IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

MASTER'S THESIS

TWITTER (X) AND INFLATION DYNAMICS: INVESTIGATING THE ROLE OF TWITTER SENTIMENT IN TÜRKİYE'S HYBRID NEW KEYNESIAN PHILLIPS CURVE

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ISTANBUL, 2025

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A thesis submitted to the School of graduate studies in partial fulfillment of the requirements for the degree of master's of Economics

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ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

TWITTER VE ENFLASYON DİNAMİKLERİ: TÜRKİYE'NİN HİBRİT YENİ KEYNESYEN PHILLIPS EĞRİSİNDE TWITTER DUYARLILIĞININ ROLÜNÜN ARAŞTIRILMASI

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Bu araştırma, kapalı ekonomi Türkiye Hibrit Yeni Keynesyen Phillips Eğrisi (NKPC) modelinde enflasyon beklentilerinin şekillenmesinde Twitter'daki duyarlılığın rolünü incelemektedir. Bu araştırma, Doğal Dil İşleme ile BERT modeli uygulayarak yeni bir Twitter tabanlı enflasyon beklentileri değişkenini (TWT) ileriye dönük bir bileşen olarak modele dahil etmekte, rasyonel beklentiler ve anket verileri gibi geleneksel yöntemlere alternatif sunmaktadır. Bulgular, geriye dönük enflasyonun beklentilerde ana itici güç olduğunu gösterirken, Twitter duyarlılığının beklentileri önemli ölçüde etkilediğini, ancak etkisinin nispeten daha zayıf olduğunu ortaya koymaktadır. Çalışma ayrıca, kapalı ekonomi modelinde çıktı açığının öneminin çok az olduğunu ortaya koyarak, enflasyon ataletinin Türkiye'nin enflasyon dinamiklerinin merkezinde yer almaya devam ettiği görüşünü güçlendirmektedir. Sonuçlar, politika yapıcıların Twitter'daki duyarlılığı stratejilerine dahil etmeyi düşünmeleri gerektiğini ve böylece halkla daha etkili ve dinamik bir iletişim kurulabileceğini göstermektedir. Politika yapıcılar, geleneksel ve sosyal medya kanalları, özellikle Twitter aracılığıyla enflasyon beklentilerini daha iyi anlayarak ve bunlara daha iyi yanıt vererek, enflasyon hedefleme ve beklenti yönetimi süreçlerine olan güvenilirliği artırabilir ve enflasyonu daha verimli bir şekilde azaltabilir.

Keywords: Phillips Curve, Sentiment Analysis, Natural Language Processing, BERT

ABSTRACT

TWITTER AND INFLATION DYNAMICS: INVESTIGATING THE ROLE OF TWITTER SENTIMENT IN TÜRKİYE'S HYBRID NEW KEYNESIAN PHILLIPS CURVE

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This inquiry explores the role of Twitter-based sentiment in shaping inflation expectations within Türkiye's Hybrid New Keynesian Phillips Curve (NKPC) in a closed economy framework. By incorporating a novel Twitter-based inflation expectations variable (TWT), derived using Natural Language Processing (NLP) with the 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 significantly influences forward-looking expectations, 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 has minimal significance, 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, enabling more effective and dynamic communication with the public. By better understanding and responding to inflation expectations through both traditional and social media channels, especially Twitter, authorities can enhance the credibility of inflation-targeting frameworks and potentially reduce inflation more efficiently.

Keywords: Inflation, Phillips Curve, Sentiment, Natural Language Processing, BERT

DEDICATION

It is dedicated to my wife…

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Enes CEBE

İSTANBUL, 2025

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LIST OF SYMBOLS AND ABBREVIATIONS

γ_b	The Coefficient of Backward Looking Inflation Expectation
γ_f	The Coefficient of Forward Looking Inflation Expectation
λ	The Coefficient of Output Gap
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
BERT	Bidirectional Encoder Representations from Transformers
CPI	Consumer Price Index
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
HNKPC	Hybrid New Keynesian Phillips Curve
IPI	Industrial Production Index
NKPC	New Keynesian Phillips Curve
OLS	Ordinary Least Squares
PP	Phillips-Perron
RBC	Real Business Cycle

CHAPTER I

INTRODUCTION

1.1. Background

Since its emergence in the late 1950s, the Phillips curve has been widely debated by different schools of economic theory, and its implications have sparked discussions across various areas of macroeconomics. The debate initially began after Phillips (1958) first demonstrated the negative correlation between wages and unemployment in the United Kingdom. Such a relationship was quite significant in terms of the effect of wages, a nominal variable, on unemployment, a real variable. This insight indicates a trade-off between inflation and unemployment, suggesting that policymakers could potentially lower unemployment at the expense of higher inflation, or reduce inflation by accepting higher levels of unemployment. Such policies were applied by Keynesian politicians until the early 1970s.

Until the 1970s, inflation studies, especially those based on the inflation-unemployment trade-off, provided a great space for Keynesian fiscal policies. But after the 1970s, when the phenomenon of stagflation (the coexistence of high inflation and unemployment) was observed, the concept of expectations came into play, and neoclassical economics started to rise again after a short break. What the classical economists say is that prices return to equilibrium according to supply and demand, and that the market clears itself. Within such a market environment, the real output of the economy is determined exclusively by the supply side thereof. Any shift on the demand side will cause a change in price, so it is not possible for a nominal factor to affect a real variable. In the 1970s, price flexibility was explained by the concept of expectations. When expectations were in play, wages moved flexibly, rendering the so-called trade-offs invalid. First with adaptive expectations (Phelps 1967; Friedman 1968) and then with rational expectations (Muth 1961; Sargent and Wallace 1975), the Phillips curve was re-modelled.

The novelty brought by the New Keynesians here is that they put forward a Phillips curve model based on rational expectations again with sticky prices by explaining the situations where wages are rigid in the short term. The first form of the New Keynesian Phillips Curve included only the rational expectations assumption in the model. In this scenario, inflation depends on future inflation expectations and marginal costs, or the output gap. After Galí and Gertler(1999) introduced the hybrid form of the New Keynesian Phillips Curve, 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 New Keynesian Phillips Curve 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 an 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. In the literature, models are analyzing the effects of money aggregates, exchange rate pass-through, oil, etc., especially open economy NKPC.

1.2. Motivation

Understanding a country's inflation dynamics is particularly important when that country has a persistent inflation problem. Such an effort aims to better understand the country's inflation problem and propose specific solutions. In our study, we sought to examine Türkiye’s inflation dynamics from an innovative perspective that includes Twitter’s public opinion through inflationary expectations, motivated by this very goal. Considering Türkiye's long-standing inflation problem, we believe that more studies of this kind will contribute to policymakers.

1.3. Research Gaps

In our study, we would like to focus only on expectations, recognizing that there may be many dynamics affecting inflation. In order to make a comparative analysis of both forward-looking and backward-looking expectations, we have worked on a Hybrid New Keynesian Phillips Curve (HNKPC). Most of those working on the hybrid model treat future inflation expectations as an endogenous dynamic under the assumption of rational expectations while setting backward-looking inflation expectations based on the assumption of adaptive expectations. Rational expectations, in particular, are unobservable and often derived indirectly through model assumptions, creating a gap between theoretical constructs and real-world data. Survey-based studies, which is a relatively new method, find a place in the model both endogenously and exogenously. While the rational expectation assumption is unobservable, the survey approach is direct and observable. An observable variable has certain advantages over a variable obtained by an assumption. Zhang et al. (2009) argue that it provides a more realistic representation of economic agents and eliminates measurement errors. However in survey expectations, the views of professional participants are generally taken into account, so the wider community is overlooked. Although authors such as Roberts (1995) and Zhang et al. (2009) base some part of their models on the Michigan survey and include consumer expectations, the proportion represented by these studies is comparatively minor.

On the other hand, specifying forward-looking expectations as endogenous or exogenous changes the estimation method. In the case of endogeneity, the endogeneity problem, which is frequently discussed in the literature, comes into play, and instrumental variables should be used.

We propose a method that has not been used in the literature before to represent forward-looking expectations. We developed a variable that is based on inflation sentiment on the Twitter (X) platform. Today, as communication opportunities are rapidly increasing, the state of the economy, possible policy instruments and evaluations are frequently discussed on social media channels. Especially the high number of Twitter users in Türkiye may be a new and important channel for politicians in terms of taking the pulse of the public and moderating expectations. When we

consider the innovations brought by survey expectations, the fact that it is direct and observable attracted attention. It also plays an important role in the representation of economic agents. We assume that the Twitter (X)-based sentiment has a few more advantages besides these. As with survey expectations, the fact that it reflects reality and is observable with certain tools attracts attention at first glance, and it may also provide an opportunity for policymakers to manage inflation more dynamically. While the expectations formed on Twitter(X) can be controlled instantaneously, politicians may be able to use the tools at their disposal more effectively and communicate with users more interactively. Moreover, a Twitter (X)-based expectations may provide more inclusive results than professional surveys as it includes many segments of society. Unlike previous studies, we include TWT as an observable element in the model. This allows us to present inflation expectations as a more dynamic process, suggesting that policymakers need to be effective in rapidly evolving communication channels.

1.4. Research Questions

In this context, one of the questions we would like to ask is whether Twitter(X)- 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, one of the questions we want to answer in this study is whether inflation inertia is valid in Türkiye. We will examine this through the lagged inflation variable in the model. As Rudd and Whelan (2007) suggest, intrinsic inflation inertia is defined as the structural dependence of inflation on its lagged values. Thus, when the lagged inflation coefficient dominates the forward-looking inflation coefficient, we can talk about the existence of inertia.

The questions mentioned above, along with their justifications, are listed below:

i. Do Twitter(X)- based expectations contribute to the formation of inflation?
ii. Is inflation inertia valid in Türkiye?

1.5. Overall Objectives

Macroeconomic indicators such as inflation are crucial for understanding the economic situation of a country. Both policymakers, investors, and consumers monitor inflation and other indicators to develop specific decision-making behaviors. To ensure that these decisions are made in a more informed manner, improvements in these indicators are expected. One way to achieve this improvement is through a better understanding and management of the expectations of the agents within society. Our intention in presenting this study is to highlight the importance of expectation management, particularly in countries such as Türkiye that are struggling with inflation, and to ensure that social media applications such as Twitter (X) are effectively incorporated into the forward guidance process.

With this study, which aims to reveal the impact of Twitter on the economy, we also want to pave the way for a comprehensive examination of topics such as communication, media, expectations, uncertainty, and public sensitivity. In this age of diversified communication tools and rapid communication, we believe that it is important to evaluate public opinion and expectations from a broader perspective. In this sense, given the increasing importance of communication in economic policymaking, especially in the digital age, the integration of social media into inflation modeling can provide policymakers with enhanced tools for forward guidance.

1.6. Research Hypothesis

H1: Twitter (X)-based expectations contribute to the formation of inflation.

This hypothesis suggests that the sentiment and expectations expressed on Twitter (X) have the capacity to exert influence over the dynamics of inflation. Specifically, when negative tweets about inflation increase, the inflation rate also increases.

H2: Inflation inertia is valid in Türkiye.

This hypothesis posits that inflation in Türkiye exhibits a degree of persistence, meaning that past inflation levels significantly influence current inflation. It suggests that inflation inertia may be a crucial factor in explaining the longevity of inflation.

1.7. Justification and Significance

This research fills a gap in the existing literature by exploring how social media, specifically Twitter (X) sentiment, influences inflation expectations in Türkiye. While expectations obtained based on the rational expectations assumption cannot be observed, survey expectations are observable. However, in most studies, professional participants are included in the survey, whereas the Twitter sentiment variable we present is both observable and has the advantage of covering a broad segment of society. By introducing Twitter (X)-based expectations into the hybrid NKPC model, this study presents a more dynamic and inclusive approach to understanding inflation expectations. This approach is novel because it provides a real-time reflection of public opinion.

Furthermore, the research will assess the concept of inflation inertia in Türkiye, exploring whether backward inflation continues to affect current inflation rates. This is vital for policymakers, as understanding inflation inertia can guide the strategies used to control inflation. If inflation inertia is present, it would indicate that inflationary pressures persist over time, requiring more time to affect the inflation outcome (Baskaya et al., 2012).

The significance of this study goes beyond theoretical aspects of inflation and expectations. Platforms like Twitter (X) 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.

The study's exploration of inflation inertia is also important for creating effective economic strategies. If inflation inertia is found to be significant, policymakers may need to implement structural reforms or stronger measures to break the cycle of persistent inflation.

This research also offers broader contributions to macroeconomics. By including Twitter sentiment in inflation models, it opens up new areas for future research on how digital platforms influence economic behavior. The findings could serve as a model for other countries to incorporate public sentiment into their inflation expectations, leading to a deeper understanding of macroeconomic dynamics.

In conclusion, this study is highly relevant for both academics and policymakers, offering new methods and valuable insights into the factors driving inflation dynamics in Türkiye. By addressing these issues, it aims to help improve economic policy and inflation management strategies, which are crucial for the stability and growth of Türkiye's economy.

1.8. Layout of the Thesis

The structure of the thesis is comprised of five primary chapters. Chapter 1, the Introduction, provides the background, motivation, research gaps, research questions, and the overall objectives of the examination, setting the stage for the investigation into the HNKPC and inflation expectations. The chapter also outlines the research hypothesis, justification, and significance of the subject. Chapter 2, the Literature Review, begins with an evaluation of the theoretical framework surrounding the Phillips Curve, discussing its traditional form, the expectations-augmented version, rational expectations, and the NKPC, which introduces the concept of sticky prices. This chapter also delves into the empirical literature, focusing on the dynamics of forward- and backward-looking expectations in the NKPC, survey-based studies, and specific research in Türkiye. Chapter 3, Methodology, outlines the data used in the study, including the sentiment analysis approach with BERT, which is employed to acquire and preprocess Twitter data for constructing a Twitter-based inflation expectation variable. The chapter also covers the estimation method, specifically Generalized Method of Moments (GMM), and details the GMM estimation for NKPC.

Chapter 4 focuses on Topic Modelling, presenting the techniques used to analyze and interpret the themes emerging from the Twitter data. Finally, Chapter 5, Results and Discussion, presents the findings of the study, interpreting the results in the context of the hypotheses, and providing a discussion of the implications for inflation management and policy-making in Türkiye.

CHAPTER II

LITERATURE REVIEW

2.1. Theoretical Framework: Evaluation of Phillips Curve

2.1.1. Traditional Phillips Curve

Initially, the Phillips curve emerged as a statistical equation, rooted in annual data from the United Kingdom, covering the period 1861-1957. This foundational analysis, spanning from 1861 to 1957, charted the relationship between percentage changes in nominal wages and the unemployment rate. The outcome of this examination was a downward-sloping, convex curve, notable for its intersection with the horizontal axis at a specific unemployment rate (Phillips, 1958). The Phillips curve[1] is defined as follows:

$$\pi_t = \alpha + \beta u_t + e_t \quad \textbf{(2.1)}$$

The term "Phillips Curve" was introduced into macroeconomics in the article of Samuelson and Solow (1960). They demonstrated that the negative relationship between unemployment and inflation (in wages or prices) observed in the UK also applied to U.S. data. In their analysis, they examined the policy implications of this stable inverse correlation, suggesting that it represented a trade-off between unemployment and inflation. For example, policymakers could maintain low unemployment indefinitely, however, this would only be possible by accepting higher inflation (Eruygur, 2011).

[1] The original version of the Phillips curve, as presented by Phillips (1958), is expressed as follows: $y+a=bx^e$ or $\log(y+a)=\log b+c\log x$ where y represents the percentage change in wages, and x denotes the percentage change in unemployment.

In the 1970s, the original Phillips curve began to lose its explanatory power. It failed to account for the stagflation observed in developed economies, where rising unemployment and accelerating inflation occurred simultaneously. This prompted Friedman (1968), a leading figure of the monetarist school, and Phelps (1967) to highlight significant misspecifications in the original Phillips curve.

2.1.2. Expectations Augmented Phillips Curve

The idea that the labour market is in equilibrium depends on real, as opposed to nominal, wages, and that expectations play a crucial role was put forward by Friedman (1968) and Phelps (1967) . Since expected real wage changes equal nominal wage inflation minus expected price inflation, the original Phillips curve should include an inflation expectations term. Workers care about their real purchasing power and factor in expected inflation when negotiating wages. However, they cannot be misled indefinitely—once they accurately perceive inflation, the workforce is calling for increased nominal salaries, with real wages and the rate of unemployment being restored to their initial levels. Ultimately, when inflation expectations are fully realized, the trade-off between inflation and unemployment disappears. They claim that inflation expectations are fully formed when they are adapted through an error correction mechanism, where expectations adjust by a fraction of the previous forecast error (Motyovszki, 2013).

In this concept, expected inflation acts as a "geometrically declining weighted average of all past rates of inflation with the weights summing to one" (Humphrey, 1985). In fact, the concept expressed by Phelps and Friedman was also articulated by Muth (1961) as adaptive expectations or backward expectations (Muth, 1961).

$$\pi_t = \gamma \pi_t^e + \beta(u_t - u_n) + e_t \qquad \textbf{(2.2)}$$

In Equation (2), namely the expectations augmented Phillips curve, $\pi^e{}_t$ represents the expected inflation, which is calculated as a weighted average of past inflation rates. This method reflects how past inflation influences current expectations. Meanwhile, u_n refers to the natural unemployment rate, which is the level of unemployment that the economy tends to revert to in the long run, absent short-term fluctuations or

external shocks. Meaning deviations from the natural rate of unemployment can only occur when there is unexpected inflation, a surprise to which economic agents' expectations adjust gradually. This delay in adjustment allows the real wage to be temporarily affected (Mankiw, 1990).

The monetarist interpretation of the Phillips curve signals a return to neoclassical theories, fundamentally asserting that the classical dichotomy holds true in the long run. This perspective suggests that once inflation expectations fully adjust to policy changes, monetary policy becomes neutral, losing its ability to influence real economic variables. In the end, demand fluctuations will influence prices but have no effect on real output. Therefore, Friedman inferred that the effects on real output is only short-lived, while inflationary effects persist in the long term. Therefore, it is preferable to avoid exploiting this short-term trade-off and instead enable the economy to operate at its natural rate of unemployment. Since this rate can align with any level of inflation, the focus should be on maintaining stable, low inflation by keeping the money supply growth steady (Motyovszki, 2013).

2.1.3. Rational Expectations

The notion of rational expectations originates from Muth's (1961) paper. Although Muth introduced the concept, different people became familiar with it. As a criticism of adaptive expectations, Sargent (1971) and Lucas (1972) argued that if workers predict real wages solely based on past inflation rates, it could lead to systematic estimation errors.

One of the most debated uses of rational expectations was by Sargent and Wallace (1975). The argument was made that there is no effect on output and employment from systematic monetary policy. Their conclusion stemmed from applying rational expectations to the expectations-augmented Phillips curve by Friedman and Phelps. This curve indicates that while expected inflation has no effect on unemployment, unexpected inflation can temporarily reduce unemployment below its natural rate. However, rational expectations imply that people cannot be surprised by events or policies that are systematic and consistent. Sargent and Wallace reasoned that systematic monetary policy can only produce expected inflation, not unexpected

inflation, and thus cannot affect unemployment. If true, this would make policy rules like "Increase money supply during a recession" ineffective (Mankiw, 1990).

The assumption of rational expectations had an important consequence: the Lucas critique. Normally, policymakers assume that historical relationships between economic variables will continue to hold even after new policies are introduced. However, Lucas (1976) disagreed with this idea. He argued that new policies change economic behavior and expectations, which can alter the relationships between variables. The Lucas critique pointed out that traditional macroeconomic models failed because they didn't account for how policy changes could shift expectations and economic behavior. Lucas suggested that policy analysis should be based on intertemporal general equilibrium models, which are grounded in microeconomic foundations. This means that instead of relying on simplified or ad hoc models, economic policy should be based on how households and firms actually make decisions. By using models based on real decision-making, Lucas believed that policy conclusions would be more reliable. While the Lucas critique applies to all macroeconometric models from the 1970s, it is often associated with the Phillips curve. During the 1960s, a discernible inverse correlation was evident between inflation and unemployment, but by the 1970s, this relationship disappeared as policymakers tried to exploit the tradeoff using new policies (Eruygur, 2011).

A notable difference from monetarism lies in the real cost of disinflation. With rational expectations being forward-looking, the monetary authority can directly influence these expectations by, for instance, implementing a zero-inflation policy. By adjusting their expectations, economic agents allow the economy to stay on the vertical long-run Phillips curve, avoiding deviations from the natural unemployment rate and preventing major losses in real output. If the policy effectively shapes expectations, the sacrifice ratio becomes effectively zero, indicating that disinflation can be achieved without significant economic trade-offs. Kydland and Prescott (1977) and Barro and Gordon (1983) demonstrated that only rule-based policies, rather than discretionary ones, can achieve this. With the rational expectations studies, the new classical school almost returned to the discourses of the original classical school. Leaving aside short-term random and unpredictable shocks under the unsystematic monetary policy, the classical dichotomy cannot be violated (Motyovszki 2013).

The movement of the new classicals back to the original classical understanding brought about the real business cycle theory. Real business cycle (RBC) theory represents the classical perspective on economic fluctuations. It is based on the idea that large random variations occur in the pace of technological progress. In reaction to these changes, individuals adjust their labor supply and consumption decisions in a rational manner. According to this theory, the business cycle emerges as a natural and efficient adjustment of the economy to shifts in production technology Mankiw (1989).

The New Classical theory fundamentally altered macroeconomic thought by integrating rational expectations, proposing that economic agents optimally utilize all available information to forecast future outcomes. Consequently, this theoretical framework posited nominal rigidities became the sole remaining mechanism through which unexpected economic shocks could cause temporary deviations of the real economy from its natural, long-run equilibrium. However, the RBC theory proposed a fundamentally different explanation because the resulting random fluctuations failed to align with observed business cycles (King et al., 1988). They argued for discarding the supposition of price rigidity altogether and reinstating the classical idea of perfect price flexibility. The door to the original classical understanding was reopened with their reintroduction of the fully flexible price concept. In this case, demand-driven fluctuations did not affect output and money became completely neutral. The classical dichotomy holds and the Phillips curve becomes perfectly vertical at the NAIRU rate (Motyovszki, 2013).

2.1.4. The New Keynesian Phillips Curve and the Return to Sticky Prices

Our discussion so far has been about flexible and sticky prices, the classical dichotomy, the neutrality of money, and the short and long-run behavior of the Phillips curve. The need for a sticky-price model arose when demand-side policies were somewhat frustrated after the flexible price proposition of real business cycles theory. The New Keynesian sticky price Phillips curve model, which is based on a micro-based explanation, emerged in this period.

The New Keynesians agree with Keynes that, unlike the classical school's assumption, prices and wages don't adjust quickly enough to clear markets. They have focused on

exploring the microeconomic foundations behind this slow adjustment process. As Mankiw and Romer (1991) highlighted, key microeconomic imperfections, such as imperfect competition and rigidity in relative prices, are crucial in explaining price stickiness within New Keynesian theory. New Keynesian economics argues that changes in nominal variables, such as money supply, influence real variables, meaning classical dichotomy does not hold. This failure is attributed to sticky prices, or nominal rigidities. While monetary policy can help close the output gap after a shock, it doesn't affect long-term potential output, which is determined by supply-side factors (Eruygur, 2011).

In the 1980s and 1990s, tensions grew between New Keynesians and Classical Economists, leading to a new synthesis combining both approaches to explain economic fluctuations Mankiw (2006). Goodfriend and King (1997) referred to this as the "New Neoclassical Synthesis." It combined Keynesian concepts, such as nominal rigidities and imperfect competition, with an intertemporal optimizing dynamic general equilibrium model that incorporated rational expectations, building on the real business cycle (RBC) theory from the 1970s. RBC models, initiated by Kydland and Prescott (1982) explained business cycles through productivity shocks, with no role for money. The new neoclassical synthesis, however, introduced nominal rigidities, meaning monetary policy could affect real variables, making it a tool for stabilization, unlike RBC models, where monetary policy did not affect real activity. These models established the standard framework for examining the effects of monetary policy in contemporary macroeconomics, aiding in the analysis of the relationship between money, inflation, and the business cycle. They are micro-founded, theoretically consistent, and provide a basis for policy and welfare analysis (Eruygur, 2011).

2.1.5. Derivation of the Pure Forward Looking and Hybrid New Keynesian Phillips Curve

In this section, we benefited from Sümer's (2020) work when deriving the Phillips curve. The New Keynesian Phillips Curve is derived from a setting where firms operate under monopolistic competition and face restrictions on price adjustments. Instead of changing prices freely, each firm is subject to a constant probability of

modifying its price. or keeping it unchanged in any given period. One common approach to modeling these constraints is through time-dependent pricing, as seen in Taylor's (1980) staggered contracts model, where firms set their prices for a predetermined number of periods. However, tracking individual price histories in such models complicates aggregation. To address this, Calvo (1983) introduced a probabilistic pricing rule, assuming that firms have a fixed likelihood of being able to adjust prices, which significantly simplifies the mathematical treatment of price stickiness. This framework provides a foundation for understanding how inflation evolves based on firms' pricing behavior under constraints Galí and Gertler (1999).

The Phillips curve, developed by Taylor (1980) and Calvo (1983), incorporates forward-looking wage and price decisions by workers and firms. The New Keynesian Phillips Curve, which represents the link between inflation and firms' real marginal costs, is given by the following expression (Calvo, 1983):

$$p_t = \theta p_{t-1} + (1-\theta)p_t^* \quad \textbf{(2.3)}$$

Where the price level that provides companies with profit maximization is represented by $pt*$, in equation (2.3), p_t represents the total price level, and p_{t-1} is the previous period's price level. p_t^* is derived as:

$$p_t^* = (1-\beta\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t\{mc_{t+i}^n\} \quad \textbf{(2.4)}$$

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: $MC_t = \frac{W_t}{P_t} \cdot \frac{1}{\frac{\partial Y_t}{\partial N_t}}$. Using the previous equation, we can express real marginal cost as $MC_t = \frac{S_t}{\alpha_n}$,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 (2.3 and 2.4) are considered, the New Keynesian Phillips Curve 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 – θ 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:

$$p_t^* = mc_{t+i}^n \quad \textbf{(2.5)}$$

In Equation (2.5), firms adjust their prices to make normal profits instead of maximum profits: where the price is set according to the current marginal cost of the firm. Given this framework, the New Keynesian Phillips Curve, in other words, pure forward-looking New Keynesian Phillips Curve, is expressed as:

$$\pi_t = \lambda mc_t + \gamma_f E_t(\pi_{t+1}) \quad \textbf{(2.6)}$$

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 these 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.

Ignoring the price rigidity, which occurs because firms maintain the same price, except for differentiated products, with prices that couldn't be adjusted in the current period remaining equal to the previous price level, led to the development of the Hybrid New Keynesian Phillips Curve (Galí and Gertler, 1999).

The expression of the Hybrid New Keynesian Phillips Curve, which includes the past inflation component, as given by Galí and Gertler (1999).

$$p_t^* = (1 - w)p_t^f + wp_t^b \quad \textbf{(2.7)}$$

In this model, w represents firms that base their expectations on past inflation, while $(1 - w)$ represents those 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:

$$p_t^f = (1-\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t\{mc_{t+i}^n\} \quad \textbf{(2.8)}$$

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

$$p_t^b = p_{t-1}^* + \pi_{t-1} \quad \textbf{(2.9)}$$

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

The Hybrid New Keynesian Phillips Curve, combining Equations (2.3), (2.7), (2.8), and (2.9), is:

$$\pi_t = \lambda mc_t + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} \quad \textbf{(2.10)}$$

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).

$$\pi_t = \lambda y_t + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} \quad \textbf{(2.11)}$$

Where the reduced-form parameters are:

$$\lambda = (1-w)(1-\theta)(1-\beta\theta)\phi^{-1}$$
$$\gamma_f = \beta\theta\phi^{-1} \quad \textbf{(2.12)}$$
$$\gamma_b = w\phi^{-1}$$

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 hybrid New Keynesian Phillips Curve (NKPC) to align with the pure forward-looking NKPC (Eq. 2.6).

2.1.6. The Role of Inflation Expectation on NKPC

In the early period, the trade-off between unemployment and inflation implied by the Phillips curve was challenged through inflation expectations. Friedman (1968) and Sargent and Wallace (1975) tried to challenge the status of this trade-off under expectations. Especially, under the assumption of a perfectly rational individual, the trade-off would not hold and active monetary policy would lose its importance. However, even if individuals have rational expectations, the market will not be able to clear itself in the short run if prices are somehow sticky. In the long run, expectations remain important in every economic school without exception.

When the new Keynesians introduced the sticky price model, they did not ignore the importance of rational expectations; on the contrary, they emphasized it. Fischer (1977) argued that even with rational expectations, systematic monetary policy could still play a role in stabilizing the economy (Mankiw 2006). From this point of view, Fischer (1977), Taylor (1980), Rotemberg (1982), and Calvo (1983) contributed to NKPC, assuming that rational inflation expectations and nominal rigidities, meaning future price expectations play a crucial role in price-setting decisions (Abbas et al., 2016).

In the standard purely forward-looking New Keynesian Phillips Curve (NKPC), lagged inflation has no theoretical role. However, Fuhrer and Moore (1995) argued that the NKPC should include lagged inflation, suggesting that inflation lacks inertia. Consequently, both future and lagged inflation were included in the baseline NKPC as determinants of current inflation. This modification resulted in the creation of the hybrid NKPC, in which firms are categorized into two groups: a fraction $(1-\omega)$ of firms are forward-looking, setting prices based on expected future marginal costs and

utilizing all available information at time t, while the remaining fraction ω are backward-looking, adjusting prices according to past aggregate price levels. (Galí and Gertler, 1999).

2.1.7. Representation of Expected Inflation

The concept of inflation expectations, Et(πt+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)

A common approach 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, πt+1 is noisier than Et(πt+1), which can make estimating the NKPC challenging, particularly when studying with limited data (Zhang et al. , 2009).

Using observed inflation survey data rather than realized future inflation values might be more 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.

In the studies conducted with the survey data, expectations in the NKPC are represented by direct measures from sources like the Survey of Professional Forecasters or the Federal Reserve's "Greenbooks," which serve as proxies. Apart from the surveys of professional forecasters, Zhang et al. (2009) took a broader approach by using a variety of survey-based inflation expectations. To test the NKPC, they employed various inflation forecast data. These included figures from the Survey of Professional Forecasters, the Green Book's quarterly GDP inflation projections, and

the general public's one-year-ahead inflation expectations as captured by the Michigan Survey.

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) discusses the potential endogeneity of inflation forecasts, while Roberts (1998) and Adam and Padula (2011) treat observed inflation forecasts as exogenous. Koc et al. (2021) argued that the information people use to form inflation expectations likely includes current inflation trends, creating a common endogeneity problem. This issue should be considered when relying on survey-based measures for inflation expectations.

Some people see the survey-based approach to estimating the New Keynesian Phillips Curve (NKPC) as allowing for price-setting that isn't based on rational expectations, because it doesn't require modeling inflation expectations. However, this lack of a dynamic model for expectations can be a downside when using the NKPC for policy, like in forecasting. Thus Fuhrer (2012) and Adam and Padula (2011) derived their expectation model without requiring rationality assumption. These studies based their idea on inflation forecasts that may not always be rational (non-rationality) in the context of the NKPC.

However, Zhang et al. (2009) are concerned that moving away from the assumption of rational expectations should be done carefully since rational expectations have been a key concept in macroeconomics for many years, and the NKPC was built on this assumption. According to him the main reason for using observed inflation forecasts, such as those from surveys, to estimate NKPC models is not about addressing whether expectations are rational or irrational. Instead, it’s about avoiding measurement errors that could arise from using realized inflation data. This approach helps produce more accurate estimates of the model’s coefficients and standard errors.

As seen in the literature, while the representation of inflation expectations was first under the assumption of adaptive and then rational expectations, survey-based expectations have been used in the last few decades and have become quite popular. Studies have differed on whether survey expectations are endogenous or exogenous

variables or whether they are rational. However, if we disregard these debates and differences, it is exactly known that survey expectations are an observed and directly measurable indicator. Therefore, it is thought that it can eliminate measurement errors. On the other hand, the surveys used in the studies differ in terms of participants. While most of these studies are based on professional market participants, some of them are based on consumers (households).

In our study, we would like to introduce an expectation variable not analyzed in the Phillips Curve literature before. We construct a sentiment index based on Twitter(X) data, as found in a few studies outside the literature, and test it in the model. Considering the novelty of survey expectations in the literature, we followed this idea and assumed the Twitter(X)-based sentiment index is observable, direct, and reflects consumer (household) expectations.

There are some challenges that we face in using a Twitter-based variable as a proxy of forward-looking inflation expectations within the framework of a New Keynesian Phillips Curve. How can Twitter content truly represent a forward-looking expectation? Some content may be related to the past, some may refer to the current situation, and some may make predictions about the future. The theoretical explanation for all content stems from the recognition that individuals who post about inflation on Twitter may do so based on various information sets: some may rely on recent inflation outcomes, others may incorporate current macroeconomic conditions or policy developments, and a portion may even form expectations informed by economic models. As such, tweets potentially reflect a combination of backward-looking (adaptive) and forward-looking (rational) components. As explained in Mankiw's textbook (2022), rational individuals use all available information to predict the future, including government policies. From this perspective, Twitter already contains a large information set with different components. In any case, it would be better to refine the data as much as possible to create a more accurate dataset that can represent forward-looking expectations. However, our dataset is relatively limited in size, and thus, unlike more big data analyses, it might be hard to decompose between these components.

Angelico et al. (2022) demonstrate that Twitter can be a viable source of high-frequency indicators of consumer inflation expectations, especially when noise is filtered using structured methods like Latent Dirichlet Allocation (LDA) and future-oriented expressions are identified through natural language processing. However, unlike Angelico et al. (2022), our study does not implement topic modeling or future-tense separation, primarily due to the relatively small sample size. As a result, the Twitter-based indicator used here is subject to potential bias stemming from noise, the inclusion of users who are not economically informed, and the difficulty of isolating genuine forward-looking statements. Still, given its high frequency and dynamic responsiveness to real-time developments, this variable can provide complementary insights to conventional survey-based expectations—particularly if future studies expand the sample size and apply more refined filtering-clearing techniques.

We treat Twitter(X) sentiment as an endogenous variable, following Koc et al. (2021) idea that since inflation expectations are influenced by current inflation trends, relying on survey-based measures can introduce endogeneity. We assume that this issue also needs to be considered when using Twitter-based expectations in analysis. Given the potential endogeneity between inflation expectations and inflation, we can conclude that Ordinary Least Squares (OLS) would be inconsistent, and the appropriate estimation method to use is Generalized Method of Moments (GMM).

2.2. Empirical Literature Review

The baseline and hybrid versions of the NKPC have historically been subject to extensive empirical testing, predominantly in developed economies, though a growing body of research has extended its application to various emerging economies. In this particular section of our study, we build upon this existing literature by analyzing the empirical performance of the closed-economy version of the NKPC specifically within the context of Türkiye. Our investigation considers both the basic model and its more comprehensive hybrid counterpart. This targeted analysis is crucial for understanding the nuances of inflation formation in an economy like Türkiye, given its unique structural characteristics. Before focusing on the studies conducted in Türkiye, we review the findings from studies conducted in various countries.

2.2.1. The Forward Looking and Backward Looking Dynamics of NKPC

The Phillips Curve literature has paid much attention to whether inflation is forward-looking or backward-looking. For instance, Galí and Gertler (1999), Sbordone (2002; 2005), and Galí, Gertler, and David López-Salido (2005) 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.

Fuhrer and Moore (1995) examine the limitations of the conventional Phelps-Taylor overlapping wage contracts model in capturing U.S. inflation and output dynamics, highlighting that it proves incapable of generating sufficient inflation persistence. To address this issue, they propose a new contracting model where agents consider relative real wages, resulting in a specification more consistent with macroeconomic data. Their findings challenge the baseline pure forward-looking New Keynesian Phillips Curve (NKPC), which theoretically excludes lagged inflation, but it is not able to take into account, on an empirical basis, the extremely persistent character of inflation. As a result, they incorporate both expected and lagged inflation as determinants of current inflation, improving the model's empirical fit and acknowledging the role of inflation inertia in price-setting behavior.

Galí and Gertler (1999) conducted a test of both the baseline and hybrid New Keynesian Phillips Curve (NKPC) models for the United States, applying the Generalised Method of Moments (GMM) estimator and treating labour income share to represent marginal cost. They discovered that, for the pure-forward-looking NKPC, the labor income share’s coefficient was statistically significant and positive. When the output gap was employed to represent changes in demand, however, the coefficient became statistically insignificant and took a negative sign. To better capture determinants of inflation, the hybrid NKPC was introduced, incorporating both expected and lagged inflation to allow for some degree of inflation inertia. In their empirical analysis, they found that in the hybrid NKPC, the coefficient on future inflation, ranging from 0.59 to 0.87, remained statistically significant and dominated the coefficient on past inflation, which ranged from 0.085 to 0.383. This provided

evidence that while forward-looking price-setting plays a key role, past inflation also influences current inflation to some extent.

In a subsequent study, Galí et al. (2001) found similar results for the Euro-area. Notably, they demonstrated that when the labor income share was utilized as an explanatory variable instead of the output gap, the model's ability to account for inflation improved considerably. Across both the baseline and the hybrid NKPC models, the coefficients associated with the labor income share consistently emerged as both positive and statistically significant. Furthermore, the research highlighted a crucial characteristic: The weight of future inflation expectations was once again found to be bigger than that of past (lagged) inflation. This finding strongly reinforces the theoretical prediction of the NKPC that inflation dynamics are predominantly driven by forward-looking decisions.

Sbordone (2002) conducts her study in the United States using a simple optimizing model of nominal price rigidity. By approximating marginal cost evolution through the paths of nominal labor compensation and labor productivity, the study examines the price-setting behavior of firms. The findings indicate a significant degree of price stickiness and strong support for the forward-looking model of price setting. These results remain robust across different forecasting models for unit labor costs, alternative measures of marginal costs, and varying specifications of price staggering, reinforcing the role of forward-looking expectations in inflation dynamics.

The use of labor income share as a proxy for marginal cost and the GMM methodology in studies by Galí and Gertler (1999) have faced criticism. Rudd and Whelan (2005) found that the NKPC had an inadequate empirical fit with U.S. data, labor income share was found to be an ineffective proxy for real economic activity, and failed to support the dominant role of future inflation. Additionally, Rudd and Whelan (2007) showed that labor income share moves countercyclically in recessions, while the output gap is procyclical, making it a more appropriate proxy.

Zhang et al. (2008) examined the New Keynesian Phillips Curve (NKPC) for the U.S. from 1960 to 2005, investigating structural changes using both inflation expectations survey data and a rational expectations approach. They found that backward-looking

inflation inertia often dominates short-run inflation dynamics, contradicting the NKPC's forward-looking framework. Their analysis showed that forward-looking behavior had a smaller influence during the high and volatile inflation period prior to 1981, but it became more prominent in the period of moderate inflation that followed, providing support for sticky price models.

Vašíček (2011) examines inflation dynamics in the Czech Republic, Hungary, Poland, and Slovakia using the New Keynesian Phillips Curve (NKPC) framework for the post-transitional period (1998–2007). The study finds compelling evidence that inflation is primarily driven by future expectations, supporting the NKPC, but also reveals a higher degree of inflation inertia compared to developed economies. This inertia is attributed to firms relying on backward-looking price-setting behavior, likely due to weak monetary policy credibility and the absence of a strong nominal anchor. Additionally, the study finds no clear evidence that real marginal costs, proxied by real unit labor costs, significantly influence inflation dynamics, while the output gap performs only marginally better.

In addition to studies conducted in US and EU countries, some NKPC studies (Abbas and Sgro, 2011; Mazumder, 2014; Wardhono et al., 2021) are also studied in other countries.

Abbas and Sgro (2011) examine the validity of the New Keynesian Phillips Curve (NKPC) for Australia. Unlike the findings of Galí and Gertler (1999), Galí et al. (2001) and Rudd and Whelan (2007), they concluded that neither the output gap nor marginal cost played a significant role as a driving force across various sets of instruments and estimators (GMM and 2SLS) during the period from 1959 to 2009. They also observe a flattening of the NKPC and a notable presence of price stickiness in the data. Specifically, the reduced-form coefficients and implied estimates from the structural parameters suggest that inflation dynamics are forward-looking, with the influence of lagged inflation becoming statistically significant only after the 1980s. Despite this, they argue that the forward-looking baseline NKPC, as opposed to the hybrid NKPC, is firmer and provides a superior explanation of inflation dynamics in the Australian economy.

Mazumder (2014) examines the validity of both the traditional Phillips Curve and the New Keynesian Phillips Curve (NKPC) in accounting for inflation dynamics in mainland China starting from the late 1980s. He concludes that the NKPC performs poorly, while the traditional Phillips Curve provides a more accurate representation. Utilizing optimal instruments GMM procedure, the study finds a counter-intuitive and statistically significant negative coefficient for the output gap within the NKPC framework. This result contradicts the theoretical underpinnings of the NKPC, which require a positive relationship between inflation and real economic activity. The findings not only reject the empirical validity of the NKPC for China but also highlight the superior explanatory power of the traditional model. Mazumder thus argues that, despite its theoretical appeal, the NKPC is less suitable for policy analysis in the Chinese context, where inflation dynamics appear to follow patterns more consistent with the older Phillips Curve framework.

Wardhono et al. (2021) examine the inflation dynamics of five ASEAN countries from 2005:Q1 to 2018:Q4 using the New Keynesian Phillips Curve (NKPC) framework. Utilizing quarterly panel data and estimating through the Generalized Method of Moments (GMM), both in system and first-difference forms, the study finds that inflation expectations in the region display both forward-looking and backward-looking behavior, with the latter being more prominent. Contrary to Galí and Gertler (1999), who argue that the output gap may not be a reliable proxy for real economic activity, they find consistent and statistically significant positive coefficients for the output gap across all estimated models.

Most of the studies conducted in different countries, especially in emerging economies, show that expectations and output gap do not solely drive inflation dynamics. For this reason, such studies (Medel 2015; Bawa et al., 2016; Koc et al., 2021b; Rohoia and Sharma, 2021; Narayan et al., 2023) have also considered other factors such as exchange rate, money supply, budget deficits and oil shocks in their models.

2.2.2. Survey Based NKPC

In NKPC estimations, actual or realized future inflation data are commonly used as a proxy for expected inflation. An alternative method is to use survey data on expected inflation, which could provide a more accurate reflection of how economic agents behave in the real world, based on the information available in the economy. Several studies, including Roberts (1995), Paloviita (2006), Brissimis and Magginas (2008), Henzel and Wollmershäuser (2008), Zhang et al. (2008; 2009), Adam and Padula (2011), Mazumder (2011), Hubert and Mirza (2019), have relied on survey-based inflation expectations to test the closed-economy baseline pure forward-looking NKPC or the hybrid NKPC or both of them.

In Roberts' study (1995), the NKPC was tested using the Michigan and Livingston surveys to represent expectations of inflation. The unemployment rate and output gap were used as proxies for real economic activity, both showing the correct positive signs and statistical significance when survey-based inflation expectations were applied. However, when actual future inflation was considered as inflation expectations, these estimates lost statistical significance.

Paloviita (2006) examined the baseline forward-looking NKPC and the hybrid NKPC for 12 European Monetary Union countries, using OECD inflation forecasts as a proxy for inflation expectations. The estimation method they used in the study is GMM. The results showed that in the Euro area, the baseline NKPC was shown to effectively explain the inflation process. This was consistently supported by both the output gap and labor income share, which proved to be fitting proxies for the crucial driving force variable, with inflation dynamics emerging as primarily forward-looking. However, while the baseline NKPC captured inflation dynamics, she concluded that the hybrid NKPC was also essential for accounting for inflation persistence in these European economies.

Brissimis and Magginas (2008) examined the New Keynesian and hybrid Phillips Curves in explaining U.S. inflation dynamics using inflation forecasts from the Federal Reserve’s Greenbook and the Survey of Professional Forecasters as proxies for inflation expectations. The study employed GMM estimation for all estimations. Their

findings strongly supported the forward-looking NKPC, particularly when deviations from rationality in inflation forecasts were considered. The study produced theoretically viable estimates of expected inflation and real unit labor costs., while also showing that the significance of lagged-inflation terms in the hybrid NKPC depended on the idea of rational expectations. When survey-based inflation forecasts were used instead of actual future inflation data, lagged inflation became insignificant, suggesting that inflation persistence often observed in empirical studies may stem from imperfect expectations rather than structural economic factors. Their work aligns with Roberts (1997), who also found that deviations from perfect rationality, rather than economic structure, explain the presence of lagged inflation in NKPC estimates.

The hybrid New Keynesian Phillips Curve (NKPC) was analyzed for a selection of Eurozone countries, the US, and the UK, using inflation expectations from the CESifo World Economic Survey instead of assuming rational expectations and applying the Generalized Method of Moments (GMM) by Henzel and Wollmershäuser (2008). By excluding weak instruments, they re-estimated the Phillips curve using TSLS and concluded that, specifically, the endogeneity of the regressors can be rejected. Their findings indicated that survey-based inflation expectations yielded more reliable empirical results than the GMM approach. The study rejected the purely forward-looking NKPC in favor of the hybrid NKPC, with estimated coefficients on past inflation being higher when using survey expectations than under the rational expectations GMM approach. However, uncertainty remained regarding whether real unit labor costs or the output gap should be the appropriate proxy for real marginal costs. Additionally, the imposition of theory-based restrictions was found to enhance the empirical fit of the model.

Zhang et al. (2009) investigated the empirical validity of the New Keynesian Phillips Curve (NKPC) in explaining U.S. inflation, using observed inflation expectations while addressing serial correlation in the standard NKPC framework. They found that, contrary to recent studies suggesting no role for the GDP gap, the output gap remained a statistically significant driver of inflation, whereas the labor income share was generally insignificant. In most estimations they did, lagged inflation played a more dominant role than inflation expectations. The study utilized GMM estimation from an econometric standpoint to address endogeneity and resolve issues related to weak

instrumental variables in NKPC estimation. Their results indicated that the weight in the inflation expectations formation is largely based on backward-looking expectations, challenging previous conclusions by Galí and Gertler (1999), Brissimis and Magginas (2008), Paloviita (2006).

Adam and Padula (2011) analyzed both the baseline and hybrid New Keynesian Phillips Curve (NKPC) for the United States employing data from the Survey of Professional Forecasters over the period 1968Q4–2003Q1. Their conclusions supported the NKPC predictions across both marginal cost and output gap measures. They additionally calculated the structural parameters of the NKPC, finding them to be positive and statistically significant with survey-based inflation expectations. Additionally, their estimate of price rigidity suggested that prices remain stable for approximately five quarters. While these findings provide empirical support for the NKPC in explaining U.S. inflation dynamics, they also showed that lagged inflation remains a significant determinant, even when accounting for potential non-rationalities in expectations through survey data.

Mazumder (2011) examined the performance of the New Keynesian Phillips Curve (NKPC) when survey-based inflation forecasts are used as proxies for inflation expectations. Previous studies, such as Brissimis and Magginas (2008), applied survey measures to the NKPC and found them to be superior to estimates based on actual future inflation data. However, their approach relied on the labor income share as a proxy for real marginal cost, which is problematic due to its countercyclical nature. In response, Mazumder developed and tested a procyclical marginal cost variable alongside various survey-based inflation forecasts while addressing the weak instrument problem that arises when estimating the model using conventional GMM. The results showed that when survey-based inflation forecasts were applied, the NKPC generated a negative and statistically significant coefficient on procyclical marginal cost. This raised substantial concerns about the empirical validity of the NKPC model, even when survey expectations were included. In addition, his findings show that future inflation expectations more dominant than lagged inflation expectations.

In a recent study, Hubert and Mirza (2019) investigate the role of backward- and forward-looking information in the formation of inflation expectations. Their results

emphasize that long-term inflation expectations are essential in determining short-term expectations. Although the impact of backward-looking information weakens over time, no evidence was found of a structural break in the expectation formation process of professional forecasters. According to their results, longer-term expectations are influenced not only by the tendency to revert to trend inflation but also by perceptions of the central bank's long-term inflation target and its credibility in maintaining inflation stability. The study also shows that professional forecasters place more weight on forward-looking information, with lagged inflation still significant, and that the estimated parameters of the NKPC-based model remain stable across different inflation regimes and forecasting horizons.

Studies relying on survey expectations consistently emphasize that directly observable data offers a superior reflection of economic agents' inflation expectations, thereby effectively mitigating measurement error inherent in other approaches. This preference may stem from the ability of surveys to capture the diverse and often heterogeneous beliefs of individuals and firms, providing a more detailed and realistic understanding of how expectations are genuinely formed in the economy. While the majority of these survey-based investigations have yielded results largely consistent with established economic literature, some have presented divergent findings, perhaps due to specific time periods analyzed. A particularly noteworthy outcome across many of these studies is the observation that when survey data are incorporated into inflation models, specifically replacing expectations derived from assuming rational expectations, the coefficient associated with lagged inflation expectation typically increases. These empirical results underscore the influence of past inflation on current and future expectations, strongly suggesting that the persistence or inertia of inflation is a deeply ingrained feature of economic behavior. In essence, it highlights how past price movements continue to heavily anchor agents' beliefs, even when more direct measures of expectations are used. Furthermore, the other thing that would be so crucial is examining whether the output gap or real marginal cost better explains inflation dynamics. Interestingly, compared to earlier research that did not incorporate survey variables, the performance of the output gap has generally been more favorable when survey-based expectations are utilized. This suggests that when directly measuring how agents anticipate inflation, the role of aggregate demand pressures, as

captured by the output gap, might become more apparent or better aligned with the survey responses.

2.2.3. Studies in Türkiye

Studies such as Yazgan and Yilmazkuday (2005), Agénor and Bayraktar (2010), Eruygur (2011) and Saz (2011) have analyzed inflation dynamics in Türkiye using the baseline and hybrid new Keynesian Phillips curve.

Yazgan and Yilmazkuday (2005) examined the New Keynesian Phillips Curve (NKPC) with regard to the Turkish economy, estimating both the benchmark and hybrid versions using Turkish data from 1988 to 2003. Unlike studies incorporating survey-based inflation expectations, they relied on inflation expectations derived under the rational expectations assumption. Their findings provide empirical support for the benchmark NKPC, contrasting previous studies on developed economies such as the U.S. and the Euro area. This support remains robust even after addressing the weak identification problem in the GMM. Additionally, their results reject the hybrid NKPC, as backward-looking behavior is statistically insignificant, reinforcing evidence that Turkish firms primarily follow forward-looking pricing strategies.

Agénor and Bayraktar (2010) made a guess at four distinct forward-looking Phillips curves for Türkiye, incorporating both traditional and extended models. Two of their specifications are based on Galí and Gertler (1999), the hybrid closed-economy NKPC and an extended version that incorporates two leads of inflation. Their findings demonstrate that the output gap is an insignificant predictor of inflation in Türkiye from 1981 to 2006, with regression results showing that lagged inflation plays a more dominant role than future inflation, although both are statistically significant.

Eruygur (2011) analyzed the short-run inflation dynamics in Turkey using a New Keynesian Phillips Curve (NKPC) framework, incorporating a constant elasticity of substitution (CES) production function with imported and domestically produced intermediate goods and incomplete exchange rate pass-through. The study estimated structural parameters using the Continuous Updating Generalized Method of Moments (CU-GMM) for robustness. Focusing on Türkiye from 1988 to 2009, the research

covered critical economic periods, including the 1994 and 2000-01 crises and the post-2001 inflation targeting period. The findings confirmed that imported intermediate goods and exchange rate pass-through played a crucial role in inflation determination, while closed-economy models underestimated inflation trends. The study found that backward-looking behavior dominated inflation dynamics throughout the period in both open and closed economy models. However, when comparing the sub-sample 1989-2001 to the full sample 1989-2009, the forward-looking component increased from 0.41 to 0.46, while the backward-looking component decreased from 0.59 to 0.53. This indicates that while backward-looking behavior remained dominant, its influence declined over time, particularly after adopting inflation targeting post-2001. The study concluded that if inflation targeting remains successful, inflation inertia could continue decreasing, leading to lower output costs of disinflation and improved monetary policy effectiveness in Türkiye.

Saz (2011) analyzed the inflation dynamics in Turkey using the New Keynesian Phillips Curve (NKPC) framework, introducing a novel measure for marginal costs—the marginal cost index (MCI)—to improve upon traditional proxies like the labor income share gap. The study used Generalized Method of Moments (GMM) and Two-Stage Least Squares (2SLS) for estimation, finding that the MCI measure was a reliable and sound approximation for marginal costs in Turkey, showing both pro-cyclical properties and a high correlation with inflation rates. The findings suggest that the conventional and hybrid NKPC are both valid descriptions of Turkey's inflation process, while the output gap Phillips curve only provided an insubstantial relationship for the period 2005-2009. In his estimation, forward-looking expectations predominate over backward-looking ones. Also, the study showed that the traditional labor income share gap is a poor proxy for marginal costs in Türkiye, with low correlation to inflation and countercyclical movements, highlighting the need for caution when using this measure.

A consistent characteristic across much of the existing research is its reliance on the assumption of rational expectations to derive inflation expectations, a methodology that, by its nature, creates an unobservable and indirect variable. This approach assumes economic agents perfectly utilize all available information, leading to forecasts that are, on average, accurate. However, as previously noted, direct and

observable variables like survey expectations offer a significant advantage, proving more reliable against measurement errors. As Zhang et al. (2009) argued, survey expectations also reflect a more realistic representation of the expectations of economic agents.

CHAPTER III

METHODOLOGY

3.1. Data

This study is based on the period between January 2014 and September 2024. The data are collected on monthly basis for the variables: Consumer Price Index (CPI), Industrial Production Index (IPI) as a proxy for the output gap, Twitter Sentiment and Interest Rate Spread as an instrumental variable. Except for Twitter Sentiment, all other data are obtained from the Central Bank of the Republic of Turkey (CBRT) and Turkstat.

Since the study is monthly, CPI is preferred instead of deflator to represent inflation. Similar studies like (Yazgan and Yilmazkuday, 2005), (Çatik et al. 2011) in Turkiye prefer CPI. Monthly CPI is obtained by subtracting the log-based inflation at time t from the log-based inflation at time t-1. 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, log-based and potential output is obtained by conducting the Hodrick-Prescott (HP) filter. 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 represented the weighted average interest rates applied to consumer loans in Turkish lira (TL) as long-term and the interest rates applied to deposit accounts in TL with maturities up to 1 month as short-term.

The tweet data required for the Twitter Sentiment Index was obtained through the Apify platform. Apify is a platform frequently used by researchers recently in data scraping processes required for sentiment analysis. Apify, which mediates between

software developers and users, facilitates data scraping by providing an easy interface for users. “Enflasyon” was chosen as the keyword in Turkish to reflect inflation expectations, and 54,717 raw tweets were extracted monthly. After cleaning the tweets, we separated them into positive and negative sentiments by applying the BERT model. Negative tweets contain a negative discourse on prices, while positive tweets include comments on the moderate course of inflation or more optimistic future expectations compared to negative tweets. We obtained the Twitter inflation expectation index by dividing negative tweets by total tweets. A brief outline and description of all of the variables used in this study can be found in **Table 3.1.**

Table 3.1. Description of Variables

Variables	Description	Formula/Notes	Source
$\boldsymbol{\pi_t}$	Monthly inflation rate	$\log(\text{CPI}_t) - \log(\text{CPI}_{t-1})$	CBRT
$\boldsymbol{\pi_{t+1}}$	Net sentiment index obtained by dividing the number of negative tweets to the total number of tweets.	$\frac{\text{Negative Tweets}}{\text{Total Tweets}}$	Apify & Python, Author Calculation
$\boldsymbol{y_t}$	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
$\boldsymbol{\text{spread}_t}$	Interest rate spread is computed as the bank lending rate minus bank deposit rate.	Logarithmic difference between bank lending rate and bank deposit rate.	CBRT

3.2. Sentiment Analysis with BERT

In this section, we will explain how Twitter data is obtained, how the raw data is cleaned, and how sentiment analysis based on the BERT model is performed.

3.2.1. Data Acquisition

We leveraged the Apify platform to scrape tweets representing inflation expectations. As it says on the platform, Apify is the ecosystem where developers build, distribute, and publish web scrapers, AI agents, and automation tools(actor). Some of these actors

are built in such a way that we can scrape Twitter data. We used one of them, apidojo/tweet-scraper, to scrape tweets. We chose this tool because we are able to get data for any location on any date.

After selecting our actor, we set the necessary parameters. We filtered the tweets in Turkish, set the search keyword as 'enflasyon' (inflation), scraped the data monthly within the period. Finally, to collect data from all parts of Türkiye, we chose a central location on the map and expanded its radius to cover the entire map, so that the latitude, longitude, and radius are as follows: 39.15000000, 34.16666670, 1000 km (Kirsehir in Türkiye and from that point, the radius was expanded 1000 km). After scraping the tweets by applying these parameters, we combined the data we obtained for each month into a single file and made it ready for the cleaning process. For data cleaning, we used the Python pandas library, which helped us remove URLs, mentions, special characters and digits, extra spaces, and convert the text to all lowercase. **Figure 3.1.** shows the data scraping process.

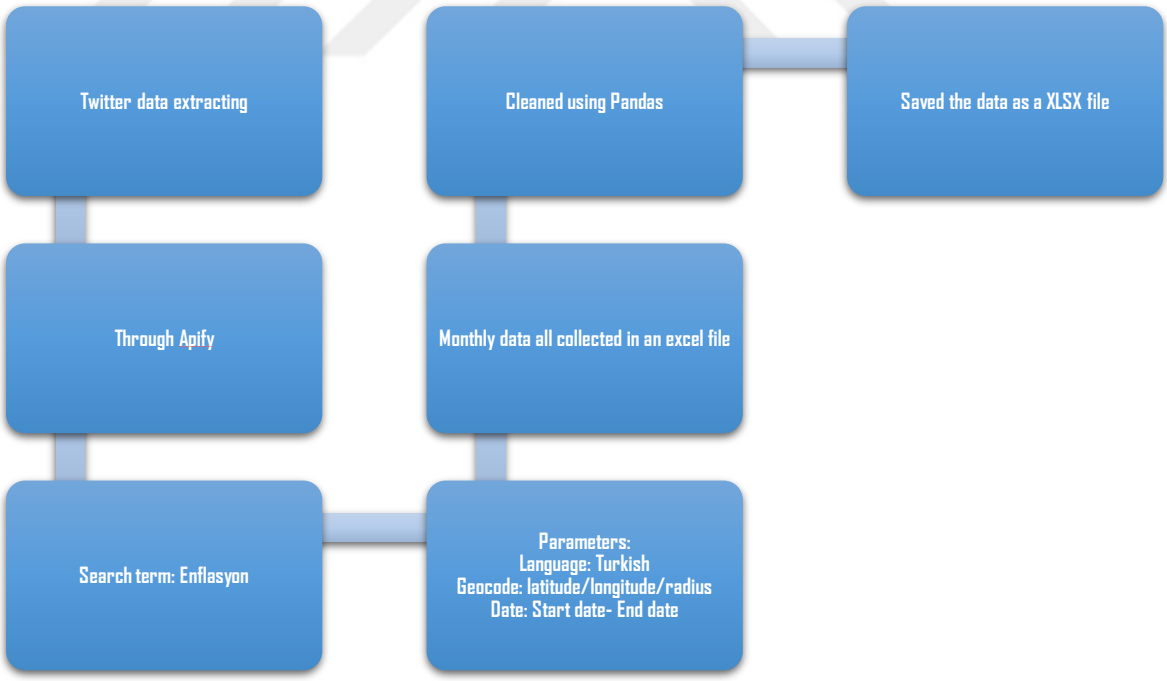


Figure 3.1. Data Extraction Workflow

3.2.2. Data Preprocessing

Text data is primarily unstructured (Sivarajah et al., 2017), 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. Therefore, we applied following steps to clean our dataset:

Removing URLs: Removes all URLs from the text (e.g., http://... or www...).

Removing Mentions: Removes mentions of other Twitter users (e.g., @username).

Removing Special Characters and Digits: Keeps only the letters (including Turkish characters) and spaces, removing any other special characters or numbers.

Removing Extra Spaces: Collapses multiple spaces into a single space for cleaner text.

Lowercasing: Converts all text to lowercase, ensuring uniformity for the BERT model.

A small sample from the dataset cleaned is shown in **Table 3.2.**

Table 3.2. Selected Cleaned Tweets in The Sample

	The texts before cleaning	The texts after cleaning	English version
1	"@x1: Enflasyon Memuru Vurdukça Vuruyor http://t.co/sW0Zdu2N9E http://t.co/njeULFrV2C"	enflasyon memuru vurdukça vuruyor	Inflation hits civil servants harder and harder
2	@x2 Bu gidişle hiper enflasyon da olur.	bu gidişle hiper enflasyon da olur	At this rate, there will be hyperinflation
3	@x3 Hocam nasıl enflasyon sorun değil herşeyin fiyatı sürekli artıyor kur desen içinden çıkılmaz bir hal içinde	hocam nasıl enflasyon sorun değil herşeyin fiyatı sürekli artıyor kur desen içinden çıkılmaz bir hal içinde	Dude how inflation is not a problem, the price of everything is constantly increasing and the exchange rate is in an inextricable state
4	"Enflasyon daha olumlu bir noktaya gelecek' http://t.co/BqNX5t9Ro1 http://t.co/DgpthAUrwh	enflasyon daha olumlu bir noktaya gelecek	Inflation will become more favorable
5	@x4 şu an emeklilik de zor, işçilik de, paralarda artış yaptınız belki ama piyasalar, zamlar, enflasyon daha da arttı DEĞİŞEN YOK!	şu an emeklilik de zor işçilik de paralarda artış yaptınız belki ama piyasalar zamlar enflasyon daha da arttı değişen yok	Right now it is difficult for the retiree and for the worker, maybe you have increased the money, but the markets, hikes, inflation have increased even more, there is no change.
6	2016, kurun gidecek mesafesinin 2015'e göre daha az olması nedeniyle kur baskısının enflasyon üzerinde hafiflemesi beklenebilir.	kurun gidecek mesafesinin e göre daha az olması nedeniyle kur baskısının enflasyon üzerinde hafiflemesi beklenebilir	In 2016, exchange rate pressure on inflation is expected to ease as the exchange rate has less room to move upwards compared to 2015
7	@x5 Her hafta alışverişe çıkarım. enflasyon rakamının gerçekle ilgisi yok. Bunu herkes biliyor. Tabii gelen mesajları okursanız	her hafta alışverişe çıkarım enflasyon rakamının gerçekle ilgisi yok bunu herkes biliyor tabii gelen mesajları okursanız	I go shopping every week. The inflation rate has nothing to do with reality. Everyone knows that. Of course, if you read the messages
8	@x6 Kamu maliyesi dizginlenmez ve üretim desteklenmezse enflasyon durdurulamaz.	kamu maliyesi dizginlenmez ve üretim desteklenmezse enflasyon durdurulamaz	Unless public finances are reined in and production is supported, inflation cannot be stopped.

After the data was cleaned, it was made ready for sentiment analysis. The sentiment analysis, will be able to classify texts and create the twitter-based inflation expectation variable.

3.2.3. 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 (Ónozó et al., 2024; Nemes and Kiss, 2021; Niţoi et al., 2023).

Over the years, various methods have been used for sentiment analysis in Natural Language Processing (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 words 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 apply classifiers like 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). Deep learning methods improve sentiment analysis by learning patterns from labeled text data, allowing them to capture 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 also applied a deep learning approach, which is the BERT model.

BERT (Bidirectional Encoder Representations from Transformers) represents a new paradigm in Natural Language Processing (NLP). It is increasingly used in sequence-to-sequence modeling tasks as well as 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

a word along with its 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 pre-trained 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).

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)). Therefore, we used the savasy/bert-base-turkish-sentiment-cased model developed specifically for Turkish fine-tuned sentiment analysis model for our study. This model is based on BERTurk for Turkish Language (dbmdz/bert-base-turkish-cased).

Yildirim (2024) merged datasets from multiple sources for his fine-tuned model. The movie review dataset was obtained from Beyazperde, consisting of 5331 positive and 5331 negative sentences. Reviews were rated on a scale from 0 to 5, with ratings of 4 or higher considered positive and 2 or lower as negative. Product reviews were collected from an online retailer, covering categories such as books, DVDs, electronics, and kitchen products, with 700 positive and 700 negative reviews per category. Positive reviews averaged a rating of 4.5, while negative reviews averaged 2.27. Additionally, a tweet dataset was collected from another source, focusing on sentiment classification of microblog messages using a robust feature representation and fusion approach. This combined dataset was then used for sentiment analysis tasks.

We applied this fine-tuned Turkish BERT model using Python libraries such as transformers, torch, requests, beautifulsoup4, pandas and numpy to our dataset and obtained the results presented in **Table 3.3.**

Table 3.3. Results of Sentiment Analysis

Sentiment Classification	**Count of classified tweets**
Negative	45164
Positive	9634
Total	54798

The sentiment classification of 54.798 tweets shows a significantly higher number of negative tweets (45.164) compared to positive ones (9.634), indicating that the overall sentiment expressed in the tweets is predominantly negative. According to this result, we will create our Twitter-based inflation expectation variable.

3.2.4. Establishment of Twitter-Based Expected Inflation Variable

We conducted sentiment analysis to create an expectation variable from Twitter data. Our assumption is that negative tweets about inflation will be effective in the formation of realized inflation. To test this in the Phillips curve, we applied the following formula for our regression model:

$$\frac{\text{Negative Tweets}}{\text{Total Tweets}} \qquad \textbf{(3.1)}$$

We chose the ratio of negative tweets to total tweets within the specified period as a variable. Thus, a ratio close to 1 indicates a negative mood in inflation expectations, while a ratio close to 0 indicates a slightly higher rate of moderate and positive expectations. Based on this, we assume that an increase in negative expectations will positively affect the inflation rate. Accordingly, when the ratio is close to 1, inflation will increase.

3.3. Estimation Method

This study estimates the New Keynesian Phillips Curve (NKPC) using the Generalized Method of Moments (GMM) to address the potential endogeneity of the regressors. We utilized Greene's book (2018) to cover the GMM approach.

3.3.1. GMM

So, what we're looking at here is the least squares estimator of the parameters in the classical linear regression model. The model is based on the following assumption:

$$E[x_i \varepsilon_i] = E[x_i(y_i - x_i'\beta)] = 0 \quad \textbf{(3.2)}$$

The equation states that for the OLS estimator to be valid, the error term $\epsilon_i = y_i - x_i'$ must be uncorrelated with the explanatory variables x_i. Specifically, the expectation of the product of the error term and the explanatory variable must be zero. This condition is called the orthogonality condition. In other words, the explanatory variables must not have any information about the error term, implying that there is no endogeneity or bias in the model.

The sample analog is:

$$\frac{1}{n}\sum_{i=1}^{n} x_i \widehat{\varepsilon_i} = \frac{1}{n}\sum_{i=1}^{n} x_i\left(y_i - x_i'\hat{\beta}\right) = 0 \quad \textbf{(3.3)}$$

This is the sample analog of the moment condition used in OLS. In practice, we use sample data, so we compute the sample mean of the product of the explanatory variables x_i and the residuals $\widehat{\varepsilon_i}$. The residuals $\widehat{\varepsilon_i}$ are the difference between the actual values y_i and the predicted values $x_i'\hat{\beta}$, where $\hat{\beta}$ is the estimated parameter. The condition tells us that, on average, the residuals must be orthogonal to the explanatory variables. This is what the OLS estimator relies on to find the best-fitting parameters. The estimator of β is found by solving these moment equations, which are the same as the normal equations used in least squares estimation. This means that the OLS estimator is a special case of the method of moments estimator.

We relied on a large sample analog of the moment condition for instrumental variables.

$$\text{plim}\left(\frac{1}{n}\sum_{i=1}^{n} z_i\varepsilon_i\right) = \text{plim}\left(\frac{1}{n}\sum_{i=1}^{n} z_i(y_i - x_i'\beta)\right) = 0 \quad \textbf{(3.4)}$$

Specifically, equation (3.4) states that the sample mean of the product of the instruments z_i and the error term ε_i must approach zero as the sample size grows large. This condition ensures that the instruments are uncorrelated with the error term, which is a necessary assumption for obtaining consistent estimates of the parameters in an IV regression.

The problem of an excess of instruments relative to parameters was addressed by identifying a solution to the equations.

$$\left(\frac{1}{n}X'Z\right)\left(\frac{1}{n}Z'Z\right)^{-1}\left(\frac{1}{n}Z'\hat{\varepsilon}\right) = \frac{1}{n}\hat{X}'\hat{\varepsilon} = \frac{1}{n}\sum_{i=1}^{n}\hat{x}_i\widehat{\varepsilon_i} = 0 \quad \textbf{(3.5)}$$

The columns of Xn represent the predicted values obtained by regressing each column of X on all the columns of Z. In other words, they are the projections of the columns of X onto the space spanned by Z, meaning Xn captures the variation in X that can be explained using Z. This addresses the issue of over-identification, which occurs when the number of instruments exceeds the number of parameters that can be estimated. In such cases, the system is over-determined, and the solution involves finding an estimator that satisfies the moment conditions. This method reconciles the excess instruments by ensuring that the estimated parameters are consistent, even when the model is over-identified.

The nonlinear least squares estimator is defined similarly, but the equations are more complex because the estimator is implicit. In the nonlinear regression model, the key orthogonality condition is that the expected value of x_i^0 and the error term ε_i is zero: $E[x_i^0\varepsilon_i] = 0$.

The empirical moment equation is:

$$\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\partial E[y_i|x_i,\beta]}{\partial\beta}\right)(y_i - E[y_i|x_i,\beta]) = 0 \quad \textbf{(3.6)}$$

Maximum likelihood estimators (MLE) are found by setting the derivative of the log-likelihood function to zero. The likelihood function describes the probability of observing the data given certain parameters, and maximizing this function helps in finding the values of the parameters that make the observed data most probable.
The scaled log-likelihood function is

$$\frac{1}{n}\ln\ L = \frac{1}{n}\sum_{i=1}^{n}\ln\ f(y_i \mid \mathbf{x}_i, \boldsymbol{\theta}) \quad \textbf{(3.7)}$$

The function $f(\cdot)$ represents the probability density function, and $\boldsymbol{\theta}$ is the vector of parameters to be estimated. As the density function meets certain regularity conditions, the maximum likelihood estimator (MLE) exhibits desirable statistical properties, especially when the sample size increase.

When the density function meets certain regularity conditions, the MLE exhibits desirable statistical properties, such as consistency (approaching to the true parameter as the sample size increase) and asymptotic normality (becoming normally distributed in large samples). These properties make the MLE a powerful and widely used estimator in econometrics and statistics.

$$E\left[\frac{\partial \ln f(y_i|x_i,\theta)}{\partial\theta}\right] = 0 \quad \textbf{(3.8)}$$

The maximum likelihood estimator is found by setting the sample-based equation to zero.

$$\frac{1}{n}\frac{\partial \ln L}{\partial\hat{\theta}} = \frac{1}{n}\sum_{i=1}^{n}\frac{\partial \ln f\left(y_i\middle|x_i,\hat{\theta}\right)}{\partial\hat{\theta}} = 0 \quad \textbf{(3.9)}$$

This sample-based equation is used in practice to estimate the parameters $\hat{\theta}$. By setting the sample derivative of the log-likelihood function equal to zero, we find the maximum likelihood estimator (MLE) for $\hat{\theta}$. The equation is essentially saying that we estimate the parameter $\hat{\theta}$ by maximizing the likelihood based on the available data.

Except for the general case of the instrumental variable estimator, the number of moment equations matches the number of parameters to estimate. This means these cases are exactly identified, leading to a unique solution where the moment equations hold exactly. However, in some cases, there are more moment equations than parameters, making the system overdetermined.

Let's define four sample moments:

$$\bar{g} = \frac{1}{n}\sum_{i=1}^{n}\left[y_i, y_i^2, \frac{1}{y_i}, \ln y_i\right] \quad \textbf{(3.10)}$$

The probability limits are given by: $\frac{P}{\lambda}$, $\frac{P(P+1)}{\lambda^2}$, $\frac{\lambda}{P-1}$, and $\psi(P) - \ln\lambda\backslash$. Each of these pairs can be utilized to predict the two parameters. However, as the previous example shows, the six different pairs result in six slightly different estimates for $\theta = (P, \lambda)$. The probability limits are expressions that describe the behavior of the estimates as the sample size increases. These limits are critical for determining the asymptotic properties of the estimators.

In situations like these, effectively using all sample information necessitates creating a method capable of reconciling the divergent estimates produced by an overdetermined system. More generally, consider a model with K parameters, represented as: $\theta = (\theta_1, \theta_2, \ldots, \theta_K)'$, where the theoretical framework provides a set of L moment conditions, with $L > K$.

$$E[m(y_i, x_i, z_i, \theta)] = E[m_i(\theta)] = 0 \quad \textbf{(3.11)}$$

Where y_i, x_i, and z_i represent the variables present in the model. The subscript i on $m_i\ (\theta)$ indicates its dependence on y_i, x_i, and z_i. The corresponding sample means are denoted as follows:

$$\bar{m}(y, X, Z, \theta) = \frac{1}{n}\sum_{i=1}^{n} m(y_i, x_i, z_i, \theta) = \frac{1}{n}\sum_{i=1}^{n} m_{il}(\theta) \quad \textbf{(3.12)}$$

In cases where the equations are not functionally dependent, the system consists of L equations with K unknown parameters. This is represented as:

$$\overline{m_l}(\theta) = \frac{1}{n}\sum_{i=1}^{n} m_l(y_i, x_i, z_i, \theta) = 0, \quad l = 1, \dots, L \quad \textbf{(3.13)}$$

However, if the equations are not independent (i.e., some equations are functionally dependent on others), the system might not provide a unique solution. This is often a problem in situations like multicollinearity in regression models, where the variables are highly correlated, leading to multiple possible solutions.

To resolve this problem of non-uniqueness, one approach is to minimize a criterion function, which helps to find a single best solution among the possible ones. A typical criterion function used in such cases is the sum of squared differences between the observed values and the predicted values from the model. This method is a standard approach in regression analysis, aiming to minimize the error (or residuals) and find the parameters that best fit the data. We define the criterion q as:

$$q = \sum_{l=1}^{L} \overline{m_l^2} = \bar{m}(\theta)'\bar{m}(\theta) \quad \textbf{(3.14)}$$

It can be shown that under the assumptions we've made, particularly that $m(\theta) = E[m(\theta)] = 0$, minimizing q gives a consistent estimator for θ, though it might be inefficient. We can use a weighted sum of squares as the criterion:

$$q = \bar{m}(\theta)' W_n \bar{m}(\theta) \quad \textbf{(3.15)}$$

Here, W_n denotes any positive definite matrix. Its characteristics may be influenced by the data, yet it remains independent of θ. This ensures we get a consistent estimator for θ. For instance, if we have knowledge about the significance of the different moments, we could apply a diagonal weight matrix. The additional assumption is that the limit of Wn is a positive definite matrix, W.

Just like how generalized least squares is preferred over ordinary least squares, it's beneficial to use a weighted criterion where the weights are inversely proportional to the variances of the moments. Let W be a diagonal matrix where each diagonal element is the reciprocal of the variance of each individual moment:

$$w_{ll} = \frac{1}{\text{Asy.Var}[\sqrt{n}\bar{m}_l]} = \frac{1}{\phi_{ll}} \quad \textbf{(3.16)}$$

Weights are assigned to each moment in equation (27), with this assignment being determined by the asymptotic variance of the sample moments. The weight w_{ll} for each individual moment m_l is the inverse of its variance, i.e. $\frac{1}{\phi_{ll}}$. The weighted least squares estimator, in this scenario, functions by minimizing the expression presented below:

$$q = \bar{m}(\theta)'\Phi^{-1}\bar{m}(\theta). \quad \textbf{(3.17)}$$

Where Φ is the matrix of weights that reflect the variances of the sample moments. Minimizing this criterion function involves adjusting the moments $\bar{m}(\theta)$ by their corresponding variances. This helps to ensure that the estimator accounts for any heteroscedasticity in the data, making it more efficient than standard least squares.

Typically, the L elements of $\bar{m}$ are not correlated. In equation (3.17), we used a diagonal matrix W to ignore this correlation. To apply generalized least squares, we define the full matrix:

$$W = \{\text{Asy.Var}[\sqrt{n}\bar{m}]\}^{-1} = \Phi^{-1} \quad \textbf{(3.18)}$$

In this equation, the full-weight matrix W is described as the inverse of the asymptotic variance of the sample moments. It helps adjust for correlation between the moments and ensures that the estimation is efficient. In GMM, the goal is to minimize the weighted sum of squared moment conditions. So, Φ^{-1} helps to give appropriate weights to the moments based on their covariance structure.

The estimators are obtained by choosing θ to minimize the criterion:

$$q = \bar{m}(\theta)' W_n \bar{m}(\theta) \quad \textbf{(3.19)}$$

The estimators described above are minimum distance estimator. The overall outcome is that if Wn is a positive definite matrix and if $\text{plim}\bar{m}(\theta) = 0$ then the minimum distance (GMM) estimator for θ is consistent. Because the OLS criterion in equation (3.14) uses $\boldsymbol{I}$, this method also gives a consistent estimator, as do the weighted least squares estimator and the full GLS estimator. What still needs to be decided is the best W to use. Intuitively, it seems (and is correct) that the one in equation (3.18) would be optimal, based on the reasoning that justifies generalized least squares. This result was first established by Hansen (1982).

The asymptotic covariance matrix of the generalized method of moments (GMM) estimator is:

$$V_{GMM} = \frac{1}{n}(\Gamma' W \Gamma)^{-1} = \frac{1}{n}(\Gamma' \Phi^{-1} \Gamma)^{-1} \quad \textbf{(3.20)}$$

The covariance matrix is adjusted by the weight matrix W (or Φ^{-1}), which reflects the variability of the sample moments. By minimizing this weighted criterion, we obtain an estimator that accounts for heteroscedasticity and autocorrelation in the error terms, resulting in an efficient and consistent estimator where Γ is the matrix of derivatives, and the jth row of Γ is given by:

$$\Gamma^j = \text{plim}\frac{\partial \overline{m_j}(\theta)}{\partial \theta} \quad \textbf{(3.21)}$$

Also, $\Phi = \text{Asy.Var}\left(\sqrt{n}\bar{m}\right)$. Ultimately, the estimator is expected to exhibit asymptotic normal distribution, a characteristic enabled by applying the central limit theorem to the sample moments and the Slutsky theorem to this procedure.

3.3.2. 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, it is 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 expectation is also endogenous which is affected past and present inflation trends.

$$E\left[Z_t\left(\pi_t - \gamma_f E_t[\pi_{t+1}] - \gamma_b \pi_{t-1} - \lambda y_t\right)\right] = 0 \quad \textbf{(3.22)}$$

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 2.11 using the Generalized Method of Moments (GMM) to address potential endogeneity in the regressors and specially in inflation.

CHAPTER IV

EMPIRICAL FINDINGS AND ASSESSMENTS

Preliminary information on the results is presented in this section through descriptive analysis in **Table 4.1.,** and correlation matrix table in **Table 4.2.**, and then interpret the results of unit root analysis and regression analysis.

Table 4.1. Descriptive Statistics

Variables	Obs	mean	std	min	max
CPI	129	0.019055	0.021783	-0.01542	0.132789
IPI	129	-0.00158	1.135233	-9.00983	1.719574
Spread	129	0.448299	0.121979	0.177537	0.727448
TWT	129	0.802596	0.054655	0.608696	0.925373

Compared the other variables, the IPI stands out for its high variability, suggesting that it fluctuates significantly over time.

Table 4.2. Correlation Matrix

	CPI	IPI	Spread	TWT
CPI	1			
IPI	0.1716	1		
Spread	0.1295	0.0667	1	
TWT	0.3295*	0.0296	-0.2019*	1

The table reveals a moderately positive correlation (0.33) between the Consumer Price Index (CPI), representing actual inflation, and TWT, our Twitter-based expected inflation variable. This suggests that as negative sentiment concerning inflation on Twitter rises, actual inflation tends to follow suit. This observed relationship underscores the potential influence of public sentiment on inflation expectations, indicating that collective online discourse may indeed play a role in shaping real-world economic outcomes.

Our analysis further reveals a negative correlation between Spread and TWT. This relationship is particularly insightful: It suggests that when market participants or the public anticipate an increase in interest rate spreads – often a signal of a strengthening economic outlook or impending monetary tightening – public sentiment regarding future inflation tends to become less negative, or more optimistic. This alignment is logically consistent, as conventional economic theory posits that rising interest rates, especially those driven by central bank policy, are typically employed to curb inflationary pressures. Therefore, a perception of increasing rates could lead to an expectation of declining inflation, fostering a more positive public outlook on future price stability.

Prior to executing our Phillips curve regression, we undertake unit root assessments to evaluate the variables' stationarity. Stationarity is a crucial 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 test and the Phillips-Perron test, which are widely used in econometrics. These tests examine whether a variable contains a unit root, and rejecting the null hypothesis in both tests indicates that the series is stationary.

Table 4.3. 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 and IPI are strongly stationary at the 1% significance level, meaning that the null hypothesis of a unit root is decisively rejected. The interest rate spread is stationary at the 5% level, indicating that the null hypothesis of a unit root is rejected at this level, though not as strongly as CPI and IPI. TWT (Twitter-based expected inflation) is stationary at the 10% significance level, meaning that while the evidence for stationarity is slightly weaker compared to the other variables, it is still sufficient to reject the null hypothesis at a conventional level. Additionally, the Phillips-Perron test confirms stationarity for TWT at the 1% level, further supporting its inclusion in our analysis. Since all variables are found to be stationary at level, we conclude that there are no unit roots, and the data are suitable for a Generalized Method of Moments (GMM) model. Given that the series are integrated at level order, estimating our Phillips curve regressions using level data is appropriate, ensuring reliable econometric results.

Table 4.3. Unit Root Test Statistics

Variables	ADF Test	Phillips-Perron
CPI(π_t)	-5.054421*** {0.0668}	-4.922152*** {0.0668}
TWT(π_{t+1})	-2.681776* {0.0976}	-8.807478*** {0.0829}
IPI (y_t)	-5.509715*** {0.0705}	-5.460889*** {0.0705}
Spread$_t$	-3.175840** {0.0394}	-2.932351** {0.0399}

Notes: The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)tests report the p-value 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 test to ensure that GMM can be applied for estimation, we turned our focus on GMM. We employ multiple sets of instruments to test the robustness of our estimates.

Lagged values of inflation, the output gap, labor income share, wage inflation, and commodity price inflation have been widely used in the literature. Conversely, the interest rate serves as a valid instrument as it is central to monetary policy and connected to expected inflation via the Fisher Effect, which asserts that the real interest rate equals the nominal interest rate minus the expected inflation rate (Abbas and Sgro, 2011).

As Mavroeidis et al., (2014) acknowledges that the case where survey expectations are endogenous and set as instrumental variables is more robust; we also use lagged values of Twitter-based inflation expectations as an instrumental variable, assuming it is an endogenous variable, as we said before. Thus, in our study, we set inflation, output gap, twitter-based inflation expectations and interest rate spread as instrumental variables and tested them on the model by applying different combinations.

The first set M1 includes three lags of inflation, Twitter-based expected inflation, and two lags of the industrial production index (IPI) gap. The second set M2 consists of four lags of Twitter-based expected inflation, two lags of inflation, and the industrial production index gap. The third set M3 incorporates four lags of inflation, three lags of the industrial production index gap, two lags of Twitter-based expected inflation, and one lag of the interest rate spread. Lastly, the fourth set M4 comprises four lags of inflation and the industrial production index gap, three lags of Twitter-based expected inflation, and one lag of the interest rate spread. By utilizing these different instrument sets, we aim to ensure that our estimation is robust while satisfying the orthogonality conditions necessary for valid inference. **Table 4.4.** demonstrates the results of our Phillips curve model.

Table 4.4. Results of Turkish Closed Economy Phillips Curve Model

	M1	**M2**	**M3**	**M4**
c	-0.082334*** {0.024281}	-0.087482*** {0.026624}	-0.089149*** {0.022661}	-0.079724*** {0.015452}
λ	0.000165 {0.001077}	0.001124 {0.001597}	0.000724 {0.000745}	0.001418** {0.000499}
γ_f	0.112174*** {0.031422}	0.119020*** {0.034349}	0.121488*** {0.028659	0.110521*** {0.019994}
γ_b	0.565225*** {0.046410}	0.565821*** {0.044467}	0.561765*** {0.030850}	0.557748*** {0.023316}
Hansen test: J-stat.	3.658383 (0.599569)	2.903622 (0.820842)	9.766330 (0.281811)	10.24128 (0.331308)
Wald Test Chi-square:				
$\gamma_b + \gamma_f = 1$	98.67648***	111.4388***	153.1692***	576.0945***
$\gamma_b = \gamma_f$	39.26268***	36.81118***	67.04743***	117.9466***
Instrumental Variables	Three lags of inflation and Twitter-based expected inflation and two lags of industrial production index gap	Four lags of Twitter-based expected inflation, two lags of inflation and industrial production index gap and one lag of interest rate spread	Four lags of inflation, three lags of industrial production index gap, two lags of Twitter-based expected inflation and interest rate spread	Four lags of inflation and industrial production index gap and three lags of Twitter-based expected inflation and one lag of interest rate spread

Notes: 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:M9. 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.

The estimation results of the New Keynesian Phillips Curve (NKPC) model suggest that both backward-looking and forward-looking components play a role in 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 economy. The hypothesis that the two components are equal ($\gamma_b = \gamma_f$) is 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 are not perfectly formed, and the Phillips Curve is not vertical in the long run (Wardhono et al., 2021).

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. In addition to inflation expectations, Koc et al., (2021) emphasized the importance of economic activity (changes in demand), exchange rate pass-through, import price pass-through in Türkiye and showed their effects on inflation formation. However, what we wanted to reveal in our study was to show the formation of expectations based on Twitter and to represent this as a variable of future expectations. Thus, this study introduced a key innovation in the NKPC literature by incorporating Twitter-based inflation expectations (TWT) as a forward-looking component instead of relying on traditional rational expectations or survey-based measures.

Our results show that TWT-based inflation expectations are statistically significant across all models, though its influence is weaker than the backward-looking component. This suggests that Twitter-based inflation sentiment does play a role in expectation formation, but past inflation remains the dominant driver. This result aligns with Agénor and Bayraktar (2010) and Eruygur (2011), showing an inflation persistence in Türkiye.

The output gap is positive in all models but insignificant except for the 4th model. In the 4th model, it is at 5% significance level with a coefficient of 0.001. According to our results, although we can say that the effect of the output gap is positive, we cannot talk about a significant and strong effect.

To assess the validity of the instrumental variables used in estimating the closed-economy New Keynesian Phillips Curve, we conduct Hansen's J-test for overidentifying restrictions Hansen (1982). The p-values for Hansen's J-statistic are reported in the table, 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. The J-statistics for models M1, M2, M3, and M4 are 3.653383, 2.903622, 9.766330, and 10.24128, respectively, with corresponding p-values of 0.599569, 0.820842, 0.281811, and 0.331308. 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., γb and γf. If the coefficient on lagged inflation is relatively high, it 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. Putting it them together, we can say that 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 indicate that money neutrality does not hold in Türkiye because inflation expectations are not perfectly formed and the Phillips curve is not vertical in the long run. As Sargent and Wallace (1975) argue that if expectations were perfectly rational, the money supply would not affect real output and active monetary policy would be invalid, but this is not the case in Türkiye. Thus, it can be said that active monetary policy is possible for Türkiye.

CHAPTER V

CONCLUSIONS

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 Phillips curve model. In this model, the determinants of inflation are analyzed through 3 main variables: output gap, 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 forward-looking expectations. 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 indisputably 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 nearly all the models we employed. Even in Model 4 (M4), where a statistically significant result for the output gap was observed, its quantitative impact on inflation proved to be very minor. 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 modeling framework. This finding might reflect the prevalence of other, potentially structural, factors or supply-side shocks that dominate inflation dynamics, or it could point to limitations in how the output gap effectively captures demand pressures in this specific economic context.

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 Central Bank of the Republic of Türkiye (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 Central Bank of the Republic of Türkiye (CBRT), the central bank currently performs 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 '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.

Our study highlights that Twitter(X)'s contents, which form a core element of our investigation, exhibit 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 Central Bank of the Republic of Türkiye (CBRT), actively integrate Twitter (X) into their expectation management process. Leveraging these 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 dedicated 'Social Media and Expectation Monitoring Unit' within the central bank's institutional structure. Such a unit might systematically conduct daily sentiment analyses, 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 Phillips curve in Türkiye is not vertical in the long term, which implies that monetary neutrality does not fully hold. This means that changes in the money supply can have real effects on the economy, even in the long run. Furthermore, the fact that expectation formations are not entirely complete in Türkiye over the long term indicates that a proactive monetary policy can be effective. Considering these insights, the Central Bank of the Republic of Türkiye (CBRT) has the potential to implement a more impactful monetary policy to manage and control inflation.

One of the limitations we faced in our study was the difficulty in obtaining clear and moderate Twitter (X) data specific to our identified keyword for Türkiye before 2014. This data ambiguity led us to focus our analysis on the period from 2014 onwards. We believe that sentiment analysis studies conducted with various keywords with a deep focus or in countries with a larger user base and a longer history of Twitter (X) usage, such as the United States, might yield more comprehensive results for expectation and uncertainty analysis.

Another limitation of the study stems from the methodological constraints associated with incorporating a Twitter-based expectation variable into the New Keynesian Phillips Curve (NKPC) framework as a forward- looking component. While Angelico et al. (2022) have demonstrated that Twitter data—when processed through topic modeling (e.g., Latent Dirichlet Allocation) and future-tense filtering—can serve as a valuable source for forward-looking inflation indicators, the present study does not employ such complex methods. This is largely due to the relatively small size of the dataset used and the limited resources available for conducting a more computationally intensive analysis.

Finally, this study has profoundly demonstrated the effectiveness of Twitter in influencing economic decision-making processes within Türkiye, underscoring its role as a crucial channel for spreading information and shaping expectations, particularly regarding inflation. Given these findings, it's now vital for policymakers, investors, and economic agents 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 (X). 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. Subsequent research should further delve into the intricate connections between social media and economic phenomena, developing more sophisticated variables and indices for improved macroeconomic forecasting, expectation and risk analysis, and a better understanding of economic uncertainty. Such continued studies will undoubtedly offer fresh and essential perspectives for covering the complexities of inflation dynamics and macroeconomic uncertainties in Türkiye and the broader global economy in our increasingly digital age.

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