CBREV 26 (2026) 100281

Contents lists available at ScienceDirect

Central Bank Review

journal homepage: www.journals.elsevier.com/central-bank-review/

Twitter (X) and inflation dynamics: Investigating the role of Twitter sentiment in Türkiye's hybrid new Keynesian Phillips curve

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ARTICLE INFO

JEL classification:
C22
E31
E52
C55

Keywords:
Inflation
Phillips curve
Sentiment analysis
Natural language processing
BERT

ABSTRACT

This study explores the role of Twitter-based sentiment in shaping inflation expectations within Türkiye's Hybrid New Keynesian Phillips Curve (HNKPC) in a closed-economy framework. By incorporating a novel Twitter-based inflation expectations variable (TWT), derived using Natural Language Processing (NLP) with the Bidirectional Encoder Representations from Transformers (BERT) model, as a forward-looking component, this research offers an alternative to traditional methods like rational expectations and survey data. The findings reveal that while backward-looking inflation (past inflation) remains the dominant driver of expectations, Twitter sentiment, representing forward-looking expectations, influences actual inflation, though with a relatively weaker effect. This suggests that while past inflation plays a crucial role, TWT offers useful, up-to-date observations of the public's views on future inflation. The study also shows that in this closed model, the output gap is not significant, reinforcing the notion that inflation persistence remains central to Türkiye's inflation dynamics. The results suggest that policymakers should consider integrating Twitter sentiment into their strategies to enable more effective and dynamic communication with the public. By better understanding and responding to inflation expectations across traditional and social media, especially Twitter, authorities can enhance the credibility of inflation-targeting frameworks and potentially reduce inflation more efficiently.

1. Introduction

The first form of the New Keynesian Phillips Curve (NKPC) included only the rational expectations assumption. In this scenario, inflation depends on future inflation expectations, marginal costs, and the output gap. After Galí and Gertler (1999) introduced the HNKPC, lagged inflation expectations were also included in the model, thus opening up space for the concept of inflation inertia. Consequently, inflation for economic agents will be influenced not only by the actual inflation in period t+1 but also by the lagged inflation in period t-1.

The NKPC contains several insights. First, it analyzes a country's inflation dynamics. It helps to determine the central bank policies to be implemented by analyzing the inflation dynamics of a country. If we consider the model in hybrid form, central banks may be more successful in inflation-targeting policies where the weight is on rational expectations, and they may not compromise economic activity too much in the disinflation process. In the case where backward-looking expectations are dominant, on the other hand, it may be possible to say that there is inflation inertia, which may require a more active and structural response on the part of both the central bank and the public sector. In cases where coefficients of expectations do not fully explain inflation, inflation may increase due to economic activity (high demand) or domestic and external shocks.

A common approach for future inflation expectations in the literature is to use the actual inflation at time t+1, along with the assumption of rational expectations, which implies that $\pi_{t+1} = E_t(\pi_{t+1}) + \epsilon_{t+1}$, where ϵ_{t+1} is white noise. This assumption makes it easier to estimate the model since there is no need for an explicit measure of inflation expectations. However, even with rational expectations, π_{t+1} is noisier than $E_t(\pi_{t+1})$, which can make estimating the NKPC challenging, particularly when working with limited data (Zhang et al., 2009).

Using observed inflation survey data rather than realized future inflation values might be preferable for measuring unobserved inflation expectations. This is because survey data could more accurately capture people's responses to economic conditions, offering a better reflection of expectations than actual forward-looking inflation (Zhang et al., 2009). This method was described by Roberts (1995) and, over time, has gained popularity. However, in survey expectations, the views of professional

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https://doi.org/10.1016/j.cbrev.2026.100281
Received 18 November 2025; Received in revised form 19 September 2026; Accepted 7 October 2026
Available online 12 October 2026
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participants are generally taken into account, so the wider community is overlooked. Although authors such as Roberts (1995) and Zhang et al. (2009) base part of their models on the Michigan survey and include consumer expectations, the proportion represented by these studies is comparatively minor.

As seen, while the representation of forward-looking inflation expectations varies, one of the main debates in the literature concerns whether the country's inflation dynamics are formed more by backward-looking expectations or forward-looking expectations. For instance, Galí et al. (2005), Galí and Gertler (1999), Sbordone (2005, 2002) and Vašíček (2011) emphasize the dominant role of future expected inflation, whereas Fuhrer and Moore (1995), Roberts (1995), Rudd and Whelan (2005) and Zhang et al. (2008) find that the backward-looking component plays a more significant role. When examining Türkiye's case, studies such as Saz (2011) and Yazgan and Yilmazkuday (2005) highlight the predominant role of forward-looking inflation expectations. In contrast, Agénor and Bayraktar (2010) and Eruygur (2011) demonstrate that the backward-looking component is also important.

The concept of future inflation expectations, $E_t(\pi_{t+1})$, is inherently endogenous and, more problematically, unobservable when actual inflation is used as its proxy. Various empirical approaches in the literature primarily differ in how they represent inflation expectations (Mavroeidis et al., 2014). The way survey data is treated in the literature, whether as endogenous or exogenous, varies. Zhang et al. (2009), Mazumder (2011) and Koc et al. (2021) discuss the potential endogeneity of inflation forecasts, while Roberts (1998) and Adam and Padula (2011) treat observed inflation forecasts as exogenous.

In our study, we introduce a new Twitter-based monthly inflation expectations variable that has not been analyzed in the Phillips Curve literature before. We construct a sentiment index based on Twitter data and test it in the model. Considering survey expectations in the literature, we followed this idea and assumed the Twitter-based sentiment index is observable and direct, similar to survey-based measures. However, unlike surveys, which capture the views of a selected group of respondents, TWT reflects the expectations of a broader and more heterogeneous segment of society, including especially consumers and households.

The most significant gap encountered in the literature, and the one that led to the development of this study, is the lack of testing of a social media-based inflation expectation variable through a theoretical model. This study aims to contribute to future research and policy-making processes by adding a social media-based inflation variable, specifically Twitter, to the Phillips Curve literature. Based on the discussions, the hypotheses and research questions of the study are as follows.

H1. Twitter-based inflation expectations contribute to the formation of inflation.

H2. Inflation inertia is valid in Türkiye.

In this context, one of the questions we would like to ask is whether Twitter-based expectations contribute to the formation of inflation. If so, policymakers should give Twitter the necessary weight in managing expectations.

The issue of inflation in Türkiye has persisted for an extended period of time. At times, inflation has reached very high levels, while at other times it has remained at more moderate levels. It is a fact that the inflation phenomenon has been on Türkiye's agenda for a long time. The existence of such an agenda also raises the question of the persistence of inflation. Thus, another question we want to answer in this study is whether inflation inertia is valid in Türkiye.

The significance of this study goes beyond theoretical aspects of inflation and expectations. Platforms like Twitter provide an immediate, real-time channel through which public sentiment can be tracked. By including Twitter-based expectations in the NKPC, this research gives central banks and policymakers a dynamic tool to monitor public opinion and anticipate inflation trends more effectively. This real-time feedback could enable quicker, more targeted policy actions to prevent inflation from becoming ingrained. Therefore, if Twitter's impact on inflation is proven, the way will be paved for further studies to conduct more comprehensive analyses. This research also offers broader contributions to macroeconomics. Including Twitter sentiment in inflation models opens new areas for future research on how digital platforms influence economic behavior.

The remainder of the study consists of the following sections: Section 2 covers the materials and methods, Section 3 presents the results of the analysis, and Section 4 contains the conclusion.

2. Data and methodology

2.1. Data

This study covers the period from January 2014 to June 2024. The data are collected on a monthly basis for the variables: Consumer Price Index (CPI), Industrial Production Index (IPI) as a proxy for the output gap, Twitter-based inflation expectations (TWT), and Interest Rate Spread (Spread) as an instrumental variable. Except for TWT, all other data are obtained from the Central Bank of the Republic of Türkiye (CBRT) and TURKSTAT.

Since the study is monthly, CPI is preferred instead of deflator to represent inflation. Similar studies in Türkiye, such as Yazgan and Yilmazkuday (2005) and Çatik et al. (2011), also prefer CPI. Since monthly GDP is not available, IPI is preferred over GDP to represent the output gap. Since IPI is known to be highly correlated with GDP, IPI can be used as a proxy variable (Özkurt, 2016). The Industrial Production Index (IPI) series is obtained monthly in log form, and potential output is estimated using the Hodrick-Prescott (HP) filter with a smoothing parameter λ set to 14,400. The final percentage form of output gap representation is obtained as calculated by Wardhono et al. (2021). Mazumder (2014) pointed out that the interest rate spread is established by subtracting the bank deposit interest rate from the bank loan interest rate. Following this definition, we have used the weighted average interest rates applied to consumer loans in Turkish lira (TL) and the interest rates applied to deposit accounts in TL with maturities up to 1 month to get Spread. Specifically, we compute Spread as the logarithmic difference between the two rates, as can be seen in Table 1.

This study utilizes tweet data from the Politus Dataset, a large-scale social media dataset constructed from Twitter and processed using privacy-preserving artificial intelligence algorithms (Yörük et al., 2025). The Politus Dataset covers a wide range of political and social discourse in Türkiye; from this huge dataset, the subset labeled under the economy category, comprising 8,668,800 tweets, was used as the primary raw

Table 1
Description of variables.

Variables	Description	Formula/Notes	Source
CPI (π_t)	Monthly inflation rate.	$\log(\text{CPI}_t) - \log(\text{CPI}_{t-1})$	TURKSTAT
TWT (π_{t+1})	Negative sentiment share obtained by dividing the number of negative tweets by the total number of tweets.	$\frac{\text{Negative Tweets}}{\text{Total Tweets}}$	Politus Project & Python, Author Calculation
IPI (y_t)	The difference between actual output and potential output as a percentage of the potential output.	$\frac{y_t^a - y_t^*}{y_t^*} \times 100$	TURKSTAT & Author Calculation
Spread_t	Interest rate spread.	Logarithmic difference between bank lending rate and bank deposit rate.	CBRT

data source. A brief outline and description of all of the variables used in this study can be found in Table 1.

2.2. Sentiment analysis with BERT

2.2.1. Domain-specific data transformation

As we discussed above, we leveraged the Politus project to get tweets about the economic context. The raw economy-labeled dataset includes 8,668,800 tweets. To get inflation-relevant content, a keyword-based filtering approach was applied using the following terms: enflasyon (inflation), deflasyon (deflation), dezenflasyon (disinflation), fiyat artışı (price increase), fiyat düşüşü (price decrease), and fiyatlar (prices). So, the filtered dataset yielded 936,462 inflation-related tweets.

To address the potential concern regarding the backward-looking nature of tweet content, a forward-looking filter was subsequently applied. Tweets were retained only if they contained future-oriented words, including Turkish future tense suffixes (-ecek, -acak), expectation-related terms (tahmin, beklenti, öngörü etc.), and temporal expressions (gelecekte, önümüzdeki, uzun vadede etc.). This filtering step reduced the dataset to 294,562 forward-looking tweets, representing 31.45% of all inflation-related tweets.

Fig. 1 shows the domain-specific filtering workflow.

2.2.2. Data preprocessing

Before model training and inference, all tweets were processed. According to Sivarajah et al. (2017), text data is primarily unstructured, which necessitates significant preprocessing efforts before conducting sentiment analysis (Tirunillai and Tellis, 2014). Due to its unorganized nature, text data often contains noise, inconsistencies, and irrelevant information.

The preprocessing steps were as follows: URLs were removed, user mentions were anonymized by replacing them with 'user', and hashtag symbols were excluded while preserving the underlying textual content. Punctuation marks and emojis were removed, Turkish-specific lowercasing was applied to ensure consistency across the corpus, and excess whitespace was normalized throughout.

A small sample from the dataset is shown in Table 2.

After the data was cleaned, it was made ready for sentiment analysis. The sentiment analysis will classify texts, allowing us to create the Twitter-based inflation expectation variable.

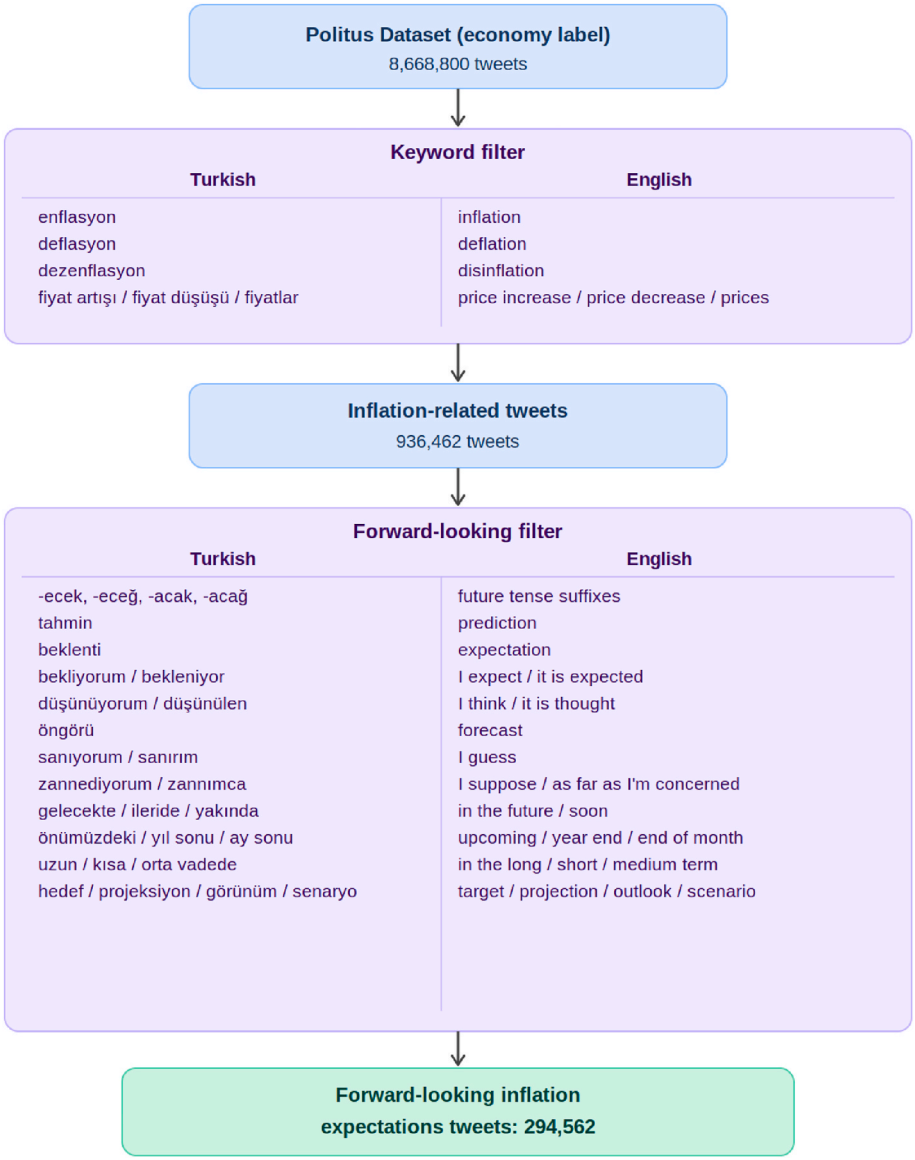


Fig. 1. Inflation expectations content filtering workflow.

Table 2
Selected cleaned tweets in the sample.

	The Turkish texts before cleaning	The Turkish texts after cleaning	English version
1	Parasal sıkılaşma ile birlikte talep düşecek ancak böyle düşer fiyatlar	parasal sıkılaşma ile birlikte talep düşecek ancak böyle düşer fiyatlar	With monetary tightening, demand will fall — prices only drop this way
2	Cumhurbaşkanı Yardımcısı Yılmaz: Orta vadede tek haneli enflasyona gitmeyi öngörüyoruz https://ift.tt/OPlZUQS	cumhurbaşkanı yardımcısı yılmaz orta vadede tek haneli enflasyona gitmeyi öngörüyoruz	Vice President Yılmaz: We forecast moving to single-digit inflation in the medium term
3	Gerçek enflasyon zaten ölüsü %100, %40 faize piyasa inanmaz. İş işten geçti artık, şimdi hiperenflasyon fazı başlayacak. Günlük çok yüksek zamlara hazır olun	gerçek enflasyon zaten ölüsü 10040 faize piyasa inanmaz iş işten geçti artık şimdi hiperenflasyon fazı başlayacak günlük çok yüksek zamlara hazır olun	Real inflation is at least 100%, if nothing else, the market won't believe a 40% rate. It's too late now, the hyperinflationary phase will begin. Prepare for very high daily price hikes
4	Peki bu değirmenin suyu nerden gelecek,iki sene boyunca? Para basılacak ve al sana % 300 enflasyon! Gidişat budur! 😩😩😩	peki bu değirmenin suyu nerden gelecek iki sene boyunca para basılacak ve al sana 300 enflasyon gidişat budur	Where the expenses come from for two years? Money will be printed and there you go, 300% inflation! That's where this is headed!
5	Tarımda üretici fiyatlarında rekor artış var. Aylık bazda Tarımda ÜFE yüzde 4,57 artmış, yıllık yüzde 24'ün üzerinde. Bu, gıda fiyatlarının daha da yükseleceği anlamına geliyor maalesef	tarımda üretici fiyatlarında rekor artış var aylık bazda tarımda üfe yüzde 457 artmış yıllık yüzde 24ün üzerinde bu gıda fiyatlarının daha da yükseleceği anlamına geliyor maalesef	There is a record increase in agricultural producer prices. Monthly agricultural PPI rose 4.57%, above 24% annually. This unfortunately means food prices will rise further
6	Merkez Bankası politika faizini beklentilere paralel 5 puan artırarak yüzde 30'a çıkardı. Aylık enflasyonun ana eğiliminde düşüşün başlayacağını belirten Merkez Bankası, sadeleşme sürecinin kademeli olarak devam edeceğini açıkladı. #faiz #faizkararı	merkez bankası politika faizini beklentilere paralel 5 puan artırarak yüzde 30a çıkardı aylık enflasyonun ana eğiliminde düşüşün başlayacağını belirten merkez bankası sadeleşme sürecinin kademeli olarak devam edeceğini açıkladı faiz faizkararı	The Central Bank raised the policy rate by 5 points in line with expectations to 30%. The Central Bank, stating that a decline in the underlying trend of monthly inflation will begin, announced that the simplification process will continue gradually
7	@x1 @x2 Ankarada konut fiyatlarının da etkileneceğini düşünmüyorum; altından fay geçmeyen ve beyaz yakalıların iş imkanı olan tek büyük şehir. İstanbuldan Ankaraya ciddi bir beyaz yaka göçü olabilir …	user user ankarada konut fiyatlarının da etkileneceğini düşünmüyorum altından fay geçmeyen ve beyaz yakalıların iş imkanı olan tek büyük şehir istanbuldan ankaraya ciddi bir beyaz yaka göçü olabilir	I don't think housing prices in Ankara will be affected; it's the only major city without a fault line and with job opportunities for white-collar workers. There could be a significant white-collar migration from Istanbul to Ankara
8	Altın fiyatlarında dikkat çeken uyarı: Rekor kıracak https://t.co/ooaZsDGA9b	altın fiyatlarında dikkat çeken uyarı rekor kıracak	Notable warning on gold prices: Will break records

The mentioned users' names are removed for ethical reasons; instead of providing their real accounts, we use x1, x2, and so on for every user in the table. No grammatical or vocabulary changes have been made to preserve the originality of the texts.

2.2.3. BERT model

Sentiment analysis seeks to determine how sentiments are conveyed in texts and classify them as positive, neutral, or negative in relation to a specific subject (Liu, 2012). Recent studies have explored the use of sentiment analysis and machine learning techniques to predict macroeconomic indicators and stock market trends. Researchers have employed various models, including BERT, to analyze economic news and central bank communications (Réka Ónozó et al., 2024; Nemes and Kiss, 2021; Niţoi et al., 2023).

Over the years, various methods have been used for sentiment analysis in NLP, particularly in financial sentiment analysis. These methods fall into three main categories: lexicon-based, machine learning, and deep learning approaches. Lexicon-based methods rely on predefined word lists to classify sentiment as positive, negative, or neutral, but they fail to consider sentence structure and context. Machine learning approaches represent text as numerical features using bag-of-words or Term Frequency-Inverse Document Frequency (TF-IDF), and then apply classifiers such as Naïve Bayes, Support Vector Machines (SVM), or Maximum Entropy. However, they ignore word order, and small training datasets can limit their effectiveness (Shapiro et al., 2022). On the other hand, deep learning methods improve sentiment analysis by learning patterns from labeled text data, thereby capturing contextual meaning. Despite their advantages, these models require large datasets for training and fine-tuning, making them resource-intensive (Niţoi et al., 2023). In this study, we applied a deep learning approach, which is the BERT model.

BERT represents a new paradigm in NLP. It is increasingly used in sequence-to-sequence modeling and classification tasks. Released by Google in 2018, BERT is a pretrained model that has consistently outperformed other models in various NLP challenges. It is a powerful language model that captures the meaning of words along with their context. For example, BERT can distinguish the word "bank" in the sentences “She went to the bank to deposit money,” and “Coconuts grow well in the river bank where the soil is rich.” It helps disambiguate the meaning of the word "bank" based on the words preceding and succeeding it (Sri, 2021).

BERT is based on the Transformer architecture (Vaswani et al., 2017). Unlike other word-embedding models like Word2vec or Embeddings from Language Models, BERT uses a bidirectional Transformer encoder that looks at both the left and right context of words at the same time. The model takes input through token embeddings (representing words), segment embeddings (representing different parts of a sentence), and position embeddings (indicating the order of words). The output is a series of vectors, where each one corresponds to a word in the input sentence. BERT is pretrained using two unsupervised tasks: Masked Language Modeling (where 15% of words are randomly hidden, and the model predicts them) and Next Sentence Prediction, where the model predicts if two sentences follow each other (Niţoi et al., 2023).

Angelico et al. (2022) demonstrate that Twitter can be a viable source of a high-frequency daily indicator of consumer inflation expectations. They employed Latent Dirichlet Allocation (LDA) and n-gram analysis and applied future-oriented expressions to obtain indicators of inflation expectations. The present study advances the methodological perspective in several respects. While Angelico et al. (2022) employ a dictionary-based approach with n-gram matching for sentiment classification, a method that, while transparent, relies on predefined lexicons and may struggle with the contextual complexity of natural language, our study utilizes a domain-specific fine-tuned BERT model trained on manually annotated inflation-related tweets. This approach enables the model to capture nuanced semantic relationships and context-dependent sentiment, offering a more sophisticated classification framework for Turkish economic discourse.

2.2.3.1. Fine-tuned BERT model. BERT works well for extracting sentiment from general text, but for specialized fields, it needs to be fine-

tuned with domain-specific data to improve performance (Howard and Ruder, 2018).

To train the dataset, we first manually annotated a sub-sample of the forward-looking corpus, consisting of 3700 tweets. Two annotators with economics backgrounds independently labeled each tweet as negative (−1), neutral (0), or positive (+1), with ambiguous tweets (not labeled) excluded to prioritize reliability over dataset size. While labeling decisions were made independently, annotators consulted one another as needed when encountering novel cases, and the annotation guidelines were refined accordingly. Tweets that did not reach consensus (labeled differently) were removed from the dataset entirely and were not included in the prediction corpus. Inter-annotator agreement was assessed using Cohen's Kappa (Cohen, 1960) on the non-ambiguous tweets, with the results reported in Section 3. The annotated sub-sample was excluded from the prediction corpus to ensure that the inference dataset consists solely of unlabeled observations.

A Turkish BERT model was fine-tuned on a manually annotated gold-standard dataset. The pre-trained model dbmdz/bert-base-turkish-cased was selected as the base architecture, as it has been pre-trained on a large Turkish text corpus and captures the morphological and semantic structure of the Turkish language.

The gold-standard dataset (tweets on which two annotators agreed) was split into training (70%), validation (15%), and test (15%) sets using stratified sampling, ensuring that the class distribution is preserved across all partitions. To further address the class imbalance during model training, class weights inversely proportional to class frequencies were applied. While stratified sampling ensures balanced representation across data splits, class weighting adjusts the model's loss function so that errors on minority classes are penalized more heavily, preventing the model from being biased toward the majority class (He and Garcia, 2009).

The model was fine-tuned using the AdamW optimizer (Loshchilov and Hutter, 2019) with a learning rate of 2e-5, following the fine-tuning procedure recommended by Devlin et al. (2019). A linear learning rate scheduler with warmup over 10% of training steps was applied, followed by linear decay to zero at the final step. The model was trained for 5 epochs with a batch size of 16 and a maximum sequence length of 128 tokens. Cross-entropy loss with class weights was used as the objective function.

To prevent overfitting, validation loss and macro F1 score were monitored after each epoch. The optimal checkpoint was identified at an epoch after which the validation loss began to increase while the training loss continued to decrease (Prechelt, 2012). The final model was subsequently evaluated on the test set and, after achieving satisfactory performance, applied to the full forward-looking corpus to generate sentiment predictions. The results of both evaluations are reported in Section 3.

2.2.4. Twitter-based inflation expectations

We conducted sentiment analysis to create an inflation expectation variable from Twitter data. Our assumption is that the sentiment tone of the tweets about inflation will be effective in the formation of realized inflation.

$$TWT = \frac{\text{Negative Tweets}}{\text{Total Tweets}} \tag{2.1}$$

Thus, a ratio close to 1 indicates a negative mood in inflation expectations, while a ratio close to 0 indicates moderate and positive expectations.

2.3. Estimation methodology

2.3.1. Theoretical model

In this section, we benefited from Sümer's (2020) work when deriving the Phillips curve. The Phillips curve, developed by Taylor (1980) and Calvo (1983), incorporates forward-looking wage and price decisions by workers and firms. The NKPC, which represents the link between inflation and firms' real marginal costs, is given by the following expression (Calvo, 1983):

$$p_t = \theta p_{t-1} + (1-\theta)p_t^* \tag{2.2}$$

where the price level that provides companies with profit maximization is represented by p_t *, in equation (2.2), p_t represents the total price level, and p_{t-1} is the previous period's price level. p_t^* is derived as:

$$p_t^* = (1-\beta\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t\{mc_{t+i}^n\} \tag{2.3}$$

mc_{t+i}^n represents the real marginal costs of firms at future periods and β is the discount factor. Using the Cobb-Douglas production function, real marginal cost is obtained. In this framework, A_t represents technology, K_t denotes capital, and N_t refers to labor. The output Y_t is given by $Y_t = A_t K_t^{\alpha_k} N_t^{\alpha_n}$. The real marginal cost is the ratio of the wage rate to the marginal product of labor. The following equation is derived from this: $C_t = \frac{W_t}{P_t}\cdot\frac{1}{\frac{\partial Y_t}{\partial N_t}}$. Using the previous equation, we can express real marginal cost as $C_t = \frac{S_t}{\alpha_n}$, where St is the labor income share or real unit labor costs, defined as $S_t = \frac{W_t N_t}{P_t Y_t}$ (Galí and Gertler, 1999).

When both equations (2.2) and (2.3) are considered, the NKPC is based on microeconomic foundations, and its parameters have a clear structural interpretation. The parameter θ represents the fraction of firms that cannot optimally adjust their prices in the current period, while $1-\theta$ is the fraction of firms that can. Firms that cannot adjust their prices are tied to past prices. However, firms must make optimal price adjustments to maximize their profits. Without this, the price level that maximizes their profit is written as:

$$p_t^* = mc_{t+i}^n \tag{2.4}$$

In Equation (2.4), firms adjust their prices to make normal profits instead of maximum profits; the price is set according to the current marginal cost of the firm. Given this framework, the NKPC, in other words, pure forward-looking NKPC, is expressed as:

$$\pi_t = \lambda mc_t + \gamma_f E_t(\pi_{t+1}) \tag{2.5}$$

π_t is the current period inflation, and $E_t(\pi_{t+1})$ is the future inflation forecast. The current inflation rate is thus determined by two key factors: the real marginal cost faced by firms and the expected future inflation levels. This relationship underscores a fundamental assumption: firms operate with a forward-looking perspective, making decisions today, including pricing, to maximize their profits based on their anticipation of future economic conditions.

However, relaxing the assumption that prices left unadjusted in the current period simply remain equal to the past price level, rather than abandoning price rigidity altogether, was effective in developing the HNKPC (Galí and Gertler, 1999). This matters because price rigidity alone does not generate inflation persistence in the reduced-form inflation equation, leaving the model purely forward-looking (Equation (2.5)). Allowing a fraction of firms to index prices to past inflation instead introduces a persistent, lagged inflation term, giving rise to the hybrid structure of the NKPC.

The expression of the HNKPC, which includes the past inflation component, is given by Galí and Gertler (1999) as:

$$p_t^* = (1-w)p_t^f + wp_t^b \tag{2.6}$$

In this model, w represents the fraction of firms that base their expectations on past inflation, while $(1-w)$ represents the fraction with forward-looking inflation expectations. The price set by firms with forward-looking expectations is denoted as p_t^f while p_t^b refers to the price set by firms with backward-looking expectations.

The price set by forward-looking firms is written as:

$$p_t^f = (1-\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t\{mc_{t+i}^n\} \tag{2.7}$$

The price set by backward-looking firms, which adjusts based on past inflation, is expressed as:

$$p_t^b = p_{t-1}^* + \pi_{t-1} \tag{2.8}$$

In this case, the price is adjusted in line with past inflation rates based on the last price correction.

The HNKPC, combining Equations (2.2), (2.6) and (2.7), and (2.8), is:

$$\pi_t = \lambda mc_t + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} \tag{2.9}$$

Assuming that firms do not have variable capital, the real marginal cost and the output will be equal, as derived from the Cobb-Douglas production function and the Taylor monetary policy rule (Rotemberg and Woodford, 1997).

$$\pi_t = \lambda y_t + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} \tag{2.10}$$

where the reduced-form parameters are:

$$\lambda = (1-w)(1-\theta)(1-\beta\theta)\phi^{-1}$$

$$\gamma_f = \beta\theta\phi^{-1}$$

$$\gamma_b = w\phi^{-1} \tag{2.11}$$

with $\phi = \theta + w[1 - \theta(1 - \beta)]$.

In this context, γ_f and γ_b represent the weights assigned to expected future inflation (forward-looking) and past inflation (backward-looking), respectively. λ is the reduced-form slope coefficient showing the elasticity of inflation to marginal cost or output gap. If all firms set prices with a forward-looking approach, the fraction of backward-looking firms would be zero, causing the HNKPC to align with the pure forward-looking NKPC (Eq. (2.5)).

2.3.2. Endogeneity of inflation

A key challenge in estimating the NKPC arises from the forward-looking nature of inflation, where current inflation is influenced by expected future inflation. Since inflation expectations are typically formed using past and present inflation trends, they are likely to be endogenous (Koc et al., 2021). Instead of survey-based measures, we use a Twitter-based sentiment ratio as a proxy for direct, observable inflation expectations. We assume that Twitter-based inflation expectations are also endogenous, as they are affected by past and present inflation trends.

$$E\left[Z_t\left(\pi_t - \gamma_f E_t[\pi_{t+1}] - \gamma_b \pi_{t-1} - \lambda y_t\right)\right] = 0 \tag{2.12}$$

The equation above ensures that the model is estimated in a way where the residuals (errors) have an average value of zero and are uncorrelated with the instrument set Z_t. This is known as an orthogonality condition (or moment condition). In this context, the instrument vector Z_t is chosen to be orthogonal to the residuals from the Phillips curve equation involving π_{t-1}. This means the instruments and residuals are linearly independent and uncorrelated. Therefore, this study estimates equation (2.10) using the Generalized Method of Moments (GMM) to address potential endogeneity in the regressors, particularly in inflation.

3. Results

The results are presented in two parts. The first covers the sentiment analysis process, encompassing the annotation procedure, BERT fine-tuning, and sentiment inference used to construct the Twitter-based inflation expectation variable. The second presents the regression analysis, including descriptive statistics for all variables and the GMM estimation results.

3.1. Sentiment analysis

3.1.1. Manual annotation

As described in Section 2, two annotators independently labeled 3700 forward-looking tweets. Inter-annotator agreement was measured using Cohen's Kappa, yielding $\kappa = 0.8979$ (ambiguous tweets were excluded from the Kappa calculation), indicating almost perfect agreement (Landis and Koch, 1977). 3489 tweets were assigned as the gold standard. The remaining ambiguous (n = 28) and conflicting (n = 183) tweets were excluded to prioritize reliability. The distribution of the resulting gold standard dataset is presented in Table 3. The annotation guidelines, including class definitions and illustrative examples, are provided in Appendix A.

Table 3 reveals a significant class imbalance. In particular, negative tweets are much more dominant than those in other classes.

3.1.2. BERT training results

As discussed above, the gold-standard dataset was split into training, validation, and test sets with the proportions of 70% (2442), 15% (523), and 15% (524), respectively. Stratified sampling was applied to ensure that the class distribution is preserved across all splits. To address class imbalance, class weights inversely proportional to class frequencies were applied during training (Negative: 0.49, Neutral: 1.57, Positive: 3.20), assigning a greater penalty to errors on minority classes. The fine-tuned model was trained for 5 epochs, with training and validation loss monitored after each epoch to identify the optimal checkpoint. Training dynamics are illustrated in Fig. 2.

The validation loss reached its minimum at epoch 3 and began to increase thereafter, while training loss continued to decline, indicating the onset of overfitting. The epoch 3 checkpoint was therefore selected as the final model and subsequently evaluated on the test set consisting of 524 tweets. Table 4 shows the classification report.

Given the class imbalance in the dataset, accuracy alone may yield a biased assessment of model performance, as the dominant negative class could inflate the overall score. The macro F1 score, which assigns equal weight to all classes regardless of their frequency, provides a more reliable evaluation metric in this context. A macro F1 score of 0.73 indicates satisfactory performance across all sentiment categories. The confusion matrix is provided in Fig. 3.

The confusion matrix reveals that misclassifications are predominantly directed toward the negative class, with the model occasionally labeling neutral and positive tweets as negative. This pattern is consistent with the dataset's class imbalance. Nevertheless, the overall classification performance remains sufficiently robust for sentiment prediction in this study.

3.1.3. Sentiment prediction

After evaluating the test set and excluding the annotated sub-sample of 3700 tweets from the prediction corpus, the optimal model was applied to the full forward-looking corpus to generate sentiment predictions. The sentiment distribution of the 290,862 labeled tweets is presented in Table 5.

A careful examination of Table 5 reveals that the distribution of predicted sentiment closely matches that of the gold-standard dataset.

Table 3
Distribution of gold standard dataset.

Class	N	%
Negative (−1)	2388	68.4
Neutral (0)	738	21.2
Positive (+1)	363	10.4
Total	3489	100.0

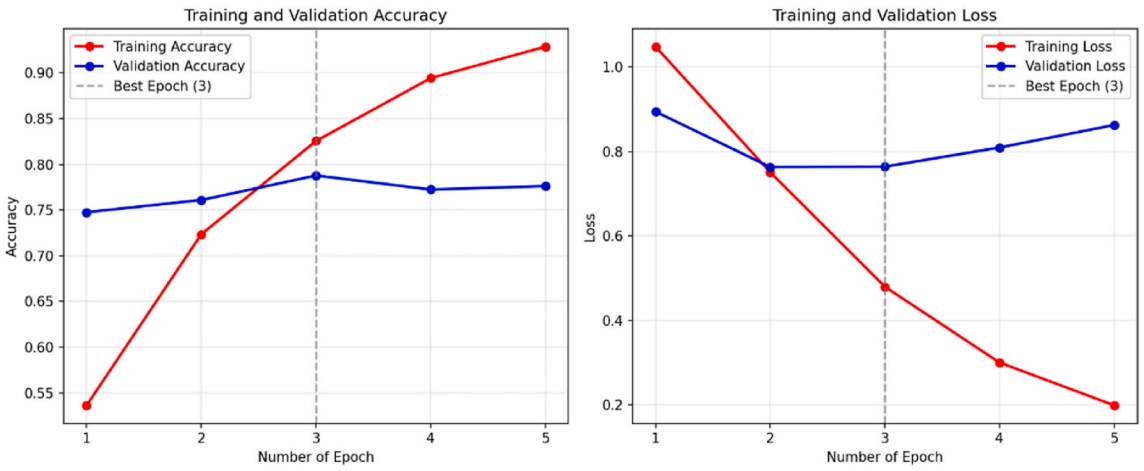


Fig. 2. Accuracy and loss curves by epoch.

Table 4
Classification report.

Class	Precision	Recall	F1-score	Support
Negative (−1)	0.88	0.85	0.87	359
Neutral (0)	0.65	0.69	0.67	111
Positive (+1)	0.64	0.69	0.66	54
Accuracy			0.80	524
Macro avg	0.72	0.74	0.73	524
Weighted avg	0.81	0.80	0.80	524

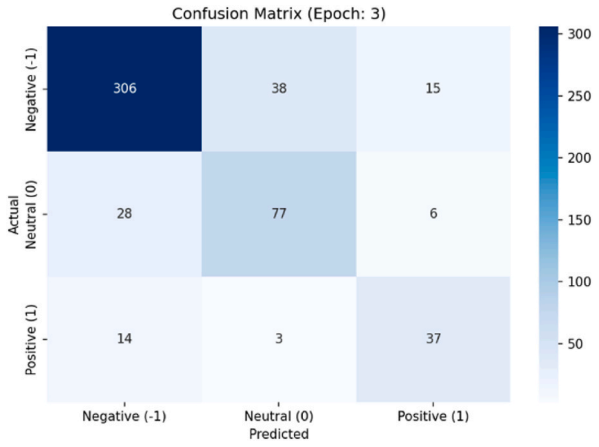


Fig. 3. Confusion matrix.

Table 5
Results of sentiment analysis.

Sentiment Classification	N	%
Negative (−1)	192,815	66.3
Neutral (0)	65,915	22.7
Positive (+1)	32,132	11.0
Total	290,862	100.0

Negative tweets remain dominant at 66.3%, while neutral (22.7%) and positive (11.0%) categories represent minorities. This consistency across manually annotated and predicted samples suggests that the model generalizes well to the broader corpus and that the gold-standard dataset represents the full forward-looking corpus well.

Following the sentiment analysis, Fig. 4 illustrates how the TWT index, constructed as described in Section 2.2.4, evolves over a selected period (June 2021–June 2024) alongside key macroeconomic events.

Note: Fig. 4 presents the 30-day moving average of the daily negative sentiment ratio alongside daily tweet volume (on a log scale) for the June 2021–June 2024 period. This sub-period was selected to ensure sufficient daily tweet volume for meaningful inference and to capture a concentrated cluster of major events that affected the Turkish economy. The figure marks seven key events: the policy rate cut (from 19% to 18%, September 2021), the introduction of the FX-protected deposit scheme (December 2021), the peak of CPI at 85.5% (October 2022), the general election (May 2023), the orthodox monetary policy turn (i.e., changes in economic management at the T.R. Ministry of Treasury and Finance and the Central Bank of the Republic of Türkiye, followed by the first interest rate hike in 27 months, June 2023), the policy rate reaching 40% (November 2023), and the local elections (March 2024).

The figure reveals several notable patterns. In the period surrounding the first policy rate cut in September 2021, negative sentiment remained persistently high. Following the introduction of the FX-protected deposit scheme in December 2021, negative sentiment began a slow and steady decline. This downward trend was briefly interrupted when CPI peaked at 85.5% in October 2022, after which it resumed its previous trend. Ahead of the May 2023 general election, negative sentiment rose again, then eased slightly in the immediate pre-election period, remaining relatively subdued during the election. Following the orthodox monetary policy turn in June 2023, a more pronounced decline in negative sentiment is observed, accompanied by a series of consecutive rate hikes that brought the policy rate to 40% by November 2023. Although rate increases continued thereafter, negative sentiment began rising again ahead of the March 2024 local elections. After the elections, sentiment resumed the downward trajectory established during the orthodox policy turn, correcting to even lower levels.

By obtaining this predicted tweet dataset, we can create the TWT described above and perform regression analysis.

3.2. *Regression analysis*

Preliminary information on the results is presented in this section through descriptive analysis in Table 6.

Table 6 presents the descriptive statistics for all variables over the sample period 2014M01–2024M06. Compared to the other variables, the IPI stands out for its high variability, suggesting that it fluctuates significantly over time. TWT's mean is approximately 0.61, indicating that negative sentiment is more dominant throughout the sample. This is consistent with the sentiment-prediction results, which show the negative class is dominant.

Before running our Phillips curve regression, we conduct unit root tests to assess the variables' stationarity. Stationarity is a crucial

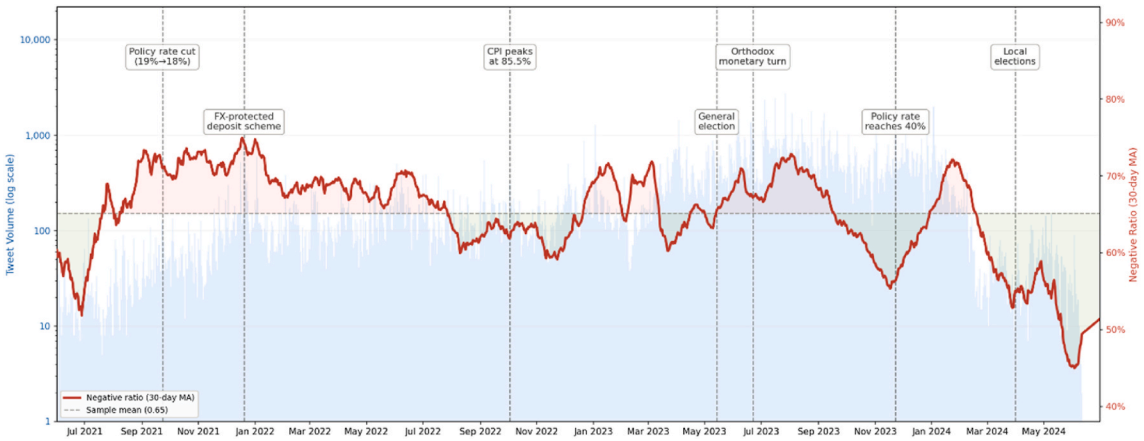


Fig. 4. Twitter inflation sentiment and key events in selected period.

Table 6
Descriptive statistics.

Variable	Obs	Mean	Std	Min	Max
CPI (π_t)	126	0.0187	0.0219	−0.0153	0.1330
IPI (y_t)	126	0.0167	1.1421	−9.0096	1.7196
Spread	126	0.4532	0.1202	0.1775	0.7274
TWT (π_{t+1})	126	0.6077	0.1097	0.1818	0.7692

condition for time series analysis, as non-stationary data can lead to spurious results in regression models. To determine whether the variables are stationary, we apply both the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips-Perron (PP) test (Phillips and Perron, 1988), which are widely used in econometrics. These tests examine whether a variable has a unit root; rejecting the null hypothesis in either test indicates that the series is stationary.

Table 7 shows the results from the unit root tests. According to these results, all variables are stationary at their levels, though at different significance levels. CPI, TWT, and IPI are strongly stationary at the 1% significance level under both the ADF and PP tests, meaning that the null hypothesis of a unit root is decisively rejected. The interest rate spread is stationary at the 5% level under both tests, indicating that the null hypothesis of a unit root is rejected at this level, though not as strongly as the other variables. Considering that TWT is stationary, it makes sense that negative tweets are proportionate to total tweets and that the value is bounded between 0 and 1. We conclude that there are no unit roots, and the data are suitable for a GMM model. Given that the series are integrated of order zero, I(0), estimating our HNKPC regressions using level data is appropriate, ensuring reliable econometric results.

Table 7
Unit root test statistics.

Variables	ADF Test	Phillips-Perron
CPI (π_t)	−4.995047***	−4.872840***
	{0.0675}	{0.0675}
TWT(π_{t+1})	−3.912287***	−5.877538***
	{0.0810}	{0.0729}
IPI (y_t)	−5.477898***	−5.426617***
	{0.0717}	{0.0717}
Spread$_t$	−3.293263**	−3.096987**
	{0.0410}	{0.0413}

Note: The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests report the test statistics for testing the null hypothesis of a unit root, where rejection of the null implies stationarity. Both tests use an intercept and linear time trend in their specifications, with the ADF test automatically selecting the lag length based on the SIC criterion, while the Phillips-Perron test implements a Bartlett kernel with Newey-West bandwidth. '***', '**', '*' indicate significance levels of 1%, 5%, and 10%, respectively. Standard Errors are in curly brackets.

After concluding the unit root tests to ensure that GMM can be applied for estimation, we turned our focus to the regression analysis. GMM estimation is widely used in the NKPC literature to address potential endogeneity (Abbas et al., 2016).

To account for endogeneity, instrumental variables should be used. Common practice is to add right-hand-side variables as instruments (Mihailov et al., 2011). Specifically, lagged values of inflation, the output gap, the labor income share, wage inflation, and commodity price inflation have been widely used in the literature. Moreover, the interest rate serves as a valid instrument as it is central to monetary policy and connected to expected inflation via the Fisher Effect (Fisher, 1930), which asserts that the real interest rate equals the nominal interest rate minus the expected inflation rate (Abbas and Sgro, 2011). Mavroeidis et al. (2014) and Koc et al. (2021) acknowledge that treating endogenous survey expectations as instrumental variables is appropriate; we therefore also use lagged values of Twitter-based inflation expectations as instruments, assuming that they are endogenous. Thus, in the final form, given their use in the literature, we set inflation, the output gap, Twitter-based inflation expectations, and the interest rate spread as instrumental variables and tested them in the model across different combinations.

The first model, M1, includes one lag of inflation, Twitter-based inflation expectations, the industrial production index gap, and the interest rate spread as instruments. The second model, M2, consists of two lags of inflation, one lag of Twitter-based inflation expectations, and the industrial production index gap as instruments. The third model, M3, incorporates two lags of the industrial production index gap, one lag of inflation, and Twitter-based inflation expectations as instruments. Lastly, the fourth model, M4, comprises two lags of the interest rate spread, one lag of inflation, Twitter-based inflation expectations, and the industrial production index gap, as instruments. By using these different instrument sets, we aim to ensure that our estimates are robust while satisfying the orthogonality conditions necessary for valid inference. Table 8 demonstrates the results of our HNKPC model.

The estimation results suggest that both backward-looking and forward-looking components contribute to shaping inflation expectations. This indicates that both past inflation and future expectations influence actual inflation. However, across all four models, the backward-looking component consistently exerts a stronger influence than the forward-looking one, highlighting inflation inertia in the Turkish economy. The results show that TWT is statistically significant across all models, though its influence is weaker than the backward-looking component. This suggests that TWT does play a role in expectation formation, but past inflation remains the dominant driver. Even though the periods differ, this result partly aligns with Agénor and Bayraktar (2010) and Eruygur (2011), indicating inflation persistence in Türkiye. The hypothesis that the two components are equal ($\gamma_b = \gamma_f$) is

Table 8
Closed-economy HNKPC model.

	M1	M2	M3	M4
γ_f	0.047311*** {0.017249}	0.044896*** {0.016546}	0.047995*** {0.017672}	0.045811*** {0.016489}
γ_b	0.599240*** {0.043646}	0.584798*** {0.051657}	0.590329*** {0.053234}	0.604597*** {0.041754}
λ	0.002409 {0.002182}	0.001637 {0.001438}	0.002712 {0.001982}	0.002304 {0.001960}
c	−0.021113** {0.009154}	−0.019854** {0.008976}	−0.021449** {0.009459}	−0.020204** {0.008692}
Hansen test J-stat:	0.160573 (0.688630)	0.219250 (0.639612)	0.153012 (0.695674)	0.277038 (0.870647)
Wald test Chi-square:				
$\gamma_f = \gamma_b$	94.77299***	70.09116***	68.40287***	105.7246***
$\gamma_f + \gamma_b = 1$	104.9148***	79.46224***	65.65516***	113.4571***
Instrumental Variables	One lag of inflation, Twitter-based expected inflation, industrial production index gap and interest rate spread	Two lags of inflation, one lag of Twitter-based expected inflation and industrial production index gap	Two lags of industrial production index gap, one lag of inflation and Twitter-based expected inflation	Two lags of interest rate spread, one lag of inflation, Twitter-based expected inflation and industrial production index gap

Note: Estimated model is $\pi_t = \gamma_f E_t[\pi_{t+1}] + \gamma_b \pi_{t-1} + \lambda y_t$. The estimation period is 2014:M1 - 2024:M6. The equation (including a constant) is estimated by the Bartlett kernel, Newey–West fixed, HAC-robust SE GMM. Lag length selection is determined by using the AIC criterion. Standard errors are in curly brackets. Probability values are indicated by asterisks ('***', '**', '*' indicate significance levels of 1%, 5%, and 10%, respectively). The p-values for Hansen's J-statistic are reported in the table (in parentheses), where a p-value of less than 0.10 is taken as evidence of invalid instruments. Two constraints were applied for forward-looking and backward-looking parameters in the Wald Test: $\gamma_b + \gamma_f = 1$ and $\gamma_b = \gamma_f$. Instrumental variables are at the bottom of the table.

tested using the Wald test. In all models, the results strongly reject this hypothesis (p-values = 0.0000), confirming that backward-looking behavior dominates inflation expectations. Similarly, when testing whether the sum of these components equals one ($\gamma_b + \gamma_f = 1$), the rejection is robust across all models, indicating that inflation expectations may not be perfectly formed, and the Phillips Curve may not be vertical in the long run (Wardhono et al., 2021), though this result should be interpreted within the context of a closed-economy framework.

Considering Türkiye's inflation history, it is understandable that the constraint $\gamma_b + \gamma_f = 1$ does not hold. Especially in emerging economies, researchers focus more on factors such as exchange rate, oil shocks, and money supply. This may be because inflation rates are more volatile and more sensitive to internal and external shocks in these countries compared to developed countries. For instance, in addition to inflation expectations, Koc et al. (2021) emphasized the importance of economic activity (changes in demand), exchange rate pass-through, and import price pass-through in Türkiye and showed their effects on inflation formation.

On the other hand, the output gap is positive across all models but is statistically insignificant in all four. So, although the effect is positive, it is not strong. This result is consistent with the findings of Agénor and Bayraktar (2010), who also report an insignificant output gap coefficient in Türkiye estimated from 1981 to 2006, albeit with a negative sign. Nevertheless, this finding should be interpreted cautiously, since the closed-economy framework and the specific time period covered may not fully capture demand-side dynamics, and alternative specifications may yield different results.

To assess the validity of the instrumental variables used in estimating the closed-economy NKPC, we conduct Hansen's J-test for overidentifying restrictions (Hansen, 1982). The p-values for Hansen's J-statistic are reported in Table 8, where a p-value of less than 0.10 is taken as evidence of invalid instruments (Mazumder, 2014). The null hypothesis of this test states that the instruments are valid, meaning they are uncorrelated with the error term and correctly excluded from the estimated equation. Since all p-values exceed the conventional 0.10 threshold, we fail to reject the null hypothesis, indicating no statistical evidence against the validity of the instruments. These results suggest that the selected instruments are appropriate and satisfy the necessary orthogonality conditions, ensuring the reliability of the GMM estimation.

The 'price' of curbing inflation is contingent on the comparative magnitude of the coefficients on past and future inflation, γ_b and γ_f. If the coefficient on lagged inflation is relatively high, inflation tends to be primarily influenced by its previous values, meaning that policy interventions may take longer to significantly impact inflation dynamics (Hornstein, 2008). Considering this, the results imply that reducing inflation in Türkiye may be more challenging because past inflation plays a dominant role in expectation formation. It is to be noted that the influence of monetary policy actions on inflation outcomes may be more protracted, and the credibility of inflation-targeting frameworks is crucial for anchoring expectations (Baskaya et al., 2012). The findings also suggest that policymakers should monitor Twitter sentiment as an additional tool for assessing inflation expectations, as it provides timely insights into public perceptions. By better understanding and responding to inflation expectations through both traditional and social media channels, authorities are likely to enhance the credibility of inflation-targeting frameworks and reduce inflation more efficiently.

Finally, our results suggest that money neutrality may not fully hold in Türkiye within the closed-economy framework employed in this study. While omitted factors, such as exchange rate dynamics and external shocks, may influence these findings, the evidence nonetheless indicates that inflation expectations are not perfectly rational, and the Phillips curve is not vertical in the long run. This is consistent with the broader literature on emerging economies, where deviations from rational expectations are observed (Agénor and Bayraktar, 2010; De Brito et al., 2019; Egan and Leddin, 2017). While Sargent and Wallace (1975) argue that perfectly rational expectations would render monetary policy ineffective, the findings suggest that there remains room for active monetary policy in Türkiye, particularly through efforts to anchor inflation expectations and enhance the credibility of monetary institutions.

4. Conclusion

In this study, we examined inflation dynamics in Türkiye, focusing particularly on inflation expectations. Since we focused on expectations, we based our analysis on the closed economy reduced-form HNKPC model. In this model, the determinants of inflation are analyzed through three main variables: the output gap and backward- and forward-looking expectations. Unlike traditional studies that primarily rely on backward-looking inflation expectations or rational expectations, this research comes up with a new approach by incorporating social media sentiment extracted from Twitter. The main finding of this study is that while backward-looking inflation remains the dominant driver of inflation expectations in Türkiye, Twitter-based sentiment still plays a significant, though relatively weaker, role in shaping actual inflation. This distinction from current literature represents an important step forward in understanding how instant public sentiment can influence economic behavior.

The results of our study demonstrated that both backward-looking and forward-looking inflation expectations play a significant role in shaping Türkiye's overall inflation dynamics. Crucially, our findings highlight a notable distinction: backward-looking expectations exert a more dominant influence compared to their forward-looking counterparts. This pronounced prevalence of past inflation trends in expectation

formation is a clear indicator of persistent inflation inertia within the Turkish economy, suggesting that past price movements heavily anchor current and future inflationary pressures.

While one might intuitively expect changes in demand, as represented by the output gap, to be a significant driver of inflation, our study in Türkiye reveals a more nuanced picture. The output gap, defined as the difference between actual and potential economic output, consistently shows a positive but statistically insignificant contribution to inflation across all the models we employed. This suggests that, unlike the prominent role of inflation expectations, especially backward-looking ones, demand-side pressures, as captured by the output gap, are not a primary determinant of inflationary trends in the Turkish economy within our closed economy modeling framework. This finding might reflect the prevalence of other open-economy factors and supply-side shocks that dominate inflation dynamics, or this finding might also reflect temporal differences.

The inflation inertia identified in our study is perhaps best understood and contextualized within the broader history of Türkiye's persistent and long-standing inflation problem. In such an economic environment, where past price movements heavily influence current and future expectations, the role of the CBRT becomes even more critical. To effectively address this long-established inflation, the CBRT must patiently maintain and execute its expectation management and targeting policy.

According to the 'Monetary Policy for 2025' report of the CBRT, the central bank currently pursues a comprehensive communication strategy aimed at enhancing transparency, predictability, and credibility in monetary policy. Under its inflation targeting regime with a medium-term target of 5% and a ± 2 percentage point uncertainty band, the CBRT employs multiple communication channels, including Monetary Policy Committee (MPC) announcements, Inflation Reports published four times a year, Financial Stability Reports released twice a year, Monthly Price Developments reports, speeches by the Governor and Deputy Governors, presentations to the Parliament, technical meetings with investors, and research publications. The bank maintains technical meetings with investors and economists. Additionally, the CBRT utilizes macroprudential measures alongside its policy rate adjustments to support monetary transmission, implements silent periods before MPC decisions to ensure operational integrity, and conducts its communication activities within the broader framework of accountability, including the submission of an 'Open Letter' to the Government if inflation outcomes deviate from the target band. While its social media engagement primarily focuses on policy announcements and educational dissemination (Economics for Everyone), the CBRT has not yet institutionalized a dedicated framework for systematic expectation monitoring through social media analytics, despite its emphasis on managing expectations to support price stability.

The CBRT recently launched the Household Expectations Survey (HES) in January 2026, representing a significant methodological advancement over the existing Consumer Tendency Survey (CTS) conducted by TURKSTAT. Unlike the CTS, which follows a standardized European Commission framework with limited flexibility for country-specific questions, the HES adopts an inflation-focused approach. So, the question wording directly refers to the "inflation rate," and participants are first provided with the previous month's actual inflation figure before being asked to form their expectations (information treatment). Additionally, the HES incorporates a three-month rotating panel structure, in which one-third of participants are replaced each month with new respondents, enabling both the capture of fresh perspectives and the tracking of changes in expectations over time. As of January 2026, the HES has replaced the CTS in the CBRT's Sectoral Inflation Expectations bulletin (Bölükbaş et al., 2026). Future research may explore comparisons between HES and TWT-like approaches to measuring household inflation expectations, as longer data series become available. Thus, more robust and integrated approaches can be leveraged.

Our study highlights that Twitter content, which forms a core element of our investigation, exhibits a significant impact on inflation in Türkiye. This finding suggests that this platform acts as a crucial channel for spreading information and shaping expectations. Therefore, we recommend that policymakers, particularly the CBRT, actively integrate Twitter into their expectation management process. Leveraging Twitter-like platforms could facilitate the development of a more dynamic, real-time, and targeted expectation management strategy and, consequently, more effective economic policies.

An innovative policy measure that could be considered involves the establishment of a kind of 'Social Media and Expectation Monitoring Unit' within the central bank's institutional structure. Such a unit might systematically conduct daily sentiment analyses and topic modeling of social media platforms, with a particular emphasis on Twitter, to identify emerging shifts in public inflation expectations and prevalent narrative dynamics. The preparation of weekly expectation monitoring reports summarizing these analyses could provide the Monetary Policy Committee with timely insights regarding public narratives and possible misinformation trends that may influence inflationary psychology. Moreover, this unit could be tasked with designing and implementing targeted communication interventions when needed, which may include the dissemination of rapid myth-busting posts or infographics to correct misinformation, the organization of interactive question-and-answer sessions or Twitter Spaces featuring central bank economists to enhance public understanding, and the creation of tailored content that addresses the specific inflation-related concerns of firms and households. Although the exact design and effectiveness of such a unit would depend on institutional capacity and broader communication strategies, it could potentially strengthen the central bank's expectation management framework by enabling more dynamic, real-time, and targeted policy communication in the Turkish context.

Our findings suggest that the HNKPC in Türkiye may not be vertical in the long term within the closed-economy framework of this study, which implies that monetary neutrality may not fully hold. While omitted factors such as exchange rate dynamics and external shocks should be acknowledged as potential influences on this result, the evidence nonetheless indicates that expectation formations do not appear to be entirely complete in Türkiye over the long term. These findings suggest that there may be room for proactive monetary policy to be effective, particularly through efforts to anchor expectations and strengthen the credibility of monetary institutions.

Despite the methodological contributions of this study, several limitations remain. The analysis is restricted to the period from 2014 onwards due to the limited availability of inflation-related Twitter data for Türkiye prior to this date, largely attributable to the smaller number of Twitter users in earlier periods. As Twitter usage continues to grow, future studies may be able to extend the analysis for a more comprehensive assessment. Furthermore, while a comprehensive forward-looking filter based on future tense suffixes, expectation terms, and temporal expressions was applied to isolate forward-looking content in our study, it is possible that some tweets lack an explicit forward-looking tone. This reflects the inherent complexity of tweets and the natural language (it is open to sarcasm, irony, etc.) rather than a limitation of the filtering approach itself. Additionally, despite extensive preprocessing and filtering steps, a small amount of noise or irrelevant content may remain in the dataset, as this is an inherent characteristic of social media data. Last but not least, future research could extend this framework in several directions. Incorporating an open-economy model to account for exchange rate dynamics and external shocks, along with Twitter-based expectations, would enrich the analysis. Additionally, a time-varying parameter framework could be employed to examine how the forward- and backward-looking coefficients evolve over time in response to major economic events, though these represent distinct research questions beyond the primary focus of this study, namely whether Twitter-based sentiment has a significant effect on realized inflation in Türkiye.

Finally, this study has clearly demonstrated Twitter's effectiveness in

influencing economic decision-making in Türkiye, underscoring its role as a crucial channel for spreading information and shaping expectations, particularly regarding inflation. Given these findings, it is now vital for policymakers, investors, and economic agents more broadly to integrate Twitter-based inflation expectations into their decision-making and strategize accordingly. This means moving beyond solely traditional indicators to account for the real-time dynamics and sentiments reflected on platforms like Twitter. The insights gleaned from this research not only validate the potential of novel data sources in economic analysis but also highlight a fertile ground for future exploration. Future studies may use additional social media channels, such as Facebook and Reddit, in addition to Twitter, work with longer time periods, and develop comprehensive methods to forecast inflation expectations and other macroeconomic indicators.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Claude Sonnet 4.6 and Grammarly to assist with grammar and language editing, and Python code development. All research design, data collection, empirical analysis, interpretation of results, and intellectual contributions are entirely the authors' own. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

The authors declare there is no conflict of interest.

Acknowledgments

I would like to thank my valuable advisor, Assist. Prof. Asad Ul Islam Khan, who guided me in this research and helped me overcome difficulties with his knowledge and experience. I would also like to thank Prof. Muhittin Kaplan, Prof. Hasan Vergil, and Assist. Prof. Mahat Maalim İbrahim for their support with the literature and methodological aspects of this research, and Research Assistant Abdülkadir Kömü for his contribution to the annotation part of the study. Finally, I would like to express my gratitude to Prof. Dr. Erdem Yörük and his team for making the Politus database available, which served as the primary Twitter data source for this study.

APPENDICES.

Appendix A: Annotation Guidelines

Class	Label	Definition	Turkish	English
Positive	+1	Tweets implying falling prices, expressing optimistic expectations about inflation, or indicating improving purchasing power. Tweets emphasizing disinflation policies, interest rate hikes aimed at reducing inflation, or deflation are also classified as positive even if the sentence itself does not carry an explicitly positive tone. Additionally, policy measures announced by politicians and bureaucrats that aim to reduce inflation or improve purchasing power are classified as positive (policies aimed at fighting inflation in general).	Enflasyonun önümüzdeki dönemde düşmeye devam etmesi bekleniyor Bu senaryo için dünya çapında enflasyonun durması sakinleşmesi gerekir Berat Albayrak enflasyonla güçlü mücadele programı açıklayacağız	Inflation is expected to continue falling in the coming period For this scenario, inflation needs to stop and calm down worldwide Berat Albayrak: We will announce a strong program to fight inflation
Neutral	0	Tweets that do not signal a directional change in inflation, convey informational or non-manipulative news language, contain official announcements without a directional indication, reference other countries' inflation data (excluding global spillover commentary), or include stock market commentary without a clear inflation signal are classified as neutral.	Kasım ayı enflasyonu memur ve emekli maaşlarında ne değişecek ABDde enflasyon beklentileri aştı Önümüzde iki enflasyon verisi var şu an için kısa vadede bullish bir bitcoin izleyeceğiz gibi duruyor fakat uzun vadede belirsizlik devam ediyor	What will change in November inflation, civil servant, and retiree salaries? Inflation in the US exceeded expectations We have two inflation data releases ahead; for now, it looks like we will see a bullish bitcoin in the short term, but uncertainty continues in the long run
Negative	−1	Tweets expressing negative expectations about inflation, anticipating price increases, conveying pessimism about purchasing power or cost of living, or making ironic and sarcastic remarks about inflation are classified as negative.	Önümüzdeki iki yıl çok yüksek enflasyon gözüküyor Türkiyede Marketteki fiyatlara dur diyecek kimse yok mu imdat artık Enflasyonist beklentiler yükselirken para politikasında hiçbir şey değişmemesi mevduat sahibini kur korumalı mevduata gayrimenkule otomobile yönlendirmeye devam anlamını taşır bu da enflasyonu daha da kalıcı hale getirir	Very high inflation looks likely in Türkiye over the next two years. Is there no one to put a stop to market prices? Help, enough already While inflationary expectations are rising, no change in monetary policy means deposit holders will continue to be directed toward exchange rate-protected deposits, real estate, and automobiles, thereby making inflation even more persistent.

The examples in Turkish are drawn directly from the cleaned dataset and presented as is, with only capitalization applied. English versions were arranged for clarity.

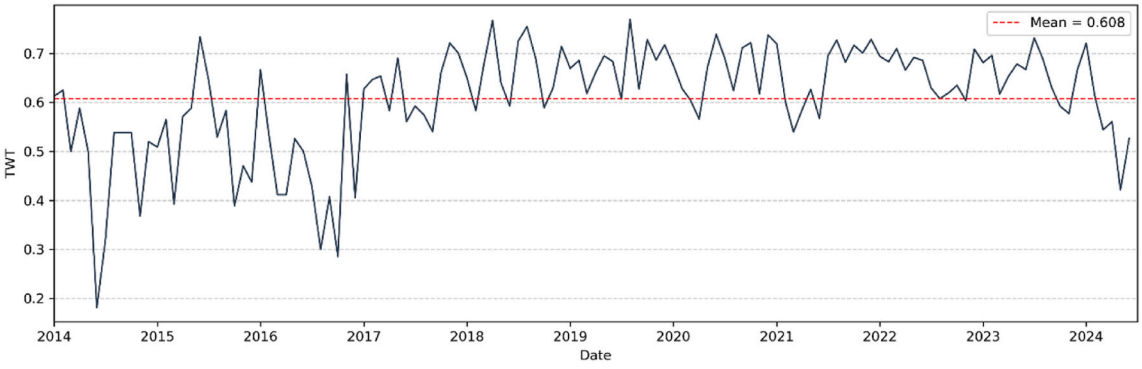
Appendix B: Additional Descriptive Statistics

B1: Unique User Statistics

	Value
Total tweets (inference dataset)	290,862
Unique users	84,588
Average tweets per user	3.44
Maximum tweets by a single user	688
Users tweeting only once	51,081 (60.4%)

Table B1 presents the user-level statistics of the inference dataset. Unique users are identified based on Twitter account usernames. With 60.4% of users contributing only a single tweet, the dataset is not dominated by a small group of highly active accounts, suggesting that the TWT index reflects a broad distribution of public sentiment.

B2: TWT Time Series



Note: Figure B2 displays the monthly TWT over the estimation period from January 2014 to June 2024. The index, defined as the ratio of negative tweets to total tweets, fluctuates around a sample mean of 0.608, reflecting a persistently negative public sentiment toward inflation throughout the period.

B3: Correlation Analysis between TWT and CBRT Survey-Based Inflation Expectations

B3.1: Contemporaneous Correlation (Lag = 0)

Survey Measure	Correlation (r)
Market Participants	0.1896**
Real Sector	0.1783*
Households	0.2941***

Note: Table B3.1 presents the contemporaneous correlations between the TWT index and three survey-based inflation expectation measures published by the CBRT: 12-month ahead annual inflation expectations of market participants, real sector, and households. *p < 0.10 **p < 0.05 ***p < 0.01. Sample period: 2015M01–2024M06.

B3.2: Cross-Correlation Analysis

Lag	Market r	Real Sector r	Households r
−6	**0.3500*** **	**0.3429*** **	**0.4495*** **
−5	**0.3489*** **	**0.3369*** **	**0.4367*** **
−4	**0.3351*** **	**0.3199*** **	**0.4167*** **
−3	**0.3117*** **	**0.2913*** **	**0.4074*** **
−2	**0.2855*** **	**0.2626*** **	**0.3797*** **
−1	**0.2302** **	**0.2100** **	**0.3408*** **
0	**0.1896** **	**0.1783***	**0.2941*** **
+1	**0.1625***	**0.1651***	**0.2650*** **
+2	**0.1499**	**0.1566***	**0.2455*** **
+3	**0.1278**	**0.1393**	**0.2266** **
+4	**0.1179**	**0.1303**	**0.2169** **
+5	**0.1004**	**0.1185**	**0.1972** **
+6	**0.0932**	**0.1200**	**0.1987** **

Note: Negative lags indicate that survey expectations lead TWT. Positive lags indicate that TWT leads survey expectations. Lag = 0 indicates contemporaneous correlation. *p < 0.10 **p < 0.05 ***p < 0.01. Sample period: 2015M01–2024M06.

Table B3.1 presents the contemporaneous correlations between the TWT index and the three CBRT-published survey-based inflation-expectation measures. As expected, the correlation between TWT and household inflation expectations is the highest among the three measures (r = 0.29). This is consistent with the nature of the TWT index, which is constructed from the general public's Twitter discourse and therefore more closely aligned with household sentiment than with the assessments of professional agents such as market participants or real sector representatives. The comparatively lower correlations with the latter two groups are not surprising, given the fundamental differences in both the sample represented and the methodology employed.

The cross-correlation analysis in Table B3.2 provides further insight. For market participants and real sector expectations, statistically significant correlations are concentrated in the negative lag region, suggesting that these professional expectations tend to lead the TWT index. For household expectations, however, statistically significant correlations are observed at both negative and positive lags, though the negative side is more pronounced. This bidirectional pattern indicates that they tend to move together over time, with household survey expectations sometimes leading TWT and TWT sometimes leading household expectations. This finding is consistent with the interpretation that TWT captures a dimension of public inflation sentiment that meaningfully overlaps with household expectations while also carrying independent informational content.

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