer observations in the United States. Their findings revealed that 35% of these customers showed awareness of the FOMC PRs.

To date, there is a lack of agreement on how the central bank's communication is transmitted to NEEA (Dräger *et al.* 2016). Several studies have identified that NEEA acquire information through intermediary channels, such as news articles (Carroll 2003; Lamla & Lein 2010; Nimark & Pitschner 2019). According to Gardt *et al.* (2022), using a survey of the respondents in Euro-area countries, NEEA rely heavily on traditional offline media like television, news articles, and radio to acquire knowledge about the European Central Bank (ECB). The news articles remain the preferred information source for about 60% of the respondents. Similarly, Conrad *et al.* (2022) surveyed German households. They discovered that 85% of the participants continue to depend on conventional media as their primary source of information regarding the ECB's monetary policy. This assertion is also consistent with the findings of Blinder and Krueger (2004). Badarinza and Buchmann (2009) used panel regression on data from the euro area, which showed that an increase in the quantity of inflation news leads to a decrease in the heterogeneity of NEEA IEs. Ehrmann *et al.* (2017) found similar results in their study conducted in the United States, using the index of news coverage intensity as a measure. Their research revealed that news coverage of inflation could potentially mitigate the biases in NEEA IEs. This assertion aligns with the findings of

Doms and Morin (2004) and Binder (2017), which suggest that media coverage significantly shapes the NEEA IEs. According to Hayo and Neuenkirch (2018), using consumer data from Germany, media coverage can potentially enhance NEEA's comprehension of monetary policy and impact their IEs. Conrad *et al.* (2022) discovered through a survey of German households that traditional media significantly influences the way economic agents build their IEs. The literature demonstrates that news articles, as an intermediary channel, are crucial in facilitating economic agents' acquisition of knowledge regarding central bank information, hence shaping their IEs.

Haldane and McMahon (2018) conjectured that the level of public comprehension may explain why central bank communication, particularly PRs, has limited direct influence on NEEA. In light of this rationale, it is imperative to formulate PRs that encompass several key attributes: clarity (Haldane & McMahon 2018), comprehensiveness (Dincer & Eichengreen 2013), and consistency (Ehrmann & Talmi 2020).

Clarity is a prominent characteristic of the linguistic style employed in PRs, as it facilitates comprehension among economic agents. This, in turn, has the potential to mitigate misinformation and enhance understanding of monetary policy decisions. Increased clarity also enhances the trustworthiness of economic agents towards the central bank, as it can potentially reduce information bias. The level of clarity can be assessed by considering both the readability level and the educational background necessary to comprehend PRs. Numerous studies have employed the concept of clarity in central bank communication. Winkler (2000) proposed measuring the significance of clarity in central bank communication to enhance information comprehension. Bholat *et al.* (2019) conducted an online experiment of 4000 participants in the UK and discovered that using plain language can enhance the comprehension of NEEA, surpassing the effectiveness of visual information. Bulíř *et al.* (2013) and Hernández-Murillo and Shell (2014) have discovered that clarity can significantly improve the level of comprehension of central bank communication. Haldane and McMahon (2018) emphasised the importance of ensuring clarity in central bank communication to enhance its accessibility for NEEA.

Comprehensiveness refers to the degree of completeness of the information in a PRs. The primary objective of the PRs is to enhance transparency and promote the understanding of economic agents regarding the underlying factors driving monetary policy decisions. Additionally, it aims to influence NEEA IEs and bolster the decision-making process. There exists a lack of consensus in the research regarding the optimal level of communication comprehensiveness. One viewpoint suggests that improved open

communication leads to beneficial outcomes, such as enhancing monetary policy decision comprehension and anchoring economic agent expectations (Woodford & Walsh 2005; Blinder *et al.* 2008). On the other hand, Mishkin (2007) observes that excessive communication by the central bank can hinder its effectiveness. Eijffinger and Geraats (2006) also noted that the comprehensiveness of information varies in degree and can have varying effects on NEEA. Hernández-Murillo and Shell (2014) and Ehrmann and Talmi (2020) investigate the extent of comprehensiveness in PRs by examining the word count utilised in these releases. Hernández-Murillo and Shell (2014) demonstrated that the length of the FOMC PRs experienced a notable expansion from a range of 50 to 200 words during the 1990s to surpassing 800 words by 2014. Ehrmann and Talmi (2020) demonstrated that there has been a notable increase in the length of Bank of Canada PRs over the years, specifically from approximately 200 words in 2002 to over 400 words in 2018. The word count measures the extent to which central banks offer additional details regarding their policy decisions in PRs. Similarly, Coenen *et al.* (2017) quantified the comprehensiveness of the CBPRs by measuring the length of words in the introduction statement of the central bank communication. According to Blinder *et al.* (2008), the extent of information the central bank provides can influence non-experts' expectations. In line with Brouwer and de Haan's (2022) study utilising the Dutch Household survey on the ECB policy instrument, they discovered that the provision of more extensive information by the central bank had a significant impact on the NEEA IEs, aligning them closely with the inflation target established by the ECB.

The consistency of PRs refers to the uniformity and coherence in communicating information inside the release. Consistency encompasses various aspects, such as the coherence of information, paragraphs' logical sequencing, and adherence to a consistent writing style. Ehrmann and Talmi (2020) analysed the consistency of PRs issued by the Bank of Canada using cosine similarity. This analysis measured the similarity between the texts of consecutive PRs. It was found that consistency influenced the market and decreased market volatility. According to Issing (2019) and Blinder *et al.* (2022), ensuring consistency in central bank communication is crucial in mitigating the potential for confusion among NEEA.

The research on the influence of central bank communication features on economic agents IEs continues to grow. However, this study specifically focused on data from developed nations. There is a scarcity of literature that examines this issue in developing countries. Among the research from developing nations, Montes *et al.* (2016) examined how central bank clarity affected economic agents' IEs disagreements in Brazil. It was discovered

that the level of clarity significantly affects the disagreements of economic agents IEs. In this sense, the disagreement refers to the disparity between the maximum and minimum IEs. Similarly, Galvis Ciro and Anzoátegui Zapata (2019) discovered that the clarity of the communication from central banks significantly reduced disagreement among economic agents IEs in Columbia. Understanding the effects of central bank communication in developing countries is particularly valuable when studying the influence of more comprehensive features due to their inflation volatility. The characteristics of economic agents may also differ, as Cavallo *et al.* (2017) discovered that households in countries with high inflation possess a higher level of knowledge regarding inflation than those in countries with low inflation. Coibion *et al.* (2020) further demonstrate that nations with a low and stable inflation history exhibit diminished interest in information about inflation. Consequently, it is valuable to examine the effect of the central bank communication features in developing nations with relatively different inflation conditions than in developed countries.

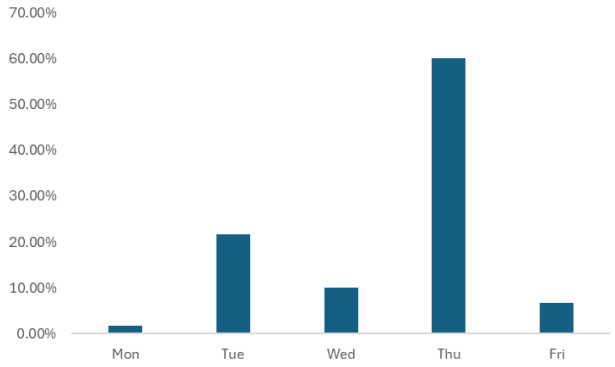
In summary, the existing literature does not reach a consensus on whether the influence of central bank communication on economic agents' IEs is direct or if it operates through an intermediary channel. Following the findings of Haldane and McMahon (2018) and Lamla and Vinogradov (2019), our understanding of the effects of central bank communication on economic agents remains unclear. Lamla and Vinogradov (2019) also stated that identifying the impact of the CBPRs is challenging due to the many events that transpired during this timeframe. There also remains a lack of research on integrating CBPRs, news articles, IEs, and inflation, as well as investigating the influence of CBPRs features: comprehensives, clarity, sentiment, and consistency. We incorporate the sentiment features as Gorodnichenko *et al.* (2023) also found that the sentiment from central bank communications influences IEs. In light of the little existing literature, this study aims to investigate the influence of CBPRs on NEEA IEs in Indonesia, a developing country with higher inflation volatility than developed countries. By examining the CBPRs from multiple perspectives in this research, we can contribute to providing a comprehensive understanding of its content and the extent of its influence.

3.3. Data

The main data utilised in this study is the official PRs acquired from Bank Indonesia, the central bank of Indonesia, from January 2009 to December 2018. The primary PRs is the official communication that announces the decision on the interest rate made by the Board of Governors of Bank Indonesia. The interest rate PR are announced monthly after the Board

of Governors meetings. Figure 3.1 illustrates that most interest rate PR during the data timeframe was announced on Thursday, accounting for 60% of the total. Tuesday, Wednesday, Friday, and Monday followed with proportions of 21.67%, 10.00%, 6.67%, and 1.67%, respectively. Bank Indonesia also began releasing the inflation PR in July 2013. This PR explains the factors contributing to inflation after the actual release by the Statistical Bureau of Indonesia.

Figure 3.1 Press Release Timing



This figure shows the proportion of the interest rate PRs timing by Bank Indonesia.

This study includes data from news articles, NEEA IEs, and inflation rates from January 2009 to December 2018. The news articles[39] use Indonesian economic news articles from the BI Cyberlibrary archives published in Bahasa Indonesia. The published news articles are sourced from ten prominent Indonesian news outlets, all of which have substantial national coverage and cover economic news[40]. The NEEA IEs data is derived from the monthly consumer survey performed by Bank Indonesia[41]. The inflation rate data is the monthly actual inflation rate on a year-on-year (YoY) basis, sourced from the Statistical Bureau of Indonesia.

3.4. Methodology

The primary variables employed in our analysis encompass the NEEA IEs, news articles, inflation rate, and CBPRs features as representations of central bank communication. We utilise Vector Autoregressions with exogenous variables (VARX) to examine the simultaneous relationship between the three endogenous variables and the CBPRs features as the exogenous variables.

[39] We examine the quantity and sentiment of news articles separately to gain a thorough understanding of the news articles.

[40] The dataset used in this study comprises 31,493 news articles obtained from two keywords: 20,900 articles from the keyword "*inflasi*" (inflation) and 10,593 articles from the keyword "*harga*" (price), along with additional keywords. For an in-depth explanation of the data set's filtering procedure, refer to Section 2.3.

[41] We transformed the consumer survey data using the extended CP method with AT and RPU assumptions.

3.4.1. Vector Autoregression

We employ the Vector Autoregression (VAR) methodology (Sims 1980), as Neuenkirch (2013), to explore the transmission of central bank policy through communication channels. Blood and Phillips (1997) also employed VAR to integrate the dynamic interaction between news, consumer sentiment, and macroeconomic variables. The primary rationale for employing the VAR is its ability to effectively address the research question, particularly in assessing the impact of CBPRs features. VAR is also a powerful method for analysing data progression across time (Thornton & Patterson 2013). In order to examine the dynamic impact of variables, we employ VARX with news articles, IEs, and inflation as endogenous variables and features of the CBPRs (comprehensiveness, clarity, and sentiment) as the exogenous variables. These features are considered independent and aligned with the monetary policy objectives of the central bank. In the VARX framework, the equation can be expressed as follows:

$$Y_t = \eta + \sum_{p=1}^{P} \mathrm{A}_p \, Y_{t-p} + \psi' X_t + \varepsilon_t \tag{3.1}$$

where Y_t is a 3 x 1 vector as a set of endogenous variables of $\left[\pi^e_{(t,t+n)}, \quad n_t^{q,s}, \quad \pi_t\right]'$; $\pi^e_{(t,t+n)}$ is the IEs at time t of the future inflation at time $t+n$; $n_t^{q,s}$ is the news articles at time t using the quantity (q) and sentiment (s) of the news; π_t is the inflation at time t; $\eta = (\eta_1, \eta_2, \eta_3)'$ is the vector intercept coefficient, A_p is the matrices of coefficient with 3 x 3 matrix of lag coefficients; ψ is the coefficient of exogenous variables $[\psi_1, \quad \psi_2, \quad \psi_3]'$, X_t is the exogenous variables; and ε_t is a vector of shocks $[\varepsilon_{1t}, \quad \varepsilon_{2t}, \quad \varepsilon_{3t}]'$.

The variables used in the equation as level variables and the number of lag selection criteria to choose for P is using the Schwarz Bayesian Information Criterion (SBIC) and Akaike information criterion (AIC). We also conducted the Granger Causality test and Impulse Response Function (IRF). In this part, we provide a more detailed explanation of the impact of the endogenous variables.

Inflation Expectations

Agents utilise all available signals or information at their disposal in order to formulate IEs. The economic agents will utilise the existing information available to them, which is derived from the signal generated by the combination of the previous signal (s_{t-p}) and the current signal at time t (s_t). The information regarding s_{t-p} is derived from the experiential knowledge of individuals in shaping IEs, while the information on s_t is obtained from the fresh data that economic agents gain. The prior signal refers to the conviction held by

economic agents regarding their expectations or the past economic agents' IEs $(\pi^{e}_{(t-p,t+n-p)})$[42].

Furthermore, in the event of market price fluctuations or situations of uncertainty, economic agents are highly motivated to engage in information-seeking behaviours. Agents are incentivised to incorporate additional information into forming IEs during this stage. The additional information originates from a reputable source so that economic agents hold confidence in the information's ability to convey the prevailing economic state. Given their apprehension over price levels and inflation, the precise measurement of the actual inflation rate is a prominent factor of interest for economic agents. In practise, when economic agents formulate their IEs, the current inflation rate is not yet available. As a result, consumers rely on the most recently published statistical inflation rate or the previous period (π_{t-1}). Moreover, Blinder *et al.* (2008), Ehrmann *et al.* (2013), and Blinder *et al.* (2022) have provided empirical evidence supporting the notion that central banks exert a significant impact on the economic agents' IEs. Nevertheless, two potential avenues exist for economic agents to get information from the central bank: directly through the central bank's communication or indirectly through intermediary channels, such as news outlets. Further, news articles (n_t) have been identified as a primary information source for economic agents to obtain knowledge about economic situations and influence their IEs formations (Carroll 2003; Lamla & Lein 2010; Larsen *et al.* 2021). However, previous studies conducted by Mankiw and Reis (2002) and Carroll (2003) have also provided evidence supporting the notion that not all economic agents receive information simultaneously. This phenomenon provides evidence for rational inattention among economic agents (Sims 2003). Consequently, certain agents continue to rely on past knowledge $(t-p)$.

News Articles

When reporting on economic news, journalists typically rely on multiple sources of information to gather data and facts for publication. The publication source is derived from both the archive source $(i_{t-p,t})$ and the current information (i_t) (Fogarty 2005; Shoemaker & Reese 2013). The archival source or historical information can be derived from the content generated through the routine creation of news, which is also based on previously published news (n_{t-p}) (Shoemaker & Reese 2013). Economic news on inflation primarily focuses on providing updates on the prevailing inflationary state. In this context, the actual inflation rate (π_t) is a key source of information for reporting purposes (Fogarty 2005). Given that the inflation rate is released monthly, the latest available inflation rate at the time of media

[42] In which we can define this as IEs at time $t-p$ of the future inflation at time $t+n-p$.

publication is from the previous month (π_{t-1}). Lamla and Lein (2010) and Binder (2017) have also acknowledged that the information about the central bank receives media attention. Further, the media-published economic news is also influenced by the economic agents' perceptions or expectations (Blood & Phillips 1995, 1997; Hester & Gibson 2003). Given the current focus on inflation in the news, the main concern is related to NEEA IEs ($\pi^{e}_{(t,t+n)}$). In disseminating economic information, the media also dedicates attention to evaluating the present economic state with previous economic performance ($t-p$) (Blood & Phillips 1995; Fogarty 2005). Furthermore, the influence of the news articles can be conveyed through the quantity (Carroll 2003; Badarinza & Buchmann 2009) and the sentiment of the articles (Li *et al.* 2014; Shapiro *et al.* 2022). Therefore, it is imperative to investigate the effects of the news articles' quantity and sentiment.

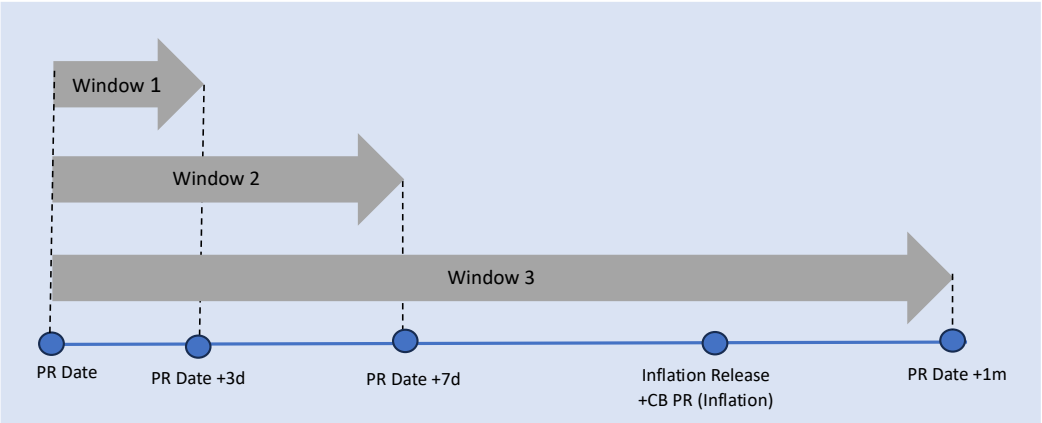
Inflation

In the context of inflation (π_t), scholars suggest that IEs ($\pi^{e}_{(t,t+n)}$) have a significant role in driving inflation. The variable that determines current inflation is also referred to as past inflation (π_{t-p}). Furthermore, the inflation rate is subject to the influence of monetary policy as the central bank endeavours to uphold price stability, which encompasses the management of inflation. The significance of the central bank's communication has been acknowledged by scholars such as Yellen (2006), Bernanke (2010), and Blinder *et al.* (2022). Therefore, it is reasonable to suggest that the central bank's communication could directly impact inflation. Moreover, the impact of news on the economy has been demonstrated by the research conducted by Blood and Phillips (1997) and Baker *et al.* (2016). The phenomenon is commonly referred to as the media malady hypothesis, which posits that economic news has the potential to influence the economy (Hester & Gibson 2003). Regarding the investigation of inflation news (n_t), it is worth considering the potential influence of such news on the actual inflation rate. Moreover, the potential delay in the impact of the variables should be considered.

3.4.2. Data Windows and Types

The investigation is conducted across three distinct windows to analyse the impact of CBPRs. As shown in Figure 3.2, the data windows are based on information gathered after the central bank interest rate PR. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to the times up to one month after the news release, which also encompasses the statistical bureau releases of actual inflation and the central bank's statement explaining the recently published inflation data.

Figure 3.2 Press Releases Data Timeframes



This figure shows the interest rate PRs data timeframes. PR date refers to the date of the CBPRs on interest rates. The +3d, +7d, and +1m indicate the time windows of three days, seven days, and one month respectively. PR (inflation) refers to the explanation of inflation by the CBPRs.

Types of the Data

News Articles Analysis

In order to achieve a comprehension of the news articles, we examine separately a quantity of news articles (n_t^q) as well as the sentiment associated with the news articles (n_t^s). The quantity of news refers to the numerical representation of news coverage. A dictionary-based method is employed to execute sentiment analysis on the news articles. The model employs linguistic characteristics and compares the words in the dictionary to differentiate between classifications. Each word in the document that matches the dictionary is assigned a score that quantifies the tone of the content. The score will be assigned to the word that is linked to the specific category in the dictionary[43]. The formula used to calculate the sentiment score for each document is as follows:

$$sc_d = \frac{\sum w_{+,d} - \sum w_{-,d}}{W_d} \tag{3.2}$$

where sc_d is the sentiment score of document d; $w_{+,d}$ is the positive word in document d; $w_{-,d}$ is the negative word in document d; W_d is the total number of words in document d. The equation used to calculate the sentiment score for a specific month is as follows:

$$n_t^s = \sum_{d=1}^{D} sc_d \tag{3.3}$$

[43] We utilised the bespoke dictionary as the benchmark, which is the second version dictionary provided in Chapter 2. The utilisation of this dictionary is aligned with the main objective of this research to assess the impact of CBPRs on NEEA IEs, as this dictionary is specifically related to the IEs. For a comprehensive explanation, refer to subsection 2.5.3.

where n_t^s is the total sentiment score of the news articles at time t.

3.4.3. Press Release Variables

When analysing the CBPRs, we include multiple variables to describe the features of the PRs. The study analyses key aspects: clarity, comprehensiveness, and sentiment.

The concept of clarity refers to the quality of being easily understood. Clarity is essential to enhance the degree of understanding of the information received by economic agents. The readability measurement in this research will be conducted using the Flesch-Kincaid score (Kincaid *et al.* 1975). The score evaluates the educational grade level necessary for comprehending the document. The Flesch-Kincaid score is calculated using the formula:

$$FK_d = 0.39\left(\frac{\sum w_d}{\sum s_d}\right) + 11.8\left(\frac{\sum syl_d}{\sum w_d}\right) - 15.59 \quad (3.4)$$

where FK is the Flesch-Kincaid score for the document d; Σw_d is the number of words in the document d; Σs_d is the number of sentences in the document d; Σsyl_d is the number of syllables in the document d.

The formula considers three crucial factors: word, sentence, and syllable counts. These three traits are derived from the premise that an increased sentence length can result in confusion. In addition, the greater the number of syllables in a word, the more intricate the phrase employed in the document, rendering the content difficult to comprehend.

Moreover, as the robustness test, we also employed the SMOG index developed by Mc Laughlin (1969). The SMOG index was employed due to its suitability for documents including more than 30 sentences, which aligns with the characteristics of our text dataset. The SMOG index is derived using the following formula:

$$SMOG_d = 3.1291 + 1.0430 \,.\sqrt{w_c} \quad (3.5)$$

where $SMOG$ is the SMOG index score for the document d; w_c is a complex word that consists of more than three syllables.

The comprehensiveness analysis examines the information features offered by the CBPRs. Comprehensiveness is achieved by integrating word count and the number of topics in the PRs. The level of information central banks provide to the economic agents is determined by the number of words used, as examined by Hernández-Murillo and Shell (2014) and Ehrmann and Talmi (2020). The quantification of the number of topics pertains to the diversity of subjects covered in the CBPRs, which is determined by the count of paragraphs contained within those releases. The number of paragraphs symbolises the subject matter since each paragraph in the CBPRs signifies a distinct primary topic of information to be disseminated. The comprehensiveness can be determine by the formula:

$$Comp_d = \sum w_d \; x \; \sum t_d \tag{3.6}$$

where $Comp_d$ is the level of comprehensiveness of the document d; w_d is the number of words in the document d; t_d is the number of topics covered in the document d.

In addition to examining the CBPRs' tonal representations, we also conduct sentiment analysis. In a manner akin to the sentiment analysis employed for the analysis of news articles, we are utilising a dictionary-based method, as outlined in Equations (3.2) and (3.3). The examination of sentiment analysis of the CBPRs can serve as a means to assess the extent to which it effectively influences the target variables.

3.4.4. Consistency and Similarity

We proceed to delve deeper into consistency and similarity. We employ the cosine similarity to assess the consistency of the CBPRs and the similarity between the CBPRs and the news articles. The cosine similarity approach measures the level of similarity between two documents. The similarity score is a value that ranges between 0 and 1. A score close to 0 indicates a significant lack of similarity between the two documents or that the vectors used in the computation are perpendicular to each other. A score close to 1 suggests a high level of similarity between the texts in terms of the words they contain, indicating a tiny vector angle between the two documents. The cosine similarity score quantifies the cosine of the angle between two vectors representing two documents[44], which can be derived from:

$$CS_{d,d^*} = \frac{\sum_{w=1}^{W} f_{w,d} f_{w,d^*}}{\left(\sqrt{\sum_{w=1}^{W} f_{w,d}^2}\right)\left(\sqrt{\sum_{w=1}^{W} f_{w,d^*}^2}\right)} \tag{3.7}$$

where CS_{d,d^*} is the cosine similarity score between document d and document d^*; $f_{w,d}$ is the frequency of word w in the document d; f_{w,d^*} is the frequency of word w in the document d^*; W is the number of words in the document d and document d^*.

During the examination of the CBPRs, an assessment is conducted to determine the degree of consistency between the releases. In this consistency analysis, we assess the similarity between two consecutive CBPRs, specifically comparing the PRs at time t with the PRs at time $t-1$. This approach aligns with the methodology employed by Ehrmann and

[44] We employed cosine similarity in this research due to several advantages, specifically relatively easy to implement; widely used in the literature, as implemented by Ehrmann and Talmi (2020); and faster to process without requiring special hardware. Although advanced techniques such as embeddings are available, this research did not utilise due to the resource constraint. The implementation could be advantageous in future studies.

Talmi (2020). The cosine similarity score is utilised to obtain the consistency score, as indicated in Equation (3.7).

We aim to determine how the consistency of CBPRs affects the similarity between PR and news articles. We utilise consistency as the independent variable and the similarity of CBPRs and news articles as the dependent factors. The similarity score for the dependent variable in certain months can be determined by calculating the average cosine similarity score between the CBPRs and all the news articles within that month, which is expressed as follows:

$$Sim_t = \frac{\sum_{d^n=1}^{D^n} CS_{d_t^n, d_t^{pr}}}{n_t^q} \tag{3.8}$$

where Sim_t is the similarity score at time t; $CS_{d_t^n, d_t^{pr}}$ is the cosine similarity score between documents of the news articles (d_t^n) at time t and document of the CBPRs (d_t^{pr}) at time t.

We also analyse N-gram similarity[45] to capture the CBPRs cited in the news articles. N-gram analysis can identify multi-word expressions because unigrams cannot capture word order (Ehrmann & Talmi 2020). N-gram analysis enhances the similarity between CBPRs and news articles by highlighting the content of CBPRs quoted in the news articles. Quoting directly from the CBPRs is crucial for accurately conveying information without altering its meaning. It ensures that the central bank's information is not misinterpreted. When doing N-gram similarity analysis, we examine 5-grams - 7-grams, which refer to sequences of five to seven consecutive words, respectively. The initial stage of N-gram similarity analysis is the filtration of N-grams extracted from the CBPRs. The N-grams selected for comparison between the CBPRs and the news articles have a minimum frequency of five occurrences in the CBPRs. The next step is to compare the N-grams extracted from the CBPRs with those in the news articles. The frequency of N-gram occurrences in the CBPRs mentioned in the news articles reflects the number of direct quotes from the CBPRs.

3.5. Empirical Result

3.5.1. The Effect of the Press Release Features.

We utilise the VARX, employing 120 monthly observations from January 2009 to December 2018. The endogenous variables include news articles, NEEA IEs, and inflation, while the exogenous variables consist of features of CBPRs: comprehensiveness, clarity, and

[45] The N-Gram similarity is used to highlight the content of CBPRs quotes in the news articles. By applying N-gram similarity, we can assess the impact of consistent N-gram usage in the CBPRs influences the content of news articles.

sentiment. Prior to doing the study utilising the time series analysis, it is essential to perform the stationarity test and the selection of the optimum lag. According to the Augmented Dickey-Fuller test (Dickey & Fuller 1979), the stationarity test indicated that all the data exhibit stationarity at the specified level. The second step of the VARX pre-test is to select the optimal lag. Since the data is collected monthly, this study employs a maximum lag of 12 periods. The lag that produces the optimal model according to the SBIC (Schwarz 1978) is lag 1, while AIC (Akaike 1998) selected lag 7.

The benchmark model employed in this study was lag 1, which was determined to be the most parsimonious model. Nevertheless, due to Indonesia's distinctive economic conditions, we employed a lag of 7 as the comparative model. Lag 7 could be a comparative model due to Indonesia's seasonality, characterised by a recurring price increase during two specific occasions. The initial occurrence occurs during the month of Ramadhan, whereby there is a surge in demand for goods and services due to a significant religious event in Indonesia and the employees' holiday allowance, which is an extra kind of compensation. The second event also occurs due to an additional salary at the end or beginning of the year. The Christmas holiday and New Year festivities contribute to the rise in demand and services during this time. The two primary events within the specified time exhibit a delay of around 6-7 months, resulting in the potential for seasonality in the data and influencing the 6-7 months horizon time that economic agents consider forming their IEs. The VARX (7) provides a thorough information model but sacrifices efficiency due to the higher number of coefficients relative to the VARX (1). Conversely, the VARX (1) model is the most parsimonious, although it may exclude important dynamics. With this consideration, this research will compare the outcomes of VARX (1) with VARX (7) side by side, focusing on the impact of employing maximal and minimal dynamic lag. We additionally tested intermediate lags for the VARX model, specifically VARX (3) and VARX (6). However, the overall results were consistent with those obtained from VARX (1) and VARX (7). We chose to present the results from VARX (1) and VARX (7), as they indicated the optimal lag leghth according to the information criteria selection.

Table 3.1 presents the key findings concerning the impact of CBPRs on the quantity of news articles and NEEA IEs. Referring to the data shown in Table 3.1 in VARX (1), it is evident that the influence of all of the CBPRs features on news articles is significant. The degree of comprehensiveness has a notable impact during Window 3. One potential rationale for this phenomenon is that the media tends to delve deeper into the information provided by the CBPRs over an extended time period. Consequently, the greater the

information the CBPRs disclose, the more material the media has to analyse and incorporate into their news articles. The importance of comprehensiveness also aligns with the findings of Dincer and Eichengreen (2013). Conversely, at briefer time intervals, the media emphasises disseminating primary information sourced from the CBPRs, where this information can be found in most PR materials.

The sentiment has a statistically significant impact during Windows 2 and 3. An increasing sentiment score[46] within the CBPRs has the potential to influence the media to raise the amount of coverage. In the period of Window 1, within the briefest timeframe, the quantity of news articles remains unaffected by the sentiment score expressed in the CBPRs. This might be because the media will cover information from the central bank regardless of the sentiment score conveyed in the PR. The clarity score generally demonstrates a statistically significant relationship, which suggests that a decrease in clarity score[47]is associated with a corresponding increase in the quantity of news articles. This finding aligns with the studies conducted by Bulíř *et al.* (2013) and Haldane and McMahon (2018), which suggest that lowering the clarity score can lead to improved comprehension of material. Generally, the results of VARX (7) align with the outcome of VARX (1). The sentiment and clarity of the CBPRs have a notable effect on the quantity of news articles in Window 2. Window 3 reveals that all CBPRs features have a statistically significant impact on the quantity of news articles. The signed result aligns with the outcome from VARX (1).

From Table 3.1, it is also found that the VARX(1) analysis indicated that the CBPRs features did not significantly affect IEs directly. However, when examining the influence on NEEA IEs in the VARX(7), the overall comprehensiveness of the PRs has a statistically significant direct impact on NEEA IEs[48]. Nevertheless, the influence appears to be limited. The sentiment and clarity have no substantial impact on the NEEA IEs. When we explored the impact of CBPRs on inflation, it showed that there is no statistically significant impact of all the features of CBPRs in both VARX(1) and VARX(7).

[46] In this context, a rising sentiment score indicates a trend towards inflation or rising prices in the information; a falling score indicates a tendency regarding deflation or decreasing prices in the information.

[47] Decreasing the clarity score in this study context refers to reduce the level of education required to understand the information content, hence making the information clearer to the reader.

[48] With regard to the NEEA IEs, increasing the comprehensiveness has a direct effect on decreasing IEs.

Table 3.1 The Effect of the CBPRs Features (Quantity of the News Articles)

VARX(1)

News Articles			
Variables	Window		
	1	2	3
Comp	0.0008	0.0013	0.0065*
PR_Sent	138.8503	375.9732*	1279.969*
Clar	-3.1944	-7.8044**	-31.0011**
Inflation Expectations			
Variables	Window		
	1	2	3
Comp	-0.00005	-0.00004	-0.00005
PR_Sent	2.5515	1.9896	-0.2002
Clar	-0.0830	-0.0984	-0.0711
Inflation			
Variables	Window		
	1	2	3
Comp	0.000017	0.00002	0.00002
PR_Sent	2.4483	2.2669	2.0137
Clar	0.0776	0.0730	0.0766

VARX(7)

News Articles			
Variables	Window		
	1	2	3
Comp	0.0007	0.0011	0.0078*
PR_Sent	194.1098	400.2529*	1262.525*
Clar	-4.10004*	-9.5474**	-38.66***
Inflation Expectations			
Variables	Window		
	1	2	3
Comp	-0.0001**	-0.0001**	-0.0001*
PR_Sent	4.0626	4.7542	1.1266
Clar	-0.1393	-0.1488	-0.0949
Inflation			
Variables	Window		
	1	2	3
Comp	0.000004	0.00001	0.00001
PR_Sent	1.4573	1.4650	-0.5236
Clar	0.0827	0.0664	0.0837

This table highlighted the effect of the CBPRs features as the exogenous variables in the VARX(1) and VARX(7). The endogenous variables are the quantity of news articles, IEs, and inflation. Comp is the comprehensiveness; PR_Sent is the sentiment of the PR; Clar is the clarity. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release. The complete results of the VARX(1) and VARX (7), along with the summary statistics are provided in the appendix.

Table 3.2 presents the outcomes of the impact of CBPRs features on the sentiment of news articles, NEEA IEs, and inflation. According to the findings presented in Table 3.2, the VARX (1) results indicate a statistically significant impact of the sentiment score expressed in CBPRs on the sentiment of news articles across all data windows. The findings indicate that the news articles will align with the sentiment expressed in the CBPRs. The PR's features of comprehensiveness and clarity do not exhibit statistical significance in influencing the sentiment of the news articles. Our analysis shows that the CBPRs features do not significantly impact IEs directly and inflation when considering the sentiment of the news articles as the endogenous variable. According to the VARX(7) investigation, there is a robust statistical relationship between the sentiment score of CBPRs and the sentiment score of news articles across all windows. Comprehensiveness also notably influences IEs, particularly when examining the data from Windows 1 and 3. The CBPRs features do not statistically impact inflation in the VARX (7) outcome.

Table 3.2 The Effect of the CBPRs Features (Sentiment of the News Articles)

VARX(1)

News Articles			
Variables	Window		
	1	2	3
Comp	0.000005	-0.000003	-0.0001
PR_Sent	14.4292*	27.8053***	77.9264**
Clar	-0.1176	-0.1612	-0.4020
Inflation Expectations			
Variables	Window		
	1	2	3
Comp	-0.000031	-0.00003	-0.00003
PR_Sent	2.2584	1.7854	0.0084
Clar	-0.1078	-0.1129	-0.1091
Inflation			
Variables	Window		
	1	2	3
Comp	0.000024	0.00002	0.00002
PR_Sent	2.1690	1.8078	1.5613
Clar	0.0656	0.0623	0.0694

VARX(7)

News Articles			
Variables	Window		
	1	2	3
Comp	-0.00002	-0.00002	-0.00003
PR_Sent	17.6437***	29.9226***	73.8375*
Clar	0.0021	-0.072098	-0.519688
Inflation Expectations			
Variables	Window		
	1	2	3
Comp	-0.00005*	-0.00005	-0.0001*
PR_Sent	5.2523	2.7438	1.4084
Clar	-0.2003*	-0.1989*	-0.1773
Inflation			
Variables	Window		
	1	2	3
Comp	0.000012	0.00001	0.00001
PR_Sent	0.4334	0.4303	-0.0308
Clar	0.0529	0.0568	0.0659

This table highlighted the effect of the CBPRs features as the exogenous variables in the VARX(1) and VARX(7). The endogenous variables are the total sentiment of the news articles, IEs, and inflation. Comp is the comprehensiveness; PR_Sent is the sentiment of the PR; Clar is the clarity. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release. The complete results of the VARX(1) and VARX (7), along with the summary statistics are provided in the appendix.

Table 3.3 presents the Granger Causality test outcomes of the influence of news articles on NEEA IEs. According to Table 3.3, VARX (1) 's results indicate the null hypothesis that the quantity of the news articles does not Granger-cause NEEA IEs can be rejected. This suggests that the frequent mention of inflation in news articles exerts a more significant influence on NEEA IEs. Consequently, economic agents have relied on news articles as a source of information to form their IEs, as evidenced by the studies conducted by Carroll (2003), Lamla and Lein (2014), and Nimark and Pitschner (2019). It also indicates that economic agents prefer more current information from news articles. This aligns with Boero *et al.* (2008), who found that the most recent news articles have a greater influence. However, the null hypothesis that the news articles' sentiment score does not Granger-cause NEEA IEs cannot be rejected. The VARX (7) results consistently demonstrated that we can reject the null hypothesis that the quantity of news articles does not Granger-cause NEEA IEs. Nevertheless, there is insufficient evidence to reject the null hypothesis that the sentiment score of the news does not Granger-cause NEEA IEs.

Table 3.3 Granger Causality Test (The Effect of the News Articles on IEs)

VARX(1)	Windows		
	1	2	3
	χ^2		
Null Hypothesis: NA does not Granger Cause NEEA IEs			
Quantity	11.89***	10.74***	6.11*
Sentiment	1.12	1.53	1.63
VARX(7)	**Windows**		
	1	**2**	**3**
	χ^2		
Null Hypothesis: NA does not Granger Cause NEEA IEs			
Quantity	31.16***	27.34***	18.29*
Sentiment	8.34	8.82	5.18

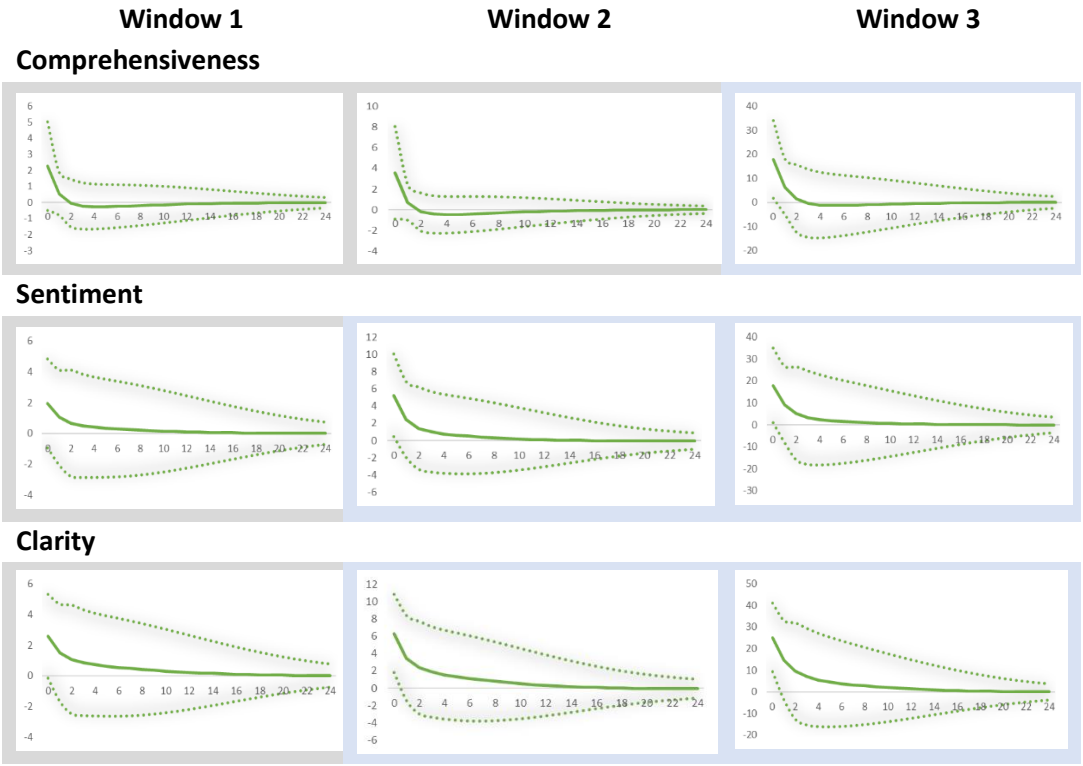
This table highlighted the Granger Causality test of the effect of the news articles on the IEs in the VARX(1) and VARX(7). The Null hypothesis is the news articles does not Granger Cause NEEA IEs. The endogenous variables in the upper position (quantity) are the quantity of news articles, IEs, and inflation. The endogenous variables in the lower position (sentiment) are the sentiment of the news articles, IEs, and inflation. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. NA stands for news articles; NEEA IEs stand for non-expert economic agents' inflation expectations. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

Overall, it is evident that the findings from VARX(1) and VARX(7) present a reasonably similar picture. The CBPRs features have a notable impact on both models regarding the quantity of news articles, as indicated in Table 3.1. This impact is particularly significant in Window 3, where all the features yield statistically significant results. Table 3.2 reveals that the sentiment score of CBPRs has a noticeable effect on the sentiment score of news articles. Both models yield statistically significant results, confirming similar conclusions. However, the effects of the CBPRs on IEs yield slightly varied outcomes. In the VARX(1), the results for all of the features are not significant. However, in the VARX(7), there is a statistically significant result, particularly regarding the impact of comprehensiveness. The contrasting outcomes of VARX(1) and VARX(7) suggest a potential lack of significant direct influence from central bank PR features on NEEA IEs. Table 3.3 reveals a similar outcome in terms of the influence of news articles on IEs. The quantity of news articles has a more significant influence on IEs than the sentiment of the news articles. In line with a cautious approach, we will draw a conclusion that provides statistically significant findings for the VARX(1) and VARX(7) models. Based on this, the CBPRs features do not have a significant direct impact on IEs. This impact seems to be mediated by the quantity of news articles, suggesting an indirect relationship. In addition, it is worth noting that the results from both VARX(1) and VARX(7) are generally consistent. Therefore, for the subsequent subsections, we will focus on analysing the VARX(1) as it is the most parsimonious model.

3.5.1.1. Impulse Response Function

Tables 3.1 and 3.2 indicate that the features of CBPRs have a statistically significant influence on the quantity of news articles. In this subsection, we simulate the impulse response function (IRF herafter) to examine the influence of comprehensiveness, sentiment, and clarity on the quantity of news articles, as depicted in Figure 3.3. Furthermore, based on the findings presented in Table 3.3, it is evident that the quantity of news articles has a considerable influence on IEs. In Figure 3.4, we examine the IRF of the quantity of news articles on IEs, indicating the indirect impact of CBPRs on IEs, mediated by news articles as an intermediary channel.

Figure 3.3 Impulse Response (CBPRs Features and News Articles)



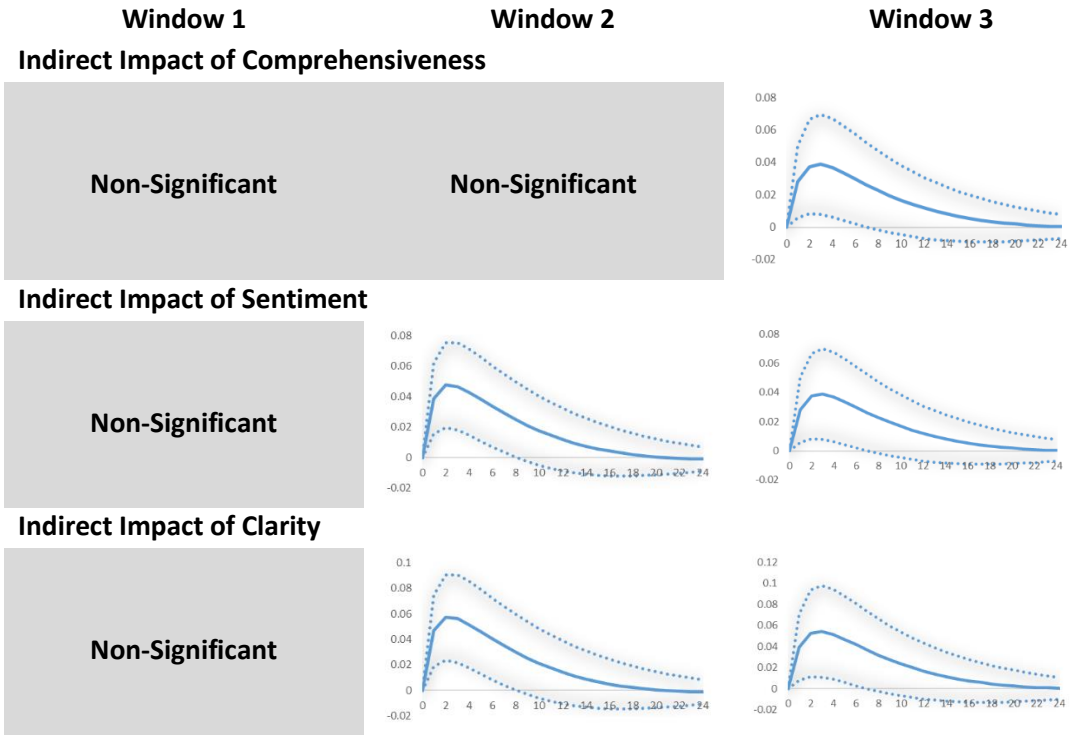
This figure shows the IRF of VARX(1). The impulse is the CBPR's features: comprehensiveness (upper side of the graph), sentiment (middle side of the graph), and clarity (bottom side of the graph), and the response is the quantity of news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, whereas the grey background indicates non-significant results. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

Based on the findings presented in Figure 3.3, which align with the results presented in Table 3.1, it is evident that comprehensiveness yields a statistically significant outcome in Window 3. Adjustment corresponding to one standard deviation of comprehensiveness is associated with a response change of 17.86 news articles[49]. The sentiment and clarity scores

[49] The one standard deviation of quantity of the news articles in the Window 3 is 122.81, so the impact is 14.54% of the one standard deviation.

of CBPRs statistically significantly influence news articles in Windows 2 and 3. The adjustment of one standard deviation in Window 3 leads to an increase in the comprehensiveness and sentiment score, while the clarity score decreases. These changes correspond to increases of 17.86, 17.92[50], and 25.11[51] news articles, respectively. This study's findings indicate that clarity score adjustment impacts news articles more than comprehensiveness and sentiment score.

Figure 3.4 Impulse Response (News Articles and IEs)



This figure shows the IRF of VARX(1). The Impulse is news articles, and the response is IEs. This figure indicates the indirect impact of CBPRs features: comprehensiveness (upper side), sentiment (middle side), and clarity (bottom side). The solid line is the IRF, and the dotted line is a 95% confidence interval. The grey background indicates the non-significant result. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

As the results in Table 3.3 indicated that the quantity of news articles impacted IEs, we also examined the impact of increasing news articles in response to an adjustment in CBPRs features on IEs. This outcome can also provide insight into the indirect influence of CBPRs on IEs via news articles as an intermediary channel. The effect on news articles, as shown in Figure 3.4, reflects a response to the increase in news articles illustrated in Figure 3.3. It is important to note that the non-statistical significance in Figure 3.3 is not presented in Figure 3.4. According to Figure 3.4, it is evident that increasing one standard deviation of comprehensiveness had an indirect effect on IEs, resulting in an approximate increase of

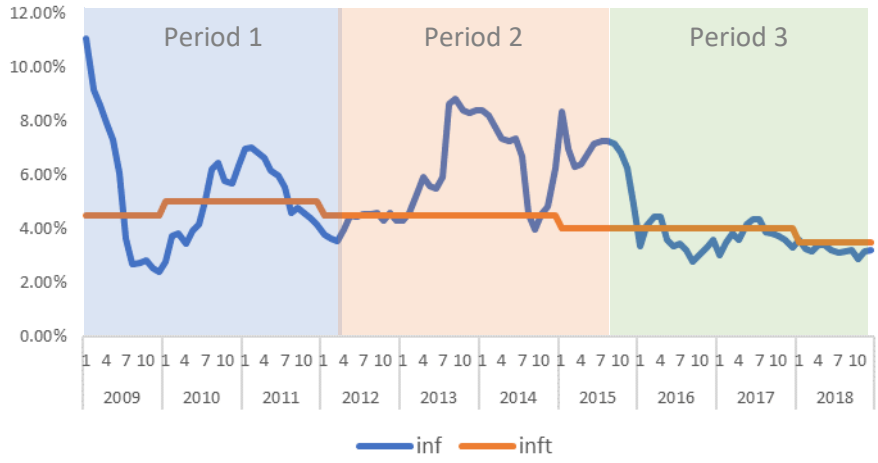
[50] The impact is 14.59% of one standard devation of the quantity of the news articles in Window 3.
[51] The impact is 20.45% of one standard devation of the quantity of the news articles in Window 3.

0.028 percentage points in IEs one month following the adjustment. The most significant indirect effect observed is the indirect effect of one standard deviation in clarity score on IEs, as mediated by the news article in Window 2. This indirect impact increased by 0.047 percentage points in IEs one month following the adjustment. The IRF exhibits a consistent pattern across all results, wherein the impact of news articles on IEs is amplified until three months after the adjustment. This impact gradually decreases over seven to eight months after the occurrence of adjustment. Subsequently, the impact is becoming less significant.

3.5.1.2. Sub-sample Analysis

In order to investigate the effect across sub-sample, within this part, our objective is to examine the noteworthy outcome derived from Figure 3.3 through the utilisation of sub-sample analysis. This investigation aims to determine the efficacy of the features of CBPRs that substantially impact the quantity of news articles, as depicted in Figure 3.3. Given the reduction in sample size offered by VARX(1) and VARX(7), we have chosen to utilise VARX(1) to conduct this subsection analysis. The data set was partitioned into three equal segments, each encompassing 40 months. The rationale behind separating it into three discrete phases is to differentiate between the stable and shock periods, allowing for a thorough analysis of the impact of CBPRs features on each period.

Figure 3.5 Inflation and Inflation Target in Indonesia



This figure illustrates Indonesia's inflation rate and target from January 2009 to December 2018. The blue line shows the inflation rate, while the orange line represents the inflation target.

Figure 3.5 illustrates the presence of distinct inflation patterns throughout three distinct sub-sample periods. The initial period, which encompasses January 2009 to April 2012, is distinguished by a decrease in inflation rates accompanied by a notable degree of inflationary volatility. The second period was characterised by instability and an increase in

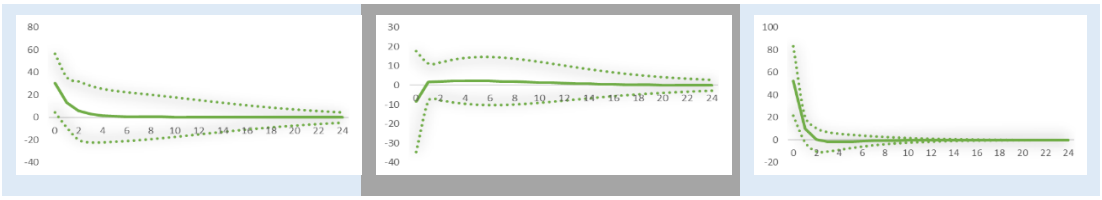
inflation due to the taper tantrum and the 2014 presidential election. These factors collectively signify the period of shocks. In the third period, there is a decrease in inflation, and the inflation conditions remain relatively stable. We have discovered evidence suggesting that comprehensiveness is effective during stable times. The findings also indicate that sentiment is useful in periods of high inflation, whereas clarity is effective in conditions of unpredictable inflation. The next portion provided an analysis of this outcome.

In order to investigate the efficacy of comprehensiveness, sentiment score, and clarity score in relation to the quantity of news articles, we simulated the IRF of CBPRs features across three time periods. The result of comprehensiveness, as in Figure 3.3, yielded a statistically significant outcome in Window 3. Consequently, we investigated the influence of Window 3 for each period. The findings in Figure 3.6 indicate a statistically significant relationship between comprehensiveness and the quantity of news articles over Periods 1 and 3. The impact of increasing comprehensiveness, measured by one standard deviation, increases to 30.53 and 52.17 news articles in Periods 1 and 3, respectively. These findings suggest that comprehensiveness is more impactful during Period 3, characterised by a relatively stable inflation condition. The evidence additionally indicates that the impact of comprehensiveness is more pronounced during periods of decreasing inflation, specifically in Periods 1 and 3. Throughout Period 2, characterised by rising inflation and significant volatility, it is indicated that the media will focus on inflation-related news, regardless of the level of detail provided in the CBPRs.

Figure 3.6 Impulse Response (Comprehensiveness and News Articles), Sub-Sample

Period 1 **Period 2** **Period 3**

Comprehensiveness (Window 3)

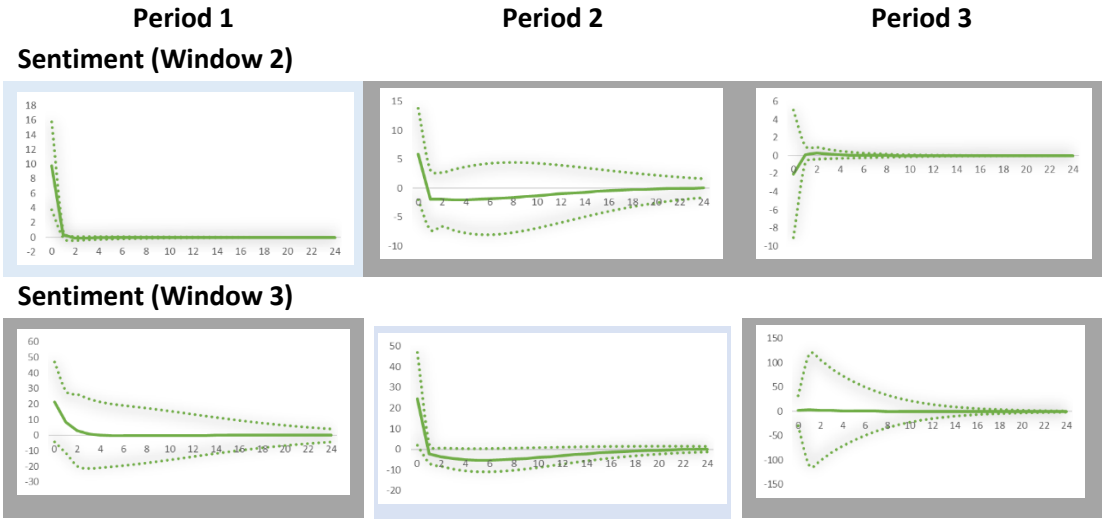


This figure shows the VARX(1) IRF of Window 3. The Impulse is the comprehensiveness of the CBPRs, and the response is the quantity of news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, and the grey background indicates non-significant results. Window 3 refers to one month after the release.

The analysis of Figure 3.3 revealed significant results of the sentiment score expressed in the CBPRs on Windows 2 and 3. Consequently, we investigated these sentiment scores' influence on Windows 2 and 3 across all periods. According to the outcome presented in Figure 3.7, there is a statistically significant result of the sentiment score of CBPRs on news articles in the short-term window of Period 1 and the long-term window of Period 2. In Window 2, the

impact of a one standard deviation adjustment on the sentiment score of CBPRs increased by 9.8 news articles during Period 1. This effect was more significant than the complete sample data, as depicted in Figure 3.3. According to Figure 3.7, the impact of a one standard deviation adjustment in the sentiment score of CBPRs for article news in Window 3 of Period 2 is statistically significant. This change increased to 24.48 news articles, surpassing the impact of an increase of 17.92 news articles in the outcome of Figure 3.3. The results suggest that the CBPRs sentiment score is impactful during periods of volatile inflation conditions. In Period 1, there is a general decrease in inflation but still volatility. When there is an increasing sentiment score from the CBPRs, the media will report inflation-related news more frequently in the short term. Nevertheless, this coverage does not last for a prolonged duration. Conversely, during Period 2, there is a statistically significant effect on the extended window. The impact in the shorter term is not substantial, perhaps due to the unstable conditions and rising inflation during this period. The number of news articles connected to the inflation topic remains high in the shorter term, regardless of the CBPRs sentiment.

Figure 3.7 Impulse Response (Sentiment and News Articles), Sub-Sample

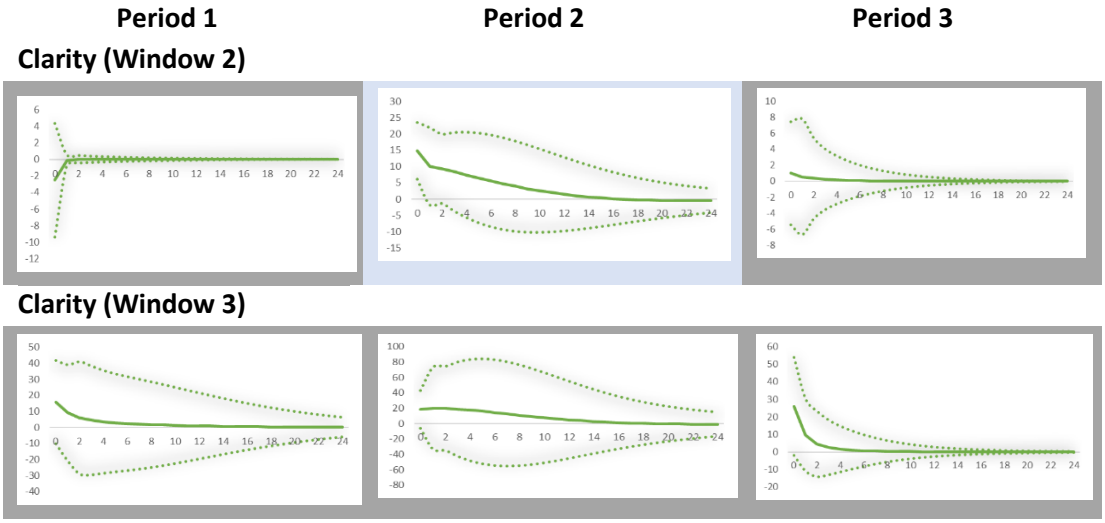


This figure shows the IRF of VARX(1). The Impulse is the sentiment of CBPRs of Window 2 (upper side), and Window 3 (bottom side), and the response is the quantity of news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, and the grey background indicates non-significant results. Window 2 refers to a duration of seven days; Window 3 refers to one month after the release.

To verify the clarity of the CBPRs, we examined the influence during Windows 2 and 3 of each period, according to Figure 3.3, which yielded a significant result. The statistical analysis in Figure 3.8 demonstrates that the adjustment of the clarity score substantially impacted Window 2 in Period 2. The quantity of news articles in Window 2 grew by 14.84 due to a one standard deviation adjustment caused by a decrease in the clarity score of the

CBPRs during Period 2. This outcome suggests the need to enhance clarity, particularly in the presence of escalating and relatively unstable inflation.

Figure 3.8 Impulse Response (Clarity and News Articles), Sub-Sample



This figure shows the IRF of VARX(1). The Impulse is the clarity of CBPRs of Window 2 (upper side), and Window 3 (bottom side), and the response is the quantity of news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, and the grey background indicates non-significant results. Window 2 refers to a duration of seven days; Window 3 refers to one month after the release.

In a nutshell, the effectiveness of comprehensiveness and its impact on news articles is potentially more pronounced in contexts characterised by generally constant inflation conditions. We found evidence that sentiment score is more influential on the quantity of news articles during periods of high inflation, whereas clarity score appears to have a more influential role during shock periods.

3.5.1.3. The Joint Effect of Press Release

Within Window 3, there is a supplementary CBPR that provides an explanation of the inflation after the actual release by the statistical bureau. This subsection examines both PRs' combined impact to assess their overall effect. By examining both PRs, we can determine whether the features of both PRs impact the news articles as intermediary channels or whether the impact is more substantial solely in the interest rate PR, as found in the previous subsections. In this subsection, we analyse both PRs by consolidating them into a single document and using the PRs features as exogenous variables. The model produced the weighting and combined score of the comprehensiveness, sentiment, and clarity scores by merging both PRs into a single document. For comparison purposes, we also measured the combined score by allocating a weight of 75% to the interest rate PR and 25% to the inflation PR. This weighting is determined by the timing of the inflation PR, which occurs at the end of the week of Window 3. The results of this weighting comparison demonstrate a similarity (the results are supplied in the appendix). Since the PR regarding inflation began in July 2013,

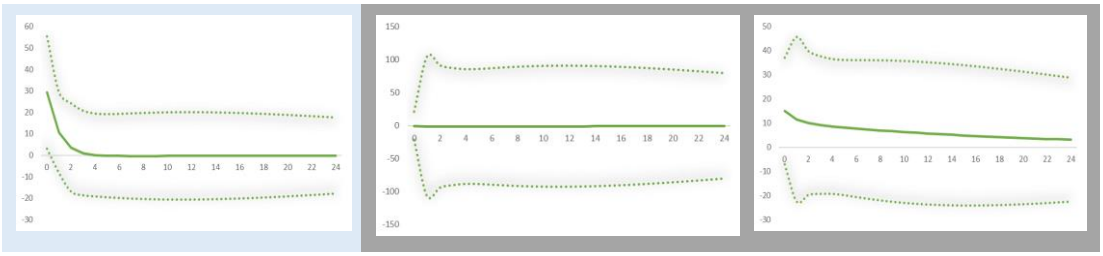
the data used in this subsection also began in July 2013. This subsection only concentrates on the implications of the significant findings depicted in Figure 3.3. Our findings reveal that the combined impact of the PRs is not as significant as the individual impact of the interest rate PR. Further information regarding this discovery is supplied in the following part.

Figure 3.9 displays the results of the joint effect of the PRs utilising the quantity of the news articles data. Figure 3.9 illustrates the statistically significant impact of comprehensiveness on the quantity of news articles. This outcome aligns with solely using the interest rate PR as the dataset. There was a statistically significant rise of 29.25 news articles in the one standard deviation adjustment on comprehensiveness, which surpassed the increase of 17.86 news articles seen in the impact of comprehensiveness only based on interest rate PR, as depicted in Figure 3.2. Nevertheless, there is no statistically significant relationship between the clarity and sentiment scores of the joint effect of the PRs and the quantity of news articles, in contrast to the interest rate PRs.

Figure 3.9 Impulse Response (CBPRs Joint Features and News Articles)

Comprehensiveness **Sentiment** **Clarity**

Window 3



This figure shows the VARX(1) IRF of Window 3. The impulse is the CBPRs features, and the response is the quantity of news articles. The left side of the graph is the impulse of comprehensiveness; the middle side is sentiment; the right is clarity. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, and the grey background indicates non-significant results. Window 3 refers to one month after the release.

The increasing influence of comprehensiveness in this collective impact can be attributed to the inflation PR, which significantly improved the explanation of the inflation situation. This enhances public understanding of the inflation situation and positively impacts news articles and multipliers for NEEA IEs. This finding aligns with the study conducted by Bholat *et al.* (2019), which showed that the Bank of England inflation report enhances the perception of the central bank among economic agents. The lack of significance in clarity may be attributed to the fact that the inflation PR is potentially more straightforward to understand from a media standpoint compared to the interest rate PR. The objective of the inflation PR is to describe the state of inflation, specifically the components and drivers of inflation, and the terminology employed in this PR simpler to

comprehend. The provision of clear information regarding inflation in this PR has the potential to influence media coverage, regardless of the clarity score associated with the PR. Furthermore, the lack of significant impact of CBPRs sentiment on the quantity of news articles may be attributed to the possibility of divergence in sentiment scores between interest rate PR and inflation PR in specific cases. The disparity stems from the observation that the interest rate PR offers insights into the inflation situation before the announcement of the interest rate, as well as the impact of the interest rate and monetary policy on future circumstances, thereby offering guidance on the forward-looking expectations. In contrast, the inflation PR pertains to the inflation rate, with the information being backward-looking.

Based on the joint PRs findings, the comprehensiveness of interest rate and inflation PRs is a significant factor in enhancing the coverage of news articles pertaining to inflation-related news. This is because a greater comprehensiveness of these PRs leads to an increased selection of topics for media coverage. However, the sentiment and clarity do not have a statistically significant impact on the quantity of the news articles. The findings from this sub-section suggest that the features present in the interest rate PR have a greater influence on economic agents, specifically through news articles as the intermediary channels, compared to the combined impact of interest rate and inflation PRs.

3.5.1.4. Robustness Checks

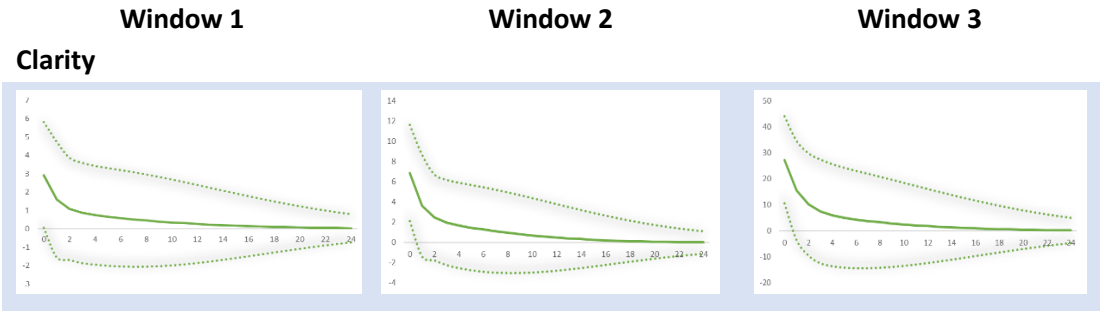
In order to conduct robustness tests on the impact of CBPRs features, we endeavoured to examine the level of clarity in the PR by utilising the SMOG reading score. Furthermore, an examination of sentiment score is conducted using the dictionary developed by Loughran and McDonald (2011). The dictionary is commonly employed to conduct sentiment analysis on news articles pertaining to finance. Given that the datasets utilised in this study are written in Bahasa Indonesia, we translate the dictionary into Bahasa Indonesia. Following the translation process, a total of 1033 words were identified as negative, while 220 words were categorised as positive. The robustness checks will assess the consistency of the statistical significance between the findings presented in Figures 3.3 and 3.4. We employed VARX(1) to conduct robustness assessments.

Clarity (SMOG Reading Score)

This subsection provides an analysis of the impact of CBPRs features employing the SMOG reading score, which is used as a metric to assess the robustness checks for clarity variables. In order to assess the robustness of the clarity results of the Flesch-Kincaid score compared with the SMOG reading score, this subsection will specifically examine the influence of clarity on endogenous variables (the complete results in the appendix). VARX(1) results

demonstrate high consistency with the outcomes obtained by utilising the Flesch-Kincaid score. In the analysis using the quantity of news articles, the clarity score remains consistent since it statistically significantly influences the quantity of news articles. The impact of the clarity score of CBPRs on NEEA IEs and inflation remains in line with the findings obtained through the Flesch-Kincaid score. The findings regarding the influence of the clarity score of CBPRs on the sentiment of news articles of the VARX(1) show no statistically significant relationship between the clarity of the CBPRs and the sentiment of the news articles. These results are similar to the results using the Flesch-Kincaid score. The findings also indicate that the influence of clarity of CBPRs on NEEA IEs and inflation is statistically insignificant. Moreover, while analysing the impact of news articles on the NEEA IEs, it becomes apparent that the quantity of news articles in VARX(1) has a statistically significant effect on the IEs of these agents. The results are consistent with the results obtained using the Flesch-Kincaid score. The analysis of the news articles' sentiment indicates that there is no empirical evidence to substantiate the claim that the sentiment of the news affects the NEEA IEs. These findings are generally consistent with the outcomes obtained by utilising the Flesch-Kincaid score.

Figure 3.10 Impulse Response (Clarity-SMOG and News Articles)



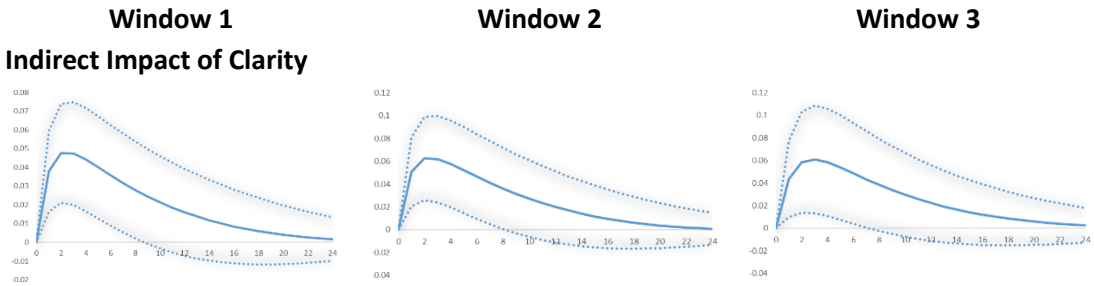
This figure shows the IRF of VARX(1). The Impulse is the clarity of CBPRs, and the response is the quantity of news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, whereas the grey background indicates non-significant results. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

Moreover, the IRF of the clarity score of CBPRs, represented as the impulse, and the quantity of the news article, represented as the response, as illustrated in Figure 3.10, demonstrates similar patterns to the previous findings presented in Figure 3.3. Compared to the findings in Figure 3.3, it was seen that decreasing the clarity score by one standard deviation in Windows 2 and 3 resulted in a 6.87 and 27.33 news article rise, respectively. The obtained results exhibit a relatively similar magnitude to the findings depicted in Figure 3.3.

Furthermore, the indirect impulse of the clarity score of the CBPRs was depicted in Figure 3.11, in comparison to Figure 3.4. Based on the data shown in Figure 3.11, which aligns with the findings in Figure 3.4, the most notable indirect impact is a one-standard deviation

adjustment in the clarity score on IEs in Window 2. The adjustment had an indirect effect, leading to a 0.051 percentage point rise in IEs after one month. Overall, the findings also demonstrated a similar outcome regarding the indirect influence of clarity score on IEs, as depicted in Figure 3.4. A consistent picture is observed in the IRF across all windows, indicating that the influence of news articles on IEs is magnified until three months after the initial adjustment. The observed impact is reduced slowly over seven to eight months after adjustment. Afterwards, the impact is fading away.

Figure 3.11 Impulse Response (News Articles and IEs), SMOG



This figure shows the IRF of VARX(1). The Impulse is news articles, and the response is IEs. This figure indicates the indirect impact of the clarity of CBPRs. The solid line is the IRF, and the dotted line is a 95% confidence interval. The grey background indicates the non-significant result. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

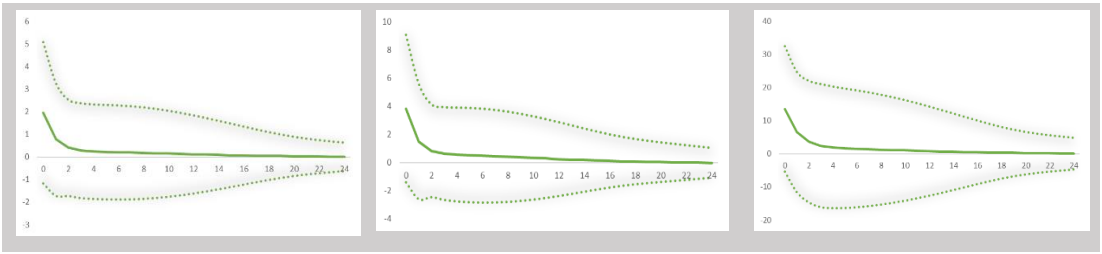
In conclusion of this subsection, the empirical analysis conducted using the SMOG reading score demonstrated that clarity's influence on the quantity of news articles exhibited a consistent outcome compared to the findings obtained through the Flesch-Kincaid score. The impact of news articles on the NEEA IEs yielded similar findings, with the quantity of news articles demonstrating a significant effect on NEEA IEs. The robustness checks conducted using the SMOG reading score provide further evidence that clarity is a significant feature of CBPRs. This feature can potentially influence NEEA IEs through the quantity of news articles that serve as intermediary channels.

Sentiment

The second robustness check involves assessing the CBPRs sentiment. In order to conduct the second robustness check, we investigate the sentiment analysis using a dictionary created by Loughran and McDonald (2011). In this subsection, we will examine the influence of sentiment score on endogenous variables (the complete results are in the appendix). As shown in Figure 3.12, the VARX(1) results suggest that no significant statistical relationship exists between the sentiment score of the CBPRs and the quantity of news articles. One plausible reason is that the Loughran and McDonald vocabulary does not align precisely with the intended focus of this research, primarily inflation. As an illustration, the terms inflation and deflation are not listed in the Loughran and McDonald's dictionary, which is an essential

term for this research. The significance of constructing the dictionary in accordance with the research context is comparable to other literature proposed, such as Hansen and McMahon (2016), Gardner *et al.* (2022), and Tadle (2022). The findings on the influence of the sentiment score of CBPRs on NEEA IEs suggest that the sentiment score of the CBPRs was statistically insignificant, which aligns with the results obtained using the type 1 dictionary. The outcomes using sentiment score as endogenous variables indicate that the sentiment score of the CBPRs does not have a statistically significant impact on all the endogenous variables. Furthermore, the impact of news articles on the NEEA IEs suggests that the quantity of news articles has a statistically significant effect on IEs. The sentiment score of the news articles does not exert a significant influence, consistent with the conclusions drawn from the results obtained using the type 1 dictionary.

Figure 3.12 Impulse Response (Sentiment-LM and News Articles)



This figure shows the IRF of VARX(1). The Impulse is the sentiment of CBPRs, and the response is news articles. The solid line is the IRF, and the dotted line is a 95% confidence interval. The blue background indicates significant results, whereas the grey background indicates non-significant results. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

To summarise, The findings of the robustness assessments conducted using the dictionary formulated by Loughran and McDonald (2011) diverge from those obtained using the type 1 dictionary. This suggests that the impact of the sentiment score of the CBPRs on news articles is comparatively limited compared to the clarity and comprehensiveness of CBPRs.

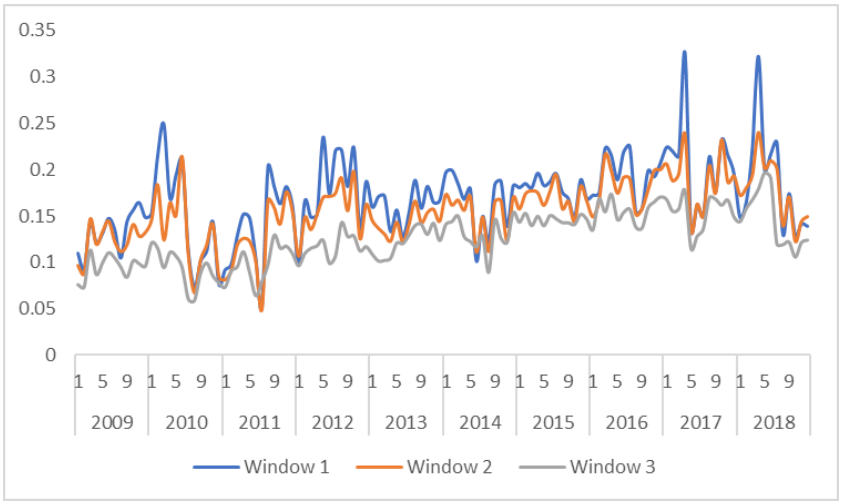
3.5.2. Similarity of the Press Releases

Based on the findings presented in the preceding subsection, it can be observed that there is a detectable tendency for information originating from CBPRs to spread through news articles as intermediary channels. In order to conduct a more comprehensive investigation, this study investigates the degree of similarity between CBPRs and news articles and examines the potential influence of PRs consistency. Our findings indicate that the consistency of CBPRs affects the similarity score between these PRs and news articles. Furthermore, continuously employing the same vocabulary in CBPRs influences news

articles, leading to direct quotations of specific phrases. The further exploration of this discovery is elucidated in this subsection.

Figure 3.13 depicts the similarity score between the CBPRs and the news articles over the three discrete windows employed in this study. Based on Figure 3.13, it is evident that the similarity score exhibited an upward trend, rising from below 10% in 2009 to approximately 15% in 2018. The news articles suggest a growing trend of central banks' assimilation of information. Not surprisingly, the impact of the CBPRs is more pronounced on the Windows that are close to the PRs. Window 1 exhibits the highest similarity score, as it can be plausibly reasoned that within shorter periods, the media prioritises reporting on the CBPRs as the key source of news regarding inflation.

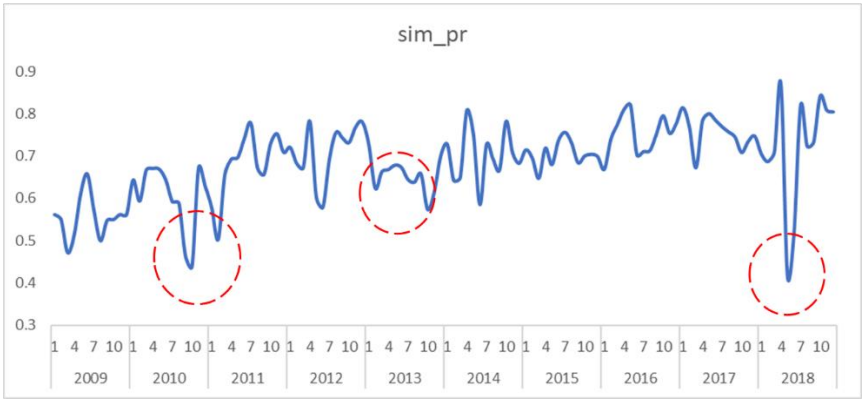
Figure 3.13 The Comparison Result of Similarity (CBPRs and News Articles)



This figure compares the similarities between CBPRs and news articles. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

Figure 3.14 presents an analysis of the CBPRs' consistency by calculating the similarity score between two consecutive PRs. Figure 3.14 exhibits a progressive improvement in consistency over the period, with an average consistency score of 0.68. The average score of Bank Indonesia PRs is comparatively greater than that of the Bank of Canada, with a score of 0.25 (Ehrmann & Talmi 2020). The average scores for the summary, inflation, BOP, and exchange rate paragraphs were 0.56, 0.46, 0.41, and 0.46, respectively. An intriguing observation pertains to the tenure of the new governor, specifically November 2010, May 2013, and May 2018, during which a decline in the consistency score was observed. One plausible rationale for this phenomenon is that a newly appointed governor often adopts a novel approach to disseminating information from the central bank.

Figure 3.14 The Consistency of CBPRs



This figure shows the CBPRs consistency of the two consecutive CBPRs.

We investigated the impact of consistency on the similarity score between the CBPRs and news articles, as presented in Table 3.4. According to the results presented in Table 3.4, consistency has a statistically significant impact on the similarity score of CBPRs and news articles, suggesting that increasing the consistency score will increase the similarity score, particularly in Windows 1 and 2. The significance of consistency aligns with the findings of Ehrman and Talmi (2020), who also underscored the need to maintain consistency in CBPRs. The results could also suggest that the journalist produced routine news content based on previous articles (Shoemaker & Reese 2013). When examining the impact per paragraph, Table 3.4 reveals that the consistency of the inflation paragraph has a more significant influence than the other paragraphs, particularly within shorter windows.

Table 3.4 The Effect of CBPRs Consistency

	Window 1			Window 2			Window 3		
sim_pr	0.136**			0.085*			-0.021		
simp_sum			0.032			0.02			0.008
simp_inf		0.112***	0.109***		0.077***	0.07**		0.009	0.003
simp_bop			0.049*			0.041*			0.006
simp_er			-0.039			-0.015			0.007
cons	0.077*	0.118***	0.095***	0.097***	0.119***	0.099***	0.143***	0.124***	0.116***
R^2	0.067	0.19	0.234	0.042	0.118	0.2	0.01	0.004	0.019

This table shows the effect of CBPRs consistency on the similarity of CBPRs and news articles. The dependent variable is the similarity score of the CBPRs and the news articles. sim_pr is the similarity of CBPRs (all content); simp_sum is the similarity of the summary paragraph; simp_inf is the similarity of the inflation paragraph; simp_bop is the similarity of the balance of payments paragraphs; simp_er is the similarity in the exchange rate paragraph. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

We also investigated whether the media directly quoted words from the CBPRs. In order to analyse this, we employ 5 to 7 consecutive words (5-gram to 7-gram) with a minimum frequency of five occurrences in the CBPRs. The news articles will be considered quoting the CBPRs if they include the words mentioned in the list. Table 3.5 displays the ratios of quoted CBPRs to the total number of news articles in the datasets. The table displays

the four primary paragraphs covered in the CBPRs. The summary paragraph pertains to the board of governors' decision about the interest rate. The summary paragraph also encompasses the additional policies implemented and the coordination and collaboration with the fiscal authorities. The balance of Payment (BOP) paragraph focused on the state of BOP in Indonesia, encompassing its background and the official declaration from the central bank regarding the BOP. The exchange rate and inflation paragraphs emphasised the current state, actions taken, and statements made to influence the market.

Table 3.5 Proportion of CBPRs Directly Quoted

Topic	Window 1	Window 2	Window 3
Summary / Policy	15.27%	10.88%	4.13%
BOP	5.80%	3.99%	2.01%
Exchange Rate	8.22%	7.03%	6.54%
Inflation	7.21%	5.13%	4.00%

This table presents the proportion of direct quotations from CBPRs in news articles. The percentage is derived from the ratio of news articles that cite the CBPRs to the total number of news articles in the dataset. Windows 1 and 2 refer to a duration of three days and seven days, respectively. Window 3 refers to one month after the release.

According to the results in Table 3.5, Window 1 displayed a more significant percentage of directly quoted N-grams from the CBPRs compared to the extended period window. According to Table 3.5, the N-grams in the summary paragraphs are directly cited in Window 1 at a rate of 15.27%. The topic encompasses N-grams that highlight the central bank's policy of maintaining economic stability, such as "*bauran kebijakan moneter dan makroprudensial"* (monetary and macroprudential policy mix) and "*upaya menjaga stabilitas makroekonomi dan sistem keuangan*" (an emphasis on maintaining macroeconomic and financial system stability). The media directly quotes the paragraph of BOP at a rate of 5.80% in Window 1. The quotes include words that imply Bank Indonesia's efforts to decrease the BOP deficit, such as "*menurunkan deficit transaksi berjalan ke…*" (reducing the current account deficit to…) and "*defisit transaksi berjalan yang terkendali*" (managing the current account deficit). The news articles directly quoted 8.22% in the exchange rate paragraph in Window 1. It also mentions Bank Indonesia's efforts to preserve the exchange rate and convince economic agents about the rupiah's fundamental value compared to the US Dollar, using phrases such as "*nilai tukar rupiah sesuai dengan nilai fundamentalnya*" (rupiah in accordance with its fundamental value) and "*untuk menjaga stabilitas nilai tukar*" (to maintain exchange rate stability). The news articles directly quote an inflation paragraph of 7.21% for Window 1. The media's direct quotations also contain persuasive language affirming that the inflation condition remains aligned with the inflation target, such as "*masih konsisten dengan pencapaian sasaran inflasi*" (still consistent with the inflation target) and

"*dengan tekanan inflasi yang rendah dan terkendali*" (with low and controlled inflation pressure). Directly transmitting information from the central bank, particularly regarding forward guidance and central bank policy, is crucial. The outcome of the quoted information can influence economic agents and enhance their level of knowledge regarding the central bank. This direct quote serves as an avenue to deliver an essential point directly to the public without allowing the media to interpret it differently (Issing 2019).

3.6. Discussions

With the importance of the CBPRs, this study analysed the influence of CBPRs on NEEA IEs. It specifically analysed if these PRs have direct or indirect effects. We examined the impact of three distinct features of CBPRs that exert a significant impact using VARX. An examination was also conducted to determine how the CBPRs' consistency impacted the level of similarity between the CBPRs and the news articles using cosine similarity. We utilised Bank Indonesia's PRs, news articles in Bahasa Indonesia, NEEA IEs, and inflation data from January 2009 to December 2018.

The research discovered that the CBPRs indirectly impacted the NEEA IEs and were conveyed through the news articles as the intermediary channel. Our findings indicate that the quantity of news articles substantially impacts economic agents more than the articles' sentiment. This impact is most pronounced in the shorter term, with a lag of 1, indicating that economic agents prefer more up-to-date information from news articles. The media tends to provide more coverage to news articles when the CBPRs contain clear messaging. The clarity score potentially exerts a more pronounced influence on the quantity of news articles during shock periods. The comprehensiveness of CBPRs was influential, especially when considering a more extended data window. The impact of comprehensiveness on news articles is indicated in environments with stable inflation conditions. The sentiment score of the CBPRs also exerts a substantial influence on the sentiment score of news articles. Sentiment suggested that it plays a considerable role in influencing the quantity of news articles during periods of high inflation. Nevertheless, the influence became negligible when we conducted the robustness checks using the Loughran and McDonald (2011) dictionary. We also found that the consistency of the CBPRs affects the similarities between news articles and CBPRs. Furthermore, we discovered that the media directly cited specific words from the CBPRs.

The finding indicates that NEEA have relied on news articles to gather information and shape their IEs, similar to studies undertaken by Carroll (2003), Lamla and Lein (2014), and Nimark and Pitschner (2019). These results indicate that when the media repeatedly

disseminates inflation information, NEEA will perceive that something exceptional is occurring. Regardless of whether the news sentiment is positive or negative, NEEA will infer a change in the inflation state. This phenomenon can occur due to the media's tendency to prioritise the coverage of negative news over positive news (Gardner *et al.* 2022). Due to this circumstance, an escalation in the quantity of news pertaining to inflation will result in a modification of NEEA IEs. Regarding the CBPRs features, increased comprehensiveness and decreased clarity score lead to enhanced NEEA comprehension of the information in the CBPRs, which could influence NEEA to align their expectations with the inflation target. The finding is also analogous to the findings of Bulíř *et al.* (2013) and Haldane and McMahon (2018), which propose that clearer information can enhance comprehension of central bank communication. The possible explanation for the impact of comprehensiveness is that the media tends to extensively analyse the material provided by the CBPRs over long periods. As a result, when the central bank provides more information in these PRs, the media has more substantial content to examine and include in their news articles. The extensive information the central bank provides could enhance the economic agents' literacy levels and facilitate their ability to make well-informed decisions. The results also underscore the significance of maintaining consistency in CBPRs, as demonstrated by Ehrmann and Talmi (2020), who concluded that central banks should adhere to a standardised information structure in their PRs. Jansen and de Haan (2013) also emphasised the significance of maintaining consistency in central bank communication. Frequent changes in terminology by the central bank can create challenges for readers in understanding the information and message intended by the central bank. Beaupain and Girard (2020) also discovered the importance of consistency in central bank communication. Furthermore, it is crucial to directly transmit information from CBPRs, particularly about the forward guidance terminology and the central bank's strategy, as the found by Jansen de Haan (2009) and Issing (2019). This information has the potential to impact NEEA and enhance their degree of knowledge regarding the central bank. Enhancing the public's knowledge and comprehension of the central bank is crucial for fostering confidence in monetary policy and establishing stable IEs aligned with the central bank's inflation target (Haldane & McMahon 2018).

While this paper has made several positive contributions, it is important to acknowledge the scope of improvements. The sentiment analysis employing a dictionary-based model yields varying findings, which could be enhanced by incorporating other methods, such as embeddings. The data employed in this study primarily focused on news articles, where the growth of non-conventional media is increasing, and its significance is

becoming more pronounced. Analysing the data in conjunction with non-traditional media sources is becoming increasingly valuable. The following research can utilise a broader range of data and examine the influence of non-traditional media. Furthermore, the methodologies employed in this research could be expanded and implemented to analyse data from other macroeconomic variables.

The outcomes of this study are essential for increasing awareness and delivering a more effective presentation of the CBPRs. The study's findings emphasise the significance of enhancing the CBPRs clarity, comprehensiveness, and consistency. This is crucial for effectively transmitting information to NEEA through intermediate channels. As economic agents get more information and knowledge, their understanding of inflation improves. They can grasp and react suitably to inflationary circumstances without engaging in excessive behaviour and modify their IEs to align with the target set by the central bank.

3.7. Summary and Conclusion

CBPRs are crucial tools for influencing NEEA IEs to correspond with the inflation target set by the central bank. However, there is still no agreement on how the CBPRs can successfully impact NEEA IEs. Given the significance of this subject and the extant gap in the literature, this study examined the impact of CBPRs on NEEA IEs. Then, we investigated the features of CBPRs that have a substantial influence. We also investigated how the consistency of CBPRs affects the similarity between the CBPRs and news articles. This study found that CBPRs indirectly impact NEEA IEs through news articles as an intermediary channel. Comprehensiveness is crucial for a longer window, especially suggested during decreasing or steady inflation periods. Clarity plays a crucial role, particularly indicated during rising and perhaps unpredictable inflation periods. The study revealed that the consistency of the CBPRs affects the similarity between the CBPRs and the news articles, particularly in the inflation paragraph.

According to the findings of this study, it is critical for the central bank to carefully consider the content of PRs to affect the NEEA IEs. Nevertheless, there is still scope for improvement in investigating non-conventional media and developing a dictionary using other methods. The research undeniably contributes to the body of knowledge regarding the transmission and fundamental features of CBPRs. The findings of this study can be applied to investigate the effect on data of other macro variables. It highlights that CBPRs exert substantial influence on news articles, underscoring the criticality of preserving their influential qualities to sway the media. Based on our research, it is imperative that the central bank maintains consistency in its PRs; if modifications are necessary, it is advisable to

implement them incrementally. The central bank could frequently provide forward guidance information in its CBPRs as the news articles directly quoted information from the CBPRs. This information may serve as an echo chamber of information for the NEEA, thereby influencing their IEs. The central bank can utilise these features as a dashboard to simulate and monitor its effects. Finally, policymakers will be offered the knowledge and opportunity to manage the features of CBPRs effectively, thanks to the results of this study.

Conclusion

IEs are vital in central banks' decision-making process and are fundamental in shaping policy decisions. In order to ensure the efficacy of formulating high-quality policies, the central bank must possess a reliable and up-to-date representation of the data. The central bank must also implement a robust strategy to influence NEEA IEs to adhere to their inflation target. Due to the importance of this topic and the current lack of research, specifically considering the volatile inflation scenario, this thesis focuses on NEEA IEs in developing countries. Chapter 1 explored the optimal methods for quantifying qualitative data under volatile inflation circumstances. We also analysed the factors influencing the NEEA IEs by including the socioeconomic variables. Chapter 2 examined the valuable information in the news articles regarding NEEA IEs utilising NLP. Having near-real-time data on NEEA IEs is extremely valuable, as the information needed to analyse them is typically time-sensitive and often updated monthly or quarterly. Therefore, using textual data from news articles as an alternative source can provide policymakers with near-real-time insights into NEEA IEs. Within this chapter, we examined the suitability of textual information as a substitute data source for analysing NEEA IEs and creating an alternative tool to forecast inflation. In Chapter 3, we analysed the influence of the features of CBPRs: comprehensiveness, sentiment, and clarity on NEEA IEs. We also examined the impact of the consistency of CBPRs on the similarity between these releases and news articles.

The outcomes from Chapter 1 indicated that the most successful method for quantifying qualitative data in a volatility dataset is the Carlson-Parkin method, which incorporates asymmetric threshold and regime period unbiasedness assumptions. This study also found that education and expenditure significantly influence NEEA IEs. The results from Chapter 2 revealed that news articles in Indonesia have the potential to offer valuable information that can be utilised to mimic consumer surveys. The results of NLP on news articles might serve as an alternative to traditional data for the representation of NEEA IEs. The study also found that applying NLP techniques to news articles performs well in predicting inflation, particularly for the 6-month horizon. The discoveries from Chapter 3 indicated that CBPRs influence NEEA IEs through news articles as an intermediary channel. The CBPRs features studied in this research are important, where the comprehensive feature is essential over a longer window, particularly indicated during declining or stable inflation periods. The clarity feature is also essential, especially in times of increasing and volatile inflation. Sentiment feature have a significant influence on the sentiment of news articles.

The study found that the consistency of the CBPRs impacted the similarity between the CBPRs and the news articles, particularly the consistency in the inflation paragraph.

This research indicates that the method used for measuring qualitative data depends on the volatility of the data's characteristics. The results of this study indicate that economic agents in a situation of somewhat volatile inflation have different expectations in both stable and shock scenarios. Moreover, the findings reported in this research offer novel perspectives on the importance of textual data, which might provide valuable input to policymakers in near-real time. It is also found that it is crucial for the central bank to manage the information provided in PRs in order to influence the NEEA IEs.

This study's findings offer policymakers a more thorough understanding that can improve the comprehension of the NEEA IEs. However, there are a few aspects that would be worthwhile investigating further. Concerning Chapter 1, integrating the study with a microdata analysis would be advantageous. In relation to Chapter 2, investigating other NLP methods, such as embeddings and unsupervised learning, would be beneficial. With Chapter 3, conducting a thorough examination of non-conventional data and developing a dictionary using other methods would be advantageous for extracting pertinent information from textual input. Therefore, it is worthwhile to investigate this aspect further for future research.

The study enhances our understanding of selecting the most effective methods for quantifying qualitative data. Applying the RPU assumptions proved beneficial in volatile inflation conditions, such as the Indonesian data. This approach could also be adopted from the standpoint of another country. For instance, the decision to implement a shock period in response to the taper tantrum could also be applied in countries such as India, Brazil, Turkey, and South Africa. These countries experienced currency depreciation against the US Dollar, resulting in inflationary pressures. The research also offers insight into the influence of socioeconomic factors on NEEA IEs in different regions. Enhancing the education level is crucial for boosting economic literacy, resulting in decreasing NEEA IEs. The findings are crucial for policymakers to possess representations of NEEA IEs, encompassing the distinctive attributes of the regions that can impact IEs.

This study recognises and understands the importance of unstructured data sources, such as news articles, and offers policymakers the chance to access an alternate and near-real-time source of information on NEEA IEs. The results of this study can be applied to monitor NEEA IEs throughout the period between surveys. News articles also offer narrative material regarding the events, bolstering comprehensive understanding for policymakers on

the narrative of inflationary events. The results of this study could also serve as an alternate means of predicting inflation in near-real time. Timely access to information is crucial for policymakers to respond effectively to the latest market conditions.

The research outcomes contribute to the current literature on the fundamental features of CBPRs. The discoveries will highlight the imperative nature of the central bank to maintain clarity, comprehensiveness, sentiment, and consistency. Enhancing clarity is crucial as it promotes clear messages, can help reduce misinformation and improve understanding of monetary policy decisions. Increasing comprehensiveness is crucial for promoting transparency and facilitating the knowledge of economic agents regarding the underlying factors driving monetary policy decisions. It is important to monitor the sentiment of the tone language used in the CBPRs since it impacts the media. Ensuring consistency in CBPRs is valuable for conveying consistent messages; if adjustments are required, it is recommended to introduce them gradually. The central bank could frequently provide forward guidance information in its CBPRs as the news articles directly quoted information from the CBPRs. This information may serve as an echo chamber of information for the NEEA, thereby influencing their IEs. The central bank can utilise these features as a dashboard to simulate and monitor its effects. Tailoring the central bank communication, especially CBPRs, is essential to influence IEs; this aligns with Draghi's statement:

"Central Bank communication is right at the heart of monetary policy. It is actually a monetary policy tool in itself" (Draghi 2014).

Appendix

Appendix A. Chapter 1

Appendix.A.1 Regional Results

Tables A.1.1 – A.1.18 compare quantifying qualitative data using BA, CP, and regression methods and the inflation rate in 18 regions in Indonesia. The DM-Test uses the CP method as the benchmark method. A negative sign indicates that the benchmark method is superior, while a positive sign indicates that the alternative method is superior. Green represents the best method derived from the lowest MAE and RMSE score with a positive DM-Stat score.

Table A.1.1 Regional Results - Jakarta

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.661	2.057	-3.328***
2	BA Method (RPU)	1.108	1.521	-2.819***
3	BA Method (STU)	1.133	1.522	-2.107**
4	CP Method	0.567	0.891	-
5	CP Method (STU)	0.536	0.869	0.423
6	CP Method (RPU)	0.529	0.863	0.714
7	CP Method (AT)	0.573	0.880	0.754
8	CP Method (RPU & AT)	0.510	0.823	1.187
9	Reg Method	1.282	1.540	-3.331***
10	Reg Method (RPU)	0.656	0.954	-0.706

Table A.1.2 Regional Results - Bandung

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.251	1.596	-3.118***
2	BA Method (RPU)	1.017	1.376	-3.123***
3	BA Method (STU)	1.017	1.370	-2.896***
4	CP Method	0.526	0.758	-
5	CP Method (STU)	0.664	0.944	-2.632***
6	CP Method (RPU)	0.510	0.725	0.825
7	CP Method (AT)	0.517	0.751	0.577
8	CP Method (RPU & AT)	0.499	0.715	0.693
9	Reg Method	1.164	1.510	-2.798***
10	Reg Method (RPU)	0.756	1.081	-2.511**

Table A.1.3 Regional Results - Semarang

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.353	1.605	-4.588***
2	BA Method (RPU)	0.952	1.175	-1.123
3	BA Method (STU)	0.884	1.124	-0.882
4	CP Method	0.691	0.985	-
5	CP Method (STU)	0.739	1.131	-1.561
6	CP Method (RPU)	0.628	0.928	1.581
7	CP Method (AT)	1.023	1.278	-1.368
8	CP Method (RPU & AT)	0.862	1.098	-1.224
9	Reg Method	1.323	1.581	-4.955***
10	Reg Method (RPU)	0.774	1.035	-0.355

Table A.1.4 Regional Results - Surabaya

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.712	2.105	-2.939***
2	BA Method (RPU)	1.186	1.586	-1.903*
3	BA Method (STU)	1.126	1.596	-2.404**
4	CP Method	0.655	0.833	-
5	CP Method (STU)	0.607	0.829	-2.106**
6	CP Method (RPU)	0.585	0.775	1.440
7	CP Method (AT)	0.656	0.833	0.088
8	CP Method (RPU & AT)	0.548	0.723	2.002**
9	Reg Method	1.402	1.641	-4.397***
10	Reg Method (RPU)	0.899	1.152	-1.938*

Table A.1.5 Regional Results - Medan

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.991	2.386	-4.914***
2	BA Method (RPU)	1.829	2.232	-4.325***
3	BA Method (STU)	1.759	2.173	-3.705***
4	CP Method	1.066	1.373	-
5	CP Method (STU)	0.791	1.083	-1.423
6	CP Method (RPU)	1.012	1.304	0.987
7	CP Method (AT)	1.049	1.357	0.517
8	CP Method (RPU & AT)	0.983	1.247	1.685*
9	Reg Method	1.409	1.759	-1.997**
10	Reg Method (RPU)	1.150	1.454	-0.766

Table A.1.6 Regional Results - Palembang

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.434	1.773	-2.369**
2	BA Method (RPU)	1.105	1.386	-1.798*
3	BA Method (STU)	1.049	1.438	-1.873*
4	CP Method	0.791	1.105	-
5	CP Method (STU)	1.095	1.424	-2.193**
6	CP Method (RPU)	0.755	1.069	0.536
7	CP Method (AT)	0.749	0.952	1.565
8	CP Method (RPU & AT)	0.656	0.868	2.004**
9	Reg Method	1.146	1.428	-1.521
10	Reg Method (RPU)	0.896	1.102	0.017

Table A.1.7 Regional Results - Banjarmasin

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.960	2.417	-2.565**
2	BA Method (RPU)	1.393	1.818	-1.189
3	BA Method (STU)	1.181	1.532	0.164
4	CP Method	1.312	1.560	-
5	CP Method (STU)	1.014	1.454	-0.759
6	CP Method (RPU)	1.094	1.391	1.871*
7	CP Method (AT)	1.063	1.358	2.227**
8	CP Method (RPU & AT)	0.806	1.051	4.327***
9	Reg Method	1.005	1.294	1.713*
10	Reg Method (RPU)	0.831	1.091	3.181***

Table A.1.8 Regional Results - Bandarlampung

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.788	2.248	-2.108**
2	BA Method (RPU)	1.462	1.924	-1.785*
3	BA Method (STU)	1.387	1.784	-1.539
4	CP Method	0.988	1.339	-
5	CP Method (STU)	0.913	1.236	-1.485
6	CP Method (RPU)	0.940	1.251	1.082
7	CP Method (AT)	0.935	1.252	1.163
8	CP Method (RPU & AT)	0.821	1.103	2.352**
9	Reg Method	1.615	1.918	-2.219**
10	Reg Method (RPU)	1.138	1.430	-0.542

Table A.1.9 Regional Results - Makassar

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.398	1.743	-1.634
2	BA Method (RPU)	1.186	1.614	-1.275
3	BA Method (STU)	1.034	1.451	-0.669
4	CP Method	0.878	1.286	-
5	CP Method (STU)	0.982	1.278	-1.262
6	CP Method (RPU)	0.871	1.238	0.729
7	CP Method (AT)	0.768	1.011	1.932*
8	CP Method (RPU & AT)	0.716	0.943	2.222**
9	Reg Method	1.335	1.578	-1.190
10	Reg Method (RPU)	0.967	1.257	0.183

Table A.1.10 Regional Results - Samarinda

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.280	1.649	-2.075**
2	BA Method (RPU)	1.184	1.583	-1.867*
3	BA Method (STU)	1.207	1.556	-1.441
4	CP Method	0.978	1.294	-
5	CP Method (STU)	1.050	1.383	-2.864***
6	CP Method (RPU)	0.872	1.198	1.332
7	CP Method (AT)	0.789	1.090	2.752***
8	CP Method (RPU & AT)	0.755	1.045	3.236***
9	Reg Method	1.235	1.607	-1.518
10	Reg Method (RPU)	1.017	1.378	-0.517

Table A.1.11 Regional Results - Denpasar

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.530	1.836	-1.406
2	BA Method (RPU)	1.153	1.416	0.231
3	BA Method (STU)	0.963	1.276	1.047
4	CP Method	1.108	1.478	-
5	CP Method (STU)	1.001	1.395	-1.632
6	CP Method (RPU)	1.038	1.350	1.184
7	CP Method (AT)	0.940	1.170	2.017**
8	CP Method (RPU & AT)	0.696	0.856	2.996***
9	Reg Method	1.335	1.587	-0.603
10	Reg Method (RPU)	0.843	1.079	1.905*

Table A.1.12 Regional Results - Padang

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.967	2.445	-4.549***
2	BA Method (RPU)	1.108	1.932	-4.01***
3	BA Method (STU)	1.512	1.894	-2.453**
4	CP Method	1.156	1.422	-
5	CP Method (STU)	0.933	1.237	-1.925*
6	CP Method (RPU)	1.057	1.324	1.161
7	CP Method (AT)	1.127	1.392	0.838
8	CP Method (RPU & AT)	0.982	1.251	1.952*
9	Reg Method	1.921	2.343	-3.042***
10	Reg Method (RPU)	1.316	1.669	-1.491

Table A.1.13 Regional Results - Pontianak

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	2.131	2.588	-3.202***
2	BA Method (RPU)	1.727	2.059	-3.163***
3	BA Method (STU)	1.411	1.856	-1.035
4	CP Method	1.376	1.625	-
5	CP Method (STU)	1.040	1.346	-1.112
6	CP Method (RPU)	1.311	1.561	0.650
7	CP Method (AT)	1.096	1.356	2.557**
8	CP Method (RPU & AT)	0.839	1.043	3.702***
9	Reg Method	1.587	1.902	-1.349
10	Reg Method (RPU)	0.874	1.087	3.584***

Table A.1.14 Regional Results - Manado

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.950	2.440	-1.90*
2	BA Method (RPU)	1.590	2.102	-0.996
3	BA Method (STU)	1.653	2.136	-1.086
4	CP Method	1.489	1.870	-
5	CP Method (STU)	1.377	1.754	-1.089
6	CP Method (RPU)	1.532	1.878	-0.164
7	CP Method (AT)	1.394	1.688	1.598
8	CP Method (RPU & AT)	1.304	1.621	1.747*
9	Reg Method	1.910	2.304	-1.338
10	Reg Method (RPU)	1.358	1.744	0.565

Table A.1.15 Regional Results - Mataram

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.838	2.349	-2.856***
2	BA Method (RPU)	1.406	1.849	-2.58***
3	BA Method (STU)	1.347	1.842	-2.099**
4	CP Method	1.047	1.347	-
5	CP Method (STU)	1.186	1.627	-2.535**
6	CP Method (RPU)	0.952	1.249	1.190
7	CP Method (AT)	0.975	1.258	1.633
8	CP Method (RPU & AT)	0.787	1.004	2.949***
9	Reg Method	1.710	2.053	-3.107***
10	Reg Method (RPU)	1.007	1.342	0.026

Table A.1.16 Regional Results - Pangkalpinang

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	2.443	2.951	-2.923**
2	BA Method (RPU)	2.143	2.615	-1.81*
3	BA Method (STU)	1.757	2.228	-0.721
4	CP Method	1.566	1.954	-
5	CP Method (STU)	1.221	1.690	-1.541
6	CP Method (RPU)	1.476	1.869	0.813
7	CP Method (AT)	1.466	1.780	2.073**
8	CP Method (RPU & AT)	1.353	1.622	1,477
9	Reg Method	1.682	2.046	-0.316
10	Reg Method (RPU)	1.343	1.625	0.946

Table A.1.17 Regional Results - Ambon

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	3.095	3.633	-4.913***
2	BA Method (RPU)	2.219	2.886	-2.621***
3	BA Method (STU)	2.355	3.058	-2.922***
4	CP Method	1.673	2.015	-
5	CP Method (STU)	1.566	2.237	-2.127**
6	CP Method (RPU)	1.575	1.936	0.898
7	CP Method (AT)	1.658	2.008	0.268
8	CP Method (RPU & AT)	1.478	1.848	1.565
9	Reg Method	1.906	2.426	-2.216**
10	Reg Method (RPU)	1.511	2.052	-0.157

Table A.1.18 Regional Results - Banten

No	Methods	MAE	RMSE	DM-Stat
1	BA Method	1.581	2.054	-1.705*
2	BA Method (RPU)	1.463	1.869	-1.096
3	BA Method (STU)	1.280	1.726	-0.507
4	CP Method	1.342	1.595	-
5	CP Method (STU)	1.279	1.638	-0.152
6	CP Method (RPU)	1.152	1.463	1.368
7	CP Method (AT)	1.023	1.278	3.244***
8	CP Method (RPU & AT)	0.862	1.098	4.114***
9	Reg Method	1.267	1.667	-0.266
10	Reg Method (RPU)	0.999	1.337	1.364

Appendix.A.2 Summary Statistics

The table provides summary statistics of Indonesia's national data and data from 18 regions used in Chapter 1.

Table A.2 Summary Statistics – Chapter 1

Variable	Mean			Std. dev.		
	Inf	Educ	Expen	Inf	Educ	Expen
National	4.95	7.94	10,251.73	1.94	0.34	683.71
Jakarta	4.84	11.24	22,104.36	1.93	0.33	1,335.90
Bandung	4.39	10.54	15,575.09	1.82	0.16	911.99
Semarang	4.71	10.25	13,459.73	1.98	0.29	1,218.61
Surabaya	4.98	10.24	15,907.88	1.92	0.25	1,070.94
Medan	5.25	11.05	14,135.11	2.16	0.30	643.51
Palembang	4.39	10.25	13,666.39	2.07	0.25	944.25
Banjarmasin	5.41	9.67	13,096.29	1.74	0.46	913.85
Bandarlampung	5.52	10.67	11,057.23	2.62	0.40	723.39
Makassar	4.99	10.82	15,612.55	1.85	0.35	798.39
Samarinda	5.36	10.25	13,781.09	2.34	0.25	588.69
Denpasar	4.98	11.04	18,794.40	2.02	0.27	795.80
Padang	5.40	11.08	13,685.90	2.69	0.36	517.08
Pontianak	6.22	9.64	13,806.40	2.37	0.44	483.48
Manado	4.62	10.96	13,067.96	2.58	0.25	633.44
Mataram	5.45	9.08	13,360.18	2.57	0.38	1,209.30
Pangkalpinang	5.94	9.71	14,724.94	2.77	0.13	794.32
Ambon	5.21	11.55	13,282.82	3.50	0.32	626.59
Banten	5.55	8.60	12,451.16	2.34	0.14	660.38

Appendix B. Chapter 2

Appendix.B.1 Dictionary Version.2

Tables contain the complete word list of dictionary version 2, consisting of 244 words that indicate increased words and 36 words that indicate decreased words.

Table B.1.1 Dictionary Version.2 - Increase Words List

No	Indonesian
1	alami
2	ambruk
3	ancam
4	aneh
5	anjlok
6	badai
7	bahaya
8	bangkrut
9	bantai
10	bayang
11	belit
12	bencana
13	bengkak
14	berat
15	biang
16	bias
17	bingung
18	blt
19	bocor
20	borong
21	boros
22	bubble
23	buruk
24	busuk
25	cabut
26	capai
27	cekik
28	celaka
29	cemas
30	crash
31	crisis
32	curiga
33	dalih
34	dampak
35	darurat
36	deficit
37	defisit
38	demo
39	depresi
40	depresiasi
41	derita
42	desak
43	devaluasi
44	dilema
45	dingin
46	disinsentif
47	disparitas
48	distorsi
49	dongkrak
50	duga

No	Indonesian
51	effect
52	ekstrem
53	enggan
54	fluktuasi
55	fluktuatif
56	fragile
57	gaduh
58	gagal
59	ganggu
60	ganjal
61	gegabah
62	gejala
63	gejolak
64	gelembung
65	gelincir
66	gelisah
67	gelombang
68	gempa
69	gerogot
70	goncangan
71	gonjang
72	goyang
73	guncang
74	halang
75	hambat
76	hancur
77	hantam
78	hantu
79	hiperinflasi
80	hot
81	idulfitri
82	ilegal
83	imbas
84	imported
85	indikasi
86	inefisiensi
87	inflasi
88	instabilitas
89	ironis
90	jahat
91	jatuh
92	jebak
93	jebol
94	jelek
95	jurang
96	kacau
97	kadang
98	kaget
99	kecam
100	kecewa

No	Indonesian
101	kemarau
102	kendala
103	kerek
104	kesah
105	ketat
106	ketidakjelasan
107	ketidakmampuan
108	ketidakpastian
109	ketidakseimbangan
110	ketidakstabilan
111	khawatir
112	kisruh
113	kolaps
114	kompetisi
115	kompleks
116	konflik
117	konsumtif
118	kontraksi
119	kontraproduktif
120	korban
121	korupsi
122	kotor
123	krisis
124	kritik
125	kritisi
126	kurang
127	laju
128	lambat
129	lambung
130	langgar
131	langka
132	lanjur
133	larut
134	ledak
135	lejit
136	lemah
137	lesu
138	liar
139	lilit
140	longsor
141	lonjak
142	lorot
143	macet
144	mafia
145	mahal
146	maksimum
147	malas
148	malu
149	mandek
150	masalah

No	Indonesian
151	meleset
152	menganggu
153	merah
154	mogok
155	momok
156	monopoli
157	mudik
158	mustahil
159	naik
160	negatif
161	outflow
162	overheating
163	paceklik
164	pahit
165	panas
166	panik
167	parah
168	pascakenaikan
169	pelik
170	penyalahgunaan
171	perang
172	perangkap
173	perosok
174	pesimis
175	pesimisme
176	pesimistis
177	picu
178	polemik
179	prihatin
180	problem
181	protes
182	pukul
183	puncak
184	ragu
185	ramadan
186	ramadhan
187	rangkak
188	rapuh
189	rawan
190	rekor
191	rembet
192	rentan
193	resah
194	resesi
195	resisten
196	roket
197	rontok
198	rumit
199	runtuh
200	rusak

No	Indonesian
201	selundup
202	sempit
203	sendat
204	sengaja
205	sengketa
206	senjang
207	sensitif
208	serbu
209	seret
210	sesal
211	shock
212	signifikan
213	sinyalir
214	sistemik
215	spekulan
216	spekulasi
217	spekulatif
218	stagnasi
219	sulit
220	suram
221	susah
222	tajam
223	tanjak
224	tantrum
225	tegang
226	tekan
227	tembus
228	tengkulak
229	tensi
230	timbul
231	timbun
232	timpang
233	tinggi
234	tsunami
235	tuai
236	tuding
237	tumbang
238	tumbuh
239	tumpuk
240	turbulensi
241	volatil
242	volatile
243	volatilitas
244	waspada

Table B.1.2 Dictionary Version.2 - Decrease Words List

No	Indonesian
1	bangkit
2	confidence
3	deflasi
4	disinflasi
5	down
6	drastis
7	efektif
8	gagas
9	gelontor
10	gembira
11	gencar
12	impor
13	inflow
14	jatuh
15	kokoh
16	kredibel
17	lancar
18	limpah
19	longgar
20	lorot
21	makmur
22	merosot
23	mitigasi
24	murah
25	nyaman
26	panen
27	positif
28	redam
29	rendah
30	surplus
31	swasembada
32	tanggulang
33	tenang
34	terjun
35	turun
36	yakin

Appendix.B.2 Annotation General Guidelines for News Articles Labelling

Labels Definitions:

- **Increase:** The information in the news articles indicates a conclusion on the presence of inflation or price increase.
- **Decrease:** Information in the news articles that indicate a conclusion that there is deflation or a price decrease.
- **Same:** Information indicating that the price remains stable or unchanged.

Label Guidelines:

- **Increase:** Analyse the article's viewpoint, particularly in sentences that include terms such as "inflation," "price hike/increase," "failure," and expressions that indicate a negative supply, price increase, or pessimistic outlook.
- **Decrease:** Seek the article's viewpoint, particularly about terms such as "deflation," "price decrease," "abundance of supply," and expressions that indicate positive supply, price decline, or optimism.
- **Same:** Consider the perspective of the articles, particularly statements that indicate the price is unchanged. We classify news articles that are not categorised as either "increase" or "decrease" categories in this category.

General Annotation Rules:

- Consider the overall context of the news articles.
- Ambiguity: When a statement includes "increase" and "decrease," prioritise the dominating information, particularly in the introduction and conclusion paragraphs. If there is uncertainty or an equal amount of information, place it in the "same" category.
- Assign a distinct label to each news article.

Annotation Outcome:

Table B.2 Annotation Outcome

Keywords	Title/Body	Classification			Total
		Increase	Same	Decrease	
Inflation	Title	2355	1061	381	3797
	Body	11991	6286	2623	20900
Price	Title	2337	7590	666	10593
	Body	3402	6540	651	10593

Appendix.B.3 General Steps for Construct a Dictionary

1. **Gather the textual content.**
   We extracted the candidate text from the news articles included in the dataset. We selected the initial filtered words based on their minimal occurrence of 50 times. From this initial phase, we have obtained a dataset consisting of 5234 words from the keyword "*inflasi*" and 3386 words from the keyword "*harga*".
2. **Filtered the words**
   During this stage, we select words relevant to the research objectives. After completing this stage, we have identified 692 words.

3. **Selection of categorisation**
   We classify the collection of words into two categories relevant to the research purpose: "decrease" and "increase" dictionaries. We have 405 words in the "increase" dictionary and 287 words in the "decrease" dictionary. We have included this list of words in our dictionary version 1.

4. **Verification and assessment**
   We utilised dictionary version 1 to compile the score and categorise each news article. The scores are transformed using the extended version of CP methods with AT and RPU assumptions.
5. **Additional refinement of the words**
   Due to the unsatisfactory results of dictionary version 1, we continued to choose the dictionary that contained 244 words in the "increase" dictionary and 36 words in the "decrease" dictionary. This dictionary is the second version of the dictionary.

Appendix.B.4 The Cross-Validation Setting

The table displays the cross-validations of five different CV methods. Green represents the best method derived from the highest accuracy score.

Table B.4 The Cross-Validation Setting

Keyword	Title/Body	Methods	Random-Split	5-fold	Strat 5-Fold	10-Fold	Strat 10-Fold
Inflasi	Title	SVC	0.849	0.893	0.892	0.900	0.899
		NB	0.790	0.776	0.776	0.786	0.787
		KNN	0.781	0.794	0.796	0.797	0.798
		DT	0.817	0.813	0.818	0.816	0.821
Inflasi	Body	SVC	0.845	0.853	0.854	0.858	0.858
		NB	0.578	0.577	0.577	0.578	0.578
		KNN	0.729	0.719	0.718	0.723	0.724
		DT	0.643	0.640	0.641	0.633	0.645
Harga	Title	SVC	0.897	0.899	0.899	0.901	0.900
		NB	0.768	0.784	0.785	0.788	0.789
		KNN	0.799	0.796	0.797	0.798	0.800
		DT	0.887	0.884	0.889	0.888	0.889
Harga	Body	SVC	0.834	0.888	0.888	0.895	0.893
		NB	0.656	0.689	0.688	0.694	0.694
		KNN	0.730	0.737	0.736	0.741	0.742
		DT	0.721	0.753	0.753	0.748	0.749

Appendix C. Chapter 3

Appendix.C.1 Summary Statistics

The table provides summary statistics of the data used in Chapter 3. News(Q)-W1 is the quantity of news article in Window 1; News(Q)-W2 is the quantity of news article in Window 2; News(Q)-W3 is the quantity of news article in Window 3; News(S)-W1 is the sentiment of news articles in Window 1; News(S)-W2 is the sentiment of news articles in Window 2; News(S)-W3 is the sentiment of news articles in Window 3; Comp is the comprehensive feature of CBPRs; Clar (F_K) is the clarity feature of CBPRs using Flesch-Kincaid Score; Sen (Dic V1) is the sentiment feature of CBPRs using version 1 dictionary; Clar (SMOG) is the clarity feature of CBPRs using SMOG score; Sent (Dic LM) is the sentiment feature of CBPRs using Loughran-McDonald dictionary.

Table C.1 Summary Statistics – Chapter 3

Variable	Mean	Std. Dev	Min	Max
IEs	4.766	1.494	2.92	8.76
Inflation	5.064	1.842	2.41	11.06
News(Q)-W1	38.517	19.540	14.00	119.00
News(Q)-W2	62.042	32.494	16.00	198.00
News(Q)-W3	263.417	122.813	36.00	674.00
News(S)-W1	1.358	1.022	0.09	5.18
News(S)-W2	2.225	1.672	-1.16	9.22
News(S)-W3	9.641	5.509	0.55	30.53
Comp	6,517	2,729	763.00	15230.00
Clar (F_K)	22.344	0.814	19.42	24.69
Sent (Dic V1)	0.025	0.014	-0.02	0.07
Clar (SMOG)	21.407	0.724	19.83	22.94
Sent (Dic LM)	0.016	0.024	-0.05	0.08

Appendix.C.2 VARX Results

Tables C.2.1 – C.2.10 display the VARX results. The head of the tables contains information on endogenous and exogenous variables. Three stars (***) = P<0.001, two stars (**) = P<0.01, and one star (*) = P<0.05.

Table C.2.1 - VARX(1)

Endogenous: News(quantity), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.1.a Endogenous: News (Quantity)

	Window 1	Window 2	Window 3
News_q			
L1.	0.4693***	0.4321***	0.5213***
Inflation			
L1.	-0.4622	-1.8885	-3.7760
Inflation Expectations			
L1.	3.8968***	7.5355***	20.6651**
Exogenous			
Comp	0.0008	0.0013	0.0065*
Sent	138.8503	375.9732*	1279.969*
Clar	-3.1944	-7.8044**	-31.0011**
Cons	66.6380	164.9292**	664.8759**
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.1.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_q			
L1.	0.0129***	0.0074***	0.0016*
Inflation			
L1.	-0.0269	-0.0270	-0.0239
Inflation Expectations			
L1.	0.7930***	0.8005***	0.8163*
Exogenous			
Comp	0.0000	0.0000	0.0000
Sent	2.5515	1.9896	-0.2002
Clar	-0.0830	-0.0984	-0.0711
Cons	2.7160	3.0206	2.4942
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.1.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_q			
L1.	0.0039	0.0024	0.0002
Inflation			
L1.	0.8265***	0.8265***	0.8267***
Inflation Expectations			
L1.	0.1819***	0.1823***	0.1992***
Exogenous			
Comp	0.000017	0.00002	0.00002
Sent	2.4483	2.2669	2.0137
Clar	0.0776	0.0730	0.0766
Cons	-2.1142	-2.0240	-2.0900
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.2 - VARX(7)

Endogenous: News(quantity), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.2.a Endogenous: News (Quantity)

	Window 1	Window 2	Window 3
News_q			
L1.	0.4811***	0.4212***	0.4958***
L2.	-0.0100	0.0552	0.0348
L3.	0.0702	-0.0016	0.1819
L4.	-0.2270*	-0.1302	-0.2605*
L5.	0.2191*	0.1929	0.0464
L6.	-0.0279	-0.1748	0.1195
L7.	0.0444	0.1169	-0.0369
Inflation			
L1.	0.1305	-3.3546	-12.6984
L2.	2.2311	4.7418	-11.4025
L3.	-1.4880	-3.2741	14.2401
L4.	0.3998	5.3926	5.9952
L5.	0.8928	-3.4773	-12.1668
L6.	-1.0697	-1.6869	7.1970
L7.	2.2443	5.3719	3.8656
Inflation Expectations			
L1.	5.7160**	11.7975***	29.6365**
L2.	1.7646	0.1003	-9.6366
L3.	-8.1899***	-9.3779*	-11.7497
L4.	2.5773	2.2102	0.9531
L5.	1.3584	0.6608	29.0833*
L6.	-0.3701	2.1616	-27.9393*
L7.	-2.8205	-4.2494	15.2806
Exogenous			
Comp	0.0007	0.0011	0.0078*
Sent	194.1098	400.2529*	1262.525*
Clar	-4.10004*	-9.5474**	-38.66***
Cons	83.283*	193.7155**	792.31***
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.2.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_q			
L1.	0.0210***	0.0102***	0.0019**
L2.	-0.0086	-0.0014	0.0006
L3.	0.0047	-0.00005	-0.0008
L4.	-0.0026	0.0004	0.0006
L5.	0.0064	0.0040	-0.0004
L6.	-0.0050	-0.0015	0.0020*
L7.	-0.0045	-0.0043	-0.0022*
Inflation			
L1.	-0.3224*	-0.3251*	-0.3635**
L2.	0.3260	0.3739*	0.4276*
L3.	-0.3694	-0.3707	-0.4500*
L4.	0.5407**	0.5128**	0.6376***
L5.	-0.2646	-0.2571	-0.4088*
L6.	-0.2102	-0.1778	-0.0926
L7.	0.0839	0.0615	0.0504
Inflation Expectations			
L1.	0.7286***	0.6939***	0.7163***
L2.	-0.1066	-0.0560	-0.0665
L3.	0.0374	0.0435	0.0726
L4.	0.2230*	0.1286	0.1152
L5.	-0.1370	-0.0877	-0.0999
L6.	0.2366*	0.2314*	0.2101
L7.	0.0136	-0.0011	0.0359
Exogenous			
Comp	-0.0001**	-0.0001**	-0.0001*
Sent	4.0626	4.7542	1.1266
Clar	-0.1393	-0.1488	-0.0949
Cons	4.1179*	4.3285*	3.2211
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.2.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_q			
L1.	0.0038	0.0041**	0.0007
L2.	0.0046	0.0016	-0.0002
L3.	-0.0047	-0.0033	0.0005
L4.	0.0022	0.0001	-0.0010
L5.	-0.0032	0.0002	0.0009
L6.	0.0058	0.0022	-0.0008
L7.	-0.0014	-0.0013	0.0005
Inflation			
L1.	1.0457***	1.0289***	1.0652***
L2.	-0.4288***	-0.3542**	-0.4262***
L3.	0.0825	0.0469	0.0723
L4.	0.1146	0.1041	0.1052
L5.	-0.0979	-0.0895	-0.0713
L6.	0.1756	0.1763	0.1398
L7.	-0.1772**	-0.1728**	-0.1520*
Inflation Expectations			
L1.	-0.0246	-0.0155	0.0080
L2.	0.0635	0.0414	0.0255
L3.	0.1174	0.1456*	0.1778**
L4.	-0.0649	-0.0691	-0.1202
L5.	0.1523*	0.1365	0.1648*
L6.	0.2498***	0.2756***	0.2607***
L7.	-0.2691***	-0.3005***	-0.2822***
Exogenous			
Comp	0.000004	0.00001	0.00001
Sent	1.4573	1.4650	-0.5236
Clar	0.0827	0.0664	0.0837
Cons	-1.8657	-1.5435	-1.8931
Hett	Yes	No	No
Ser-Corr	No	No	No

Table C.2.3 - VARX(1)

Endogenous: News(sentiment), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.3.a Endogenous: News (Sentiment)

	Window 1	Window 2	Window 3
News_s			
L1.	0.0990	0.0909	0.3505***
Inflation			
L1.	-0.0621	-0.0682	-0.2822
Inflation Expectations			
L1.	0.3759***	0.6349***	1.3470***
Exogenous			
Comp	0.000005	-0.000003	-0.0001
Sent	14.4292*	27.8053***	77.9264**
Clar	-0.1176	-0.1612	-0.4020
Cons	1.9798	2.2831	8.6740
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.3.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_s			
L1.	0.0830	0.0619	0.0219
Inflation			
L1.	-0.0261	-0.0270	-0.0205
Inflation Expectations			
L1.	0.8535***	0.8462***	0.8359***
Exogenous			
Comp	-0.00003	-0.00003	-0.00003
Sent	2.2584	1.7854	0.0084
Clar	-0.1078	-0.1129	-0.1091
Cons	3.2673	3.4014	3.3108
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.3.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_s			
L1.	0.0884	0.0537	0.0077
Inflation			
L1.	0.8288***	0.8274***	0.8288***
Inflation Expectations			
L1.	0.1755***	0.1756***	0.1925***
Exogenous			
Comp	0.00002	0.00002	0.00002
Sent	2.1690	1.8078	1.5613
Clar	0.0656	0.0623	0.0694
Cons	-1.8314	-1.7450	-1.9250
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.4 - VARX(7)

Endogenous: News(sentiment), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.4.a Endogenous: News (Sentiment)

	Window 1	Window 2	Window 3
News_s			
L1.	0.1694	0.2116*	0.3744***
L2.	0.0165	0.0922	0.0756
L3.	-0.0957	-0.0472	0.1390
L4.	-0.1443	-0.2701***	-0.1810
L5.	0.1281	0.2275**	0.1338
L6.	0.1156	0.0569	0.0146
L7.	-0.2084**	-0.1665*	-0.0782
Inflation			
L1.	0.0095	0.1823	-1.7178*
L2.	0.1455	0.2472	1.7588
L3.	0.0926	-0.3282	-1.7230
L4.	-0.2230	0.0597	1.8392
L5.	0.1433	0.2915	-1.1717
L6.	-0.0488	-0.2925	0.6990
L7.	0.0042	0.1409	-0.4136
Inflation Expectations			
L1.	0.4292***	0.7738***	1.8854***
L2.	0.2396	0.1136	-0.7672
L3.	-0.5855***	-0.7425***	-0.9960
L4.	0.1984	0.4323*	0.0516
L5.	-0.1109	-0.2788	0.9283
L6.	0.2030	0.3544	0.5150
L7.	-0.2077	-0.4791*	-0.0183
Exogenous			
Comp	-0.00002	-0.00002	-0.00003
Sent	17.6437***	29.9226***	73.8375*
Clar	0.0021	-0.0721	-0.5197
Cons	-0.3653	0.7419	10.9504
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.4.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_s			
L1.	0.1619	0.1217*	0.0274
L2.	-0.0648	-0.0073	-0.0017
L3.	0.0541	0.04002	0.0055
L4.	-0.0706	-0.0288	-0.0012
L5.	0.0651	0.0358	0.0011
L6.	-0.0328	-0.0456	0.0114
L7.	-0.1187	-0.0631	-0.0256
Inflation			
L1.	-0.3121*	-0.3512*	-0.3189*
L2.	0.2998	0.2898	0.3071
L3.	-0.3008	-0.3263	-0.3508
L4.	0.4877*	0.5290**	0.5748**
L5.	-0.2439	-0.2449	-0.3435
L6.	-0.2269	-0.2288	-0.1578
L7.	0.1362	0.1240	0.1031
Inflation Expectations			
L1.	0.7606***	0.7441***	0.7355***
L2.	-0.0308	-0.0650	-0.0221
L3.	0.0288	0.0481	0.0592
L4.	0.1591	0.1434	0.0985
L5.	-0.0949	-0.0768	-0.0399
L6.	0.2238	0.2346	0.1576
L7.	-0.0047	0.0367	0.0443
Exogenous			
Comp	-0.00005*	-0.00005	-0.0001*
Sent	5.2523	2.7438	1.4084
Clar	-0.2003*	-0.1989*	-0.1773
Cons	5.3113	5.2992**	4.8910*
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.4.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_s			
L1.	0.1206*	0.0748*	0.0155
L2.	0.0515	0.0317	0.0129
L3.	-0.0482	-0.0448	-0.0086
L4.	-0.0474	-0.0477	-0.0146
L5.	-0.0820	-0.0429	-0.0019
L6.	0.0120	0.0142	-0.0205
L7.	-0.0077	-0.0053	-0.0012
Inflation			
L1.	1.0337***	1.0162***	1.0036***
L2.	-0.3948***	-0.3853***	-0.3397**
L3.	0.0332	0.0364	-0.0046
L4.	0.1573	0.1724	0.1654
L5.	-0.0932	-0.0914	-0.1030
L6.	0.1698	0.1500	0.1497
L7.	-0.1682**	-0.1687**	-0.1561*
Inflation Expectations			
L1.	0.0050	0.0192	0.0213
L2.	-0.0057	-0.0050	-0.0034
L3.	0.1416*	0.1509*	0.1833**
L4.	-0.0398	-0.0408	-0.0675
L5.	0.2048**	0.1907**	0.1959**
L6.	0.2986***	0.3028***	0.3115***
L7.	-0.3359***	-0.3271***	-0.3016***
Exogenous			
Comp	0.00001	0.00001	0.00001
Sent	0.4334	0.4303	-0.0308
Clar	0.0529	0.0568	0.0659
Cons	-1.2738	-1.3903	-1.5927
Hett	No	No	No
Ser-Corr	No	No	No

Table C.2.5 - VARX(1)

Endogenous: News(quantity), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (SMOG)

Table C.2.5.a Endogenous: News (Quantity)

	Window 1	Window 2	Window 3
News_q			
L1.	0.4664***	0.4337***	0.5252***
Inflation			
L1.	-0.3586	-1.6204	-2.7078
Inflation Expectations			
L1.	4.1390***	8.0058***	22.4495***
Exogenous			
Comp	0.0011*	0.0019*	0.0088**
Sent	122.5453	333.4136	1106.0020
Clar	-4.0423*	-9.4883**	-37.7216***
Cons	78.9049	187.0800**	753.6360**
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.5.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_q			
L1.	0.0130***	0.0074***	0.0016*
Inflation			
L1.	-0.0229	-0.0227	-0.0206
Inflation Expectations			
L1.	0.7937***	0.8030***	0.8166***
Exogenous			
Comp	-0.00004	-0.00003	-0.00005
Sent	1.8770	1.2755	-0.7819
Clar	-0.0697	-0.0949	-0.0648
Cons	2.3235	2.8021	2.2592
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.5.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_q			
L1.	0.0040	0.0024	0.0002
Inflation			
L1.	0.8240***	0.8241***	0.8241***
Inflation Expectations			
L1.	0.1759***	0.1775***	0.1944***
Exogenous			
Comp	0.00001	0.00001	0.00001
Sent	2.8383	2.6466	2.4252
Clar	0.0990	0.0913	0.0955
Cons	-2.4292	-2.2829	-2.3540
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.6 - VARX(1)

Endogenous: News(sentiment), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type 1 dictionary), Clarity (SMOG)

Table C.2.6.a Endogenous: News (Sentiment)

	Window 1	Window 2	Window 3
News_s			
L1.	0.0939	0.0894	0.3458***
Inflation			
L1.	-0.0571	-0.0625	-0.2743
Inflation Expectations			
L1.	0.3809***	0.6452***	1.3980***
Exogenous			
Comp	0.00001	0.00001	-0.00001
Sent	13.5856*	26.9082**	77.0671**
Clar	-0.1117	-0.1901	-0.5962
Cons	1.6831	2.6207	11.9729
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.6.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_s			
L1.	0.0783	0.0597	0.0206
Inflation			
L1.	-0.0214	-0.0221	-0.0160
Inflation Expectations			
L1.	0.8577***	0.8506***	0.8410***
Exogenous			
Comp	-0.00003	-0.00002	-0.00003
Sent	1.4603	0.9867	-0.6779
Clar	-0.0990	-0.1073	-0.0975
Cons	2.9256	3.1145	2.9109
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.6.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_s			
L1.	0.0908	0.0540	0.0085
Inflation			
L1.	0.8269***	0.8255***	0.8270***
Inflation Expectations			
L1.	0.1693***	0.1707***	0.1854***
Exogenous			
Comp	0.00002	0.00002	0.00002
Sent	2.4567	2.1040	1.7975
Clar	0.0881	0.0812	0.0904
Cons	-2.1846	-2.0315	-2.2429
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.7 - VARX(1)

Endogenous: News(quantity), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (Loughran-Mcdonald), Clarity (Flesch-Kincaid)

Table C.2.7.a Endogenous: News (Quantity)

	Window 1	Window 2	Window 3
News_q			
L1.	0.4430***	0.4049***	0.5115***
Inflation			
L1.	-0.9676	-2.9188	-7.4046
Inflation Expectations			
L1.	4.2759***	8.4684***	23.1956***
Exogenous			
Comp	0.0006	0.0007	0.0044
Sent	81.2727	159.1418	561.6061
Clar	-2.6566	-6.2902*	-25.9407**
Cons	60.3142	144.6881*	598.3736**
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.7.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_q			
L1.	0.0135***	0.0078***	0.0017**
Inflation			
L1.	-0.0170	-0.0164	-0.0099
Inflation Expectations			
L1.	0.7977***	0.8032***	0.8111***
Exogenous			
Comp	-0.00005	-0.00004	-0.00004
Sent	-1.9647	-2.0488	-2.4098
Clar	-0.0738	-0.0922	-0.0712
Cons	2.5011	2.8549	2.4110
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.7.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_q			
L1.	0.0055	0.0035	0.0007
Inflation			
L1.	0.8537***	0.8546***	0.8563***
Inflation Expectations			
L1.	0.1841***	0.1831***	0.1907***
Exogenous			
Comp	0.00002	0.00003	0.00002
Sent	-5.0782*	-5.2222*	-5.2156*
Clar	0.0857	0.0782	0.0865
Cons	-2.4115	-2.2714	-2.4406
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.8 - VARX(1)

Endogenous: News(sentiment), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (Loughran & McDonald), Clarity (Flesch-Kincaid)

Table C.2.8.a Endogenous: News (Sentiment)

	Window 1	Window 2	Window 3
News_s			
L1.	0.1167	0.1187	0.4439***
Inflation			
L1.	-0.0500	-0.0814	-0.2356
Inflation Expectations			
L1.	0.4074***	0.6798***	1.3010***
Exogenous			
Comp	0.0000003	-0.00003	-0.0001
Sent	-3.1277	0.5844	-6.8606
Clar	-0.0669	-0.0625	-0.1843
Cons	1.0585	0.7103	5.1899
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.8.b Endogenous: Inflation Expectations

	Window 1	Window 2	Window 3
News_s			
L1.	0.0832	0.0638	0.0222
Inflation			
L1.	-0.0298	-0.0278	-0.0194
Inflation Expectations			
L1.	0.8578***	0.8491***	0.8357***
Exogenous			
Comp	-0.00003	-0.00003	-0.00003
Sent	0.5120	0.0234	-0.1836
Clar	-0.0990	-0.1066	-0.1093
Cons	3.1366	3.3004	3.3106
Hett	Yes	Yes	Yes
Ser-Corr	No	No	No

Table C.2.8.c Endogenous: Inflation

	Window 1	Window 2	Window 3
News_s			
L1.	0.1008	0.0714	0.0150
Inflation			
L1.	0.8522***	0.8540***	0.8568***
Inflation Expectations			
L1.	0.1826***	0.1758***	0.1849***
Exogenous			
Comp	0.00003	0.00003	0.00003
Sent	-4.3378	-4.8548*	-4.6295
Clar	0.0698	0.0619	0.0665
Cons	-2.0220	-1.8530	-1.9900
Hett	Yes	Yes	Yes
Ser-Corr	Yes	Yes	Yes

Table C.2.9 - VARX(1) -Joint Press Releases - Model Weighting

Endogenous: News(quantity-left side; sentiment-right side), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type-1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.9.a Endogenous: News (Quantity-Left side; Sentiment-Right side)

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.4386***	0.2908*
Inflation		
L1.	5.4374	0.0827
Inflation Expectations		
L1.	28.5712**	1.3544***
Exogenous		
Comp	0.0071*	0.0001
Sent	-39.5250	-5.4553
Clar	-22.3100	-0.7295
Cons	365.0541	12.6887
Hett	No	Yes
Ser-Corr	No	No

Table C.2.9.b Endogenous: Inflation Expectations

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.0010	0.0454
Inflation		
L1.	0.0181	0.0240
Inflation Expectations		
L1.	0.8632***	0.8213***
Exogenous		
Comp	-0.00002	-0.00001
Sent	-3.4316	-6.0591
Clar	-0.3087*	-0.2928*
Cons	7.2522**	6.9757**
Hett	Yes	Yes
Ser-Corr	No	Yes

Table C.2.9.c Endogenous: Inflation

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.0013	0.0870**
Inflation		
L1.	0.7796***	0.7900***
Inflation Expectations		
L1.	0.1118	0.0024
Exogenous		
Comp	-0.00002	-0.00001
Sent	3.1983	-2.0800
Clar	0.2615*	0.2986*
Cons	-5.2096*	-5.8519*
Hett	Yes	Yes
Ser-Corr	Yes	Yes

Table C.2.10 - VARX(1) -Joint Press Releases – 75% weight of interest rate PR & 25% of inflation PR

Endogenous: News(quantity-left side; sentiment-right side), Inflation, Inflation Expectations

Exogenous: Comprehensiveness, Sentiment (type-1 dictionary), Clarity (Flesch-Kincaid)

Table C.2.10.a Endogenous: News (Quantity-Left side; Sentiment-Right side)

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.4207***	0.2901
Inflation		
L1.	3.2118	0.0377
Inflation Expectations		
L1.	30.9680**	1.3806
Exogenous		
Comp	0.0200**	0.0004
Sent	-50.0841	-3.6208
Clar	-31.5165	-0.8628
Cons	551.2066	15.2615
Hett	No	No
Ser-Corr	No	No

Table C.2.10.b Endogenous: Inflation Expectations

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.0010	0.0461
Inflation		
L1.	0.0146	0.0196
Inflation Expectations		
L1.	0.8617***	0.8172
Exogenous		
Comp	-0.00004	-0.00003
Sent	-3.3101	-5.6860
Clar	-0.2504*	-0.2362
Cons	6.0374*	5.8080
Hett	Yes	Yes
Ser-Corr	Yes	Yes

Table C.2.10.c Endogenous: Inflation

	Window 3	
	Quantity	**Sentiment**
News		
L1.	0.0014	0.0847
Inflation		
L1.	0.7856***	0.7946
Inflation Expectations		
L1.	0.0924	-0.0086
Exogenous		
Comp	-0.00008	-0.00005
Sent	3.0334	-1.3309
Clar	0.3314**	0.3626
Cons	-6.5617	-7.0758
Hett	Yes	Yes
Ser-Corr	No	No

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