DYNAMICS OF POST-PANDEMIC INFLATION IN TÜRKİYE

A Master's Thesis

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To the poet Ahmet Güntan

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The Graduate School of Economics and Social Sciences
of
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by

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by Mahmut Sefa İpek

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Arts in Economics.

Refet S. Gürkaynak
Advisor

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ABSTRACT

DYNAMICS OF POST-PANDEMIC INFLATION IN TÜRKİYE

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August 2024

In the post-pandemic period, Turkish inflation increased to levels last seen in the 1990s. Both the average level and dynamics of inflation in Türkiye were different from inflation in other Emerging European countries. This study employs a six-variable Bayesian vector autoregression (BVAR) model with stochastic volatility to estimate the historical decomposition of inflation in Türkiye during the post-pandemic period. The findings suggest that this period can be divided into two distinct episodes: from November 2021 to May 2023, inflation was driven by both domestic and global factors, with domestic ones being more dominant. From June 2023 onwards, inflation accelerated entirely by domestic factors.

Keywords: Bayesian method, Inflation, Vector autoregression model, Stochastic volatility

ÖZET

TÜRKİYE'DE PANDEMİ SONRASI ENFLASYON DİNAMİKLERİ

İpek, Mahmut Sefa
Yüksek Lisans, İktisat Bölümü
Tez Danışmanı: Prof. Dr. Refet S. Gürkaynak

Ağustos 2024

Pandemi sonrası dönemde, Türkiye'deki enflasyon en son 1990'lı yıllarda görülen seviyelere yükseldi. Türkiye'deki enflasyonun hem ortalama seviyesi hem de dinamikleri, diğer Gelişen Avrupa ülkelerindeki enflasyondan farklıydı. Bu çalışma, pandemi sonrası dönemde Türkiye'deki enflasyonun tarihsel ayrışımını tahmin etmek için stokastik volatiliteye sahip altı değişkenli bir Bayesyen vektör otoregresyon (BVAR) modeli kullanmaktadır. Bulgular, bu dönemin iki farklı bölüme ayrılabileceğini göstermektedir: Kasım 2021'den Mayıs 2023'e kadar enflasyon, hem iç hem de küresel faktörler sebebiyle yükselmiş olup, iç faktörler daha baskındır. Haziran 2023'ten itibaren ise enflasyon tamamen iç faktörler sebebiyle yükselmiştir.

Anahtar Kelimeler: Bayes yöntemi, Enflasyon, Vektör otoregresyon modeli, Stokastik volatilite

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I salute my captain Ahmet Güntan, who raised me as a perseverant sailor in the turbulent ocean of life. His belief in me is a wind that fills my sails, pushing me forward to dream, to create, to build. His wisdom is a compass I always carry with me.

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Last but not least, to my family, whose love and support have meant more to me than words can express—thank you! The values you have instilled in me and the sacrifices you have made are woven into every success I achieve. This accomplishment is as much yours as it is mine.

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CHAPTER 1

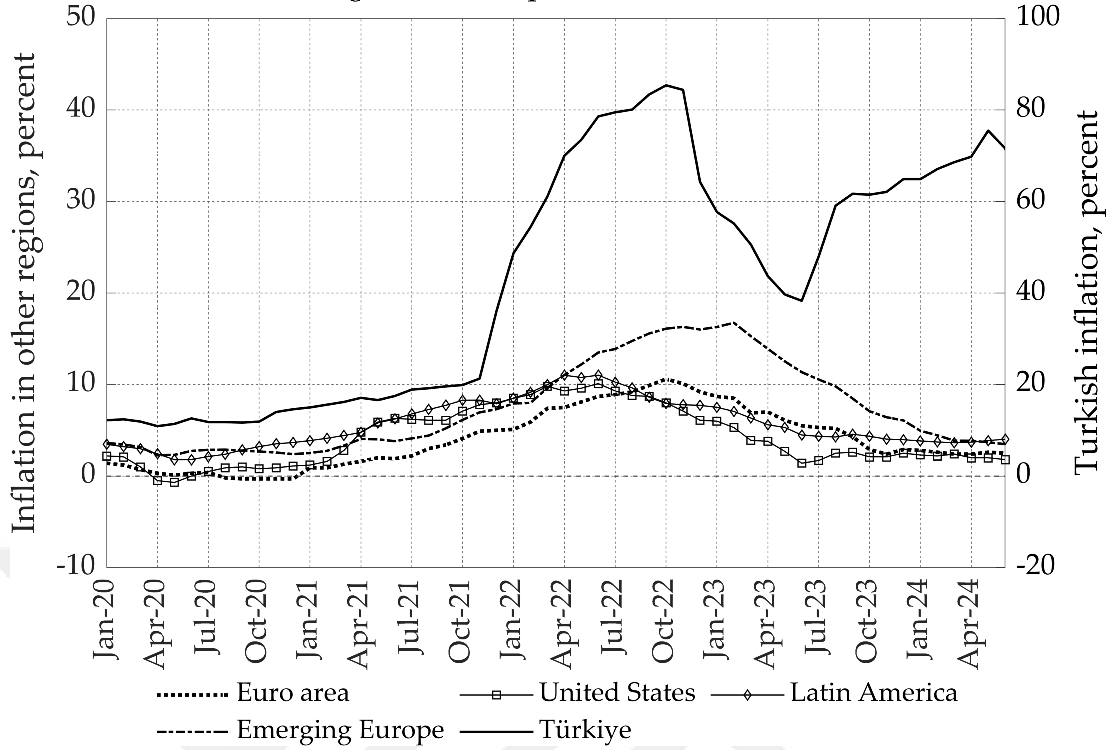
INTRODUCTION

Post-pandemic inflation emerged as a global phenomenon. Inflation rates reached historically high levels in both developed and developing economies between 2022 and 2023, prompting researchers to investigate the underlying causes and dynamics. Various explanations include commodity price shocks, supply chain disruptions (Bernanke and Blanchard, 2024; Dao et al., 2024; Gürkaynak, 2024; Medina and Wlasiuk, 2024), large fiscal expansions (Bianchi et al., 2023), and excessive markups (Weber and Wasner, 2023).

Turkish inflation also surged in this period. However, its timing and magnitude diverged from global trends, as Figure 1 shows. Turkish inflation, already elevated before the pandemic, began to climb parallel to the worldwide post-pandemic inflation. But, at the end of 2021, it started accelerating suddenly unlike in other economies. Also, its reacceleration in mid-2023 is dissimilar to other post-pandemic inflation patterns in the world. These distinct characteristics of inflation in Türkiye warrant a focused investigation.

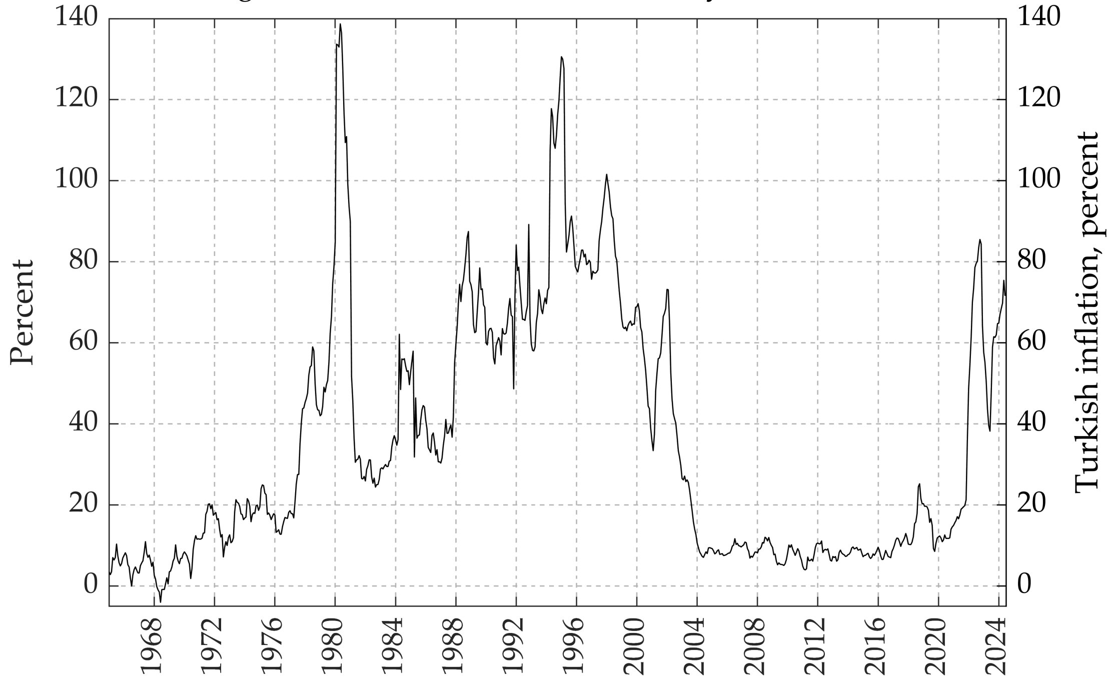
Türkiye had a challenging history of inflation that predates the Covid-19 pandemic, as Figure 2 shows. Following a period of high and volatile inflation in the 1990s, a stabilization program was initiated in 2002, leading to a sharp decrease in inflation, which mostly remained below ten percent. This era of stability persisted until 2017, after which the annual inflation rate rarely

Figure 1: Post-pandemic inflation



Note: The last observation is from June 2024. The right axis is for Turkish inflation; the left axis is for inflation in other regions. Emerging European and Latin American inflation rates are GDP-weighted averages (Table A.1 lists included countries). Sources: Eurostat, national statistics offices, and central banks.

Figure 2: Annual inflation in Türkiye (1965-2024)



Note: The period covered is from January 1965 to June 2024. Source: Turkstat returned to the single digits. Instead, it has approached three digits in the post-pandemic era. Towards the end of 2022, inflation decreased by forty percentage points before climbing again in mid-2023. This study aims to understand the drivers of these recent aggregate price movements by estimating historical decompositions. These allow for distinguishing the primary drivers of inflation from transmission mechanisms and identifying their relative importance over time. Policy implications follow naturally.

I build on the recent literature that estimates historical decompositions to study inflation dynamics during the post-pandemic period. For instance, Bernanke and Blanchard (2023), henceforth BB, decompose post-pandemic inflation in the U.S. using a linear structural vector autoregression (SVAR) identified by Cholesky factorization. Their findings suggest that commodity price shocks and supply constraints mainly drove post-pandemic inflation, noting that inflation from tight labor markets is more persistent, implying that price stability requires ensuring a more balanced labor market. In a follow-up paper, they argue that inflation dynamics in the U.K., Japan, Canada, the euro area, and its key countries are similar (Bernanke and Blanchard, 2024). However, their model does not quite explain the Turkish case, suggesting that inflation dynamics in Türkiye were fundamentally different.

First, wage levels in Türkiye are primarily determined by government decisions rather than labor market slackness, as detailed in Section 2.3. Second, exchange rates play a critical role in Turkish inflation dynamics, as elaborated in Section 2.1. Third, while inflation expectations serve only as a transmission mechanism in the BB analysis, their nonlinear response to macroeconomic developments in Türkiye, as shown by Gülşen and Kara (2021), causes the inflation expectation variable to be a shock itself. Additionally, the BB model may not fully capture the time-varying nature of Turkish inflationary pressures discussed by Kara et al. (2017), Koç et al. (2021), and Gülşen and Kara (2021).

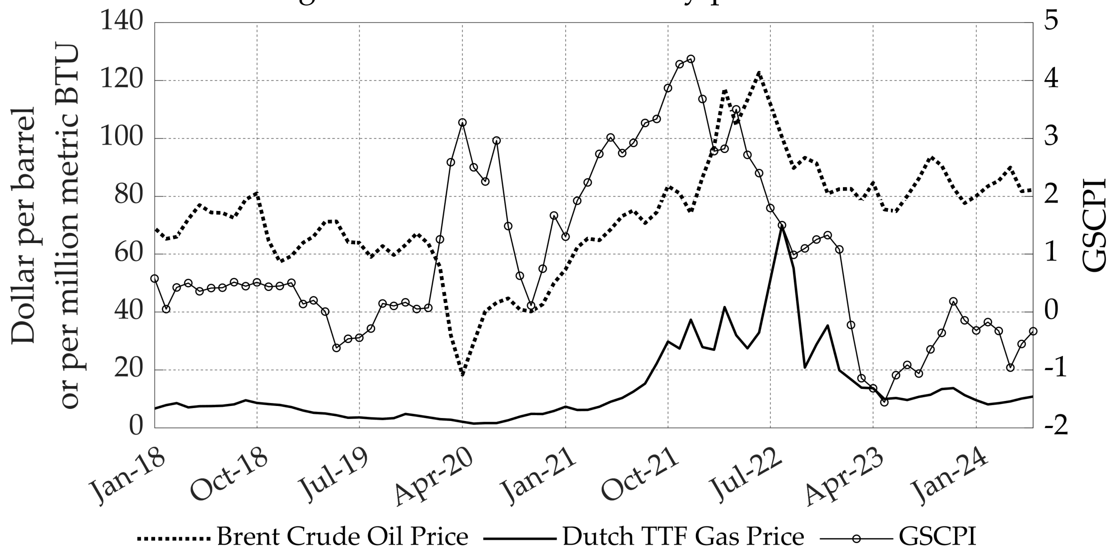
Also, Bańbura et al. (2023) estimate historical decompositions of euro area inflation in the post-pandemic era, proposing a Bayesian VAR model identified by sign restrictions. Their findings indicate that the majority of core and services inflation in the euro area after 2021 was driven by supply-side shocks, particularly supply bottlenecks and energy price increases, with gas prices playing a significant role. The identification strategy and the Bayesian approach employed in their analysis serve as a methodological starting point for my investigation of Turkish inflation, which will be discussed in Section 3.2.

My analysis is also related to the studies of the high inflation in Türkiye. Gürkaynak et al. (2015) and Gürkaynak et al. (2023) argue that high inflation in Türkiye until 2021Q3 was chiefly driven by weak monetary policy. They find that the weak response of the central bank to inflation, pushed the exchange rate upward non-linearly and, hence, Turkish prices to excessive levels. However, their sample period ends at the onset of the global energy crisis while supply chain pressures were elevated.

The commodity prices and the supply chain pressures due to the pandemic were indeed surging at the time, as Figure 3 displays. As imports account for 6 to 7 % of Turkish households' consumption (see Table A.2) and Turkish production heavily relies on imports (Erduman et al., 2020), these global factors may have inflated the prices in Türkiye. It raises the question of how much Turkish inflation is attributable to these global factors versus domestic factors such as monetary policy, which historical decompositions can help answer.

Lastly, the Minister of Treasury and Finance's statements about the minimum wage started a discussion about whether these increases have any inflationary effect, as documented in Adal (2024). Yeldan et al. (2023) oppose the minister's statement by arguing that excessive corporate profits are responsible for surging prices in Türkiye rather than wages. Historical decompositions

Figure 3: External inflationary pressures



Note: The last observation is from June 2024. Source: FRED, NY Fed

can also show whether minimum wage increases or idiosyncratic price shocks triggered inflation and, if so, the extent of the effect.

This study presents a six-variable Bayesian VAR(12) model with stochastic volatility exercise, identified with sign restrictions. Estimated historical decompositions indicate that post-pandemic inflation in Türkiye has two distinct episodes. Between November 2021 and May 2023, exchange rate shocks, deanchored inflation expectations, and import prices caused excessive inflation in that period. The relative slowdown towards the end of this episode was due to the controlled exchange rate and mitigated inflation expectations. In the second episode, beginning in June 2023, the drivers of reaccelerated inflation, the exchange rate, and real wages are purely domestic, and they are accompanied by non-increasing contributions from import prices.

CHAPTER 2

VARIABLE SELECTION

This chapter discusses the information set that the BVAR works with. It is in the spirit of BB, but the Turkish case needs some deviations from the standard applications. The variables included are exchange rates, wages, consumer credit interest rates, inflation expectations, and import prices. Additionally, the chapter includes a digression on the inflation series to assess the reliability of inflation measures.

2.1 Exchange rate

The exchange rate pass-through is a significant mechanism in the inflation dynamics of Türkiye, as Kara and Sarıkaya (2021) discuss. One way in which exchange rate increases spill over into inflation is through the cost of imported inputs in production. When the exchange rate depreciates, production costs in Türkiye rise, particularly due to the country's high energy dependency rate of approximately 70 percent (see Figure A.3). Furthermore, the exchange rate spillover on inflation also works through inflation expectations. Gülşen and Kara (2021) verify this by documenting that the most prominent indicator that forms the inflation expectations of the CBRT survey respondents is the exchange rate depreciation. Thus, unlike other decompositions of recent inflationary episodes, I include the exchange rate in the analysis.

Incorporating the exchange rate as not only a transmission variable but also a source of shocks is justified, to begin with, because the CBRT has frequently and irregularly intervened in the foreign exchange market in recent years to prevent extreme depreciation of the Turkish lira. As shown in Figure 4, the CBRT has extensively and sporadically utilized international reserves, particularly after 2018. These foreign exchange interventions reflect a crucial aspect of the CBRT monetary policy stance, thereby legitimizing the inclusion of exchange rates as a source of shocks in the analysis.

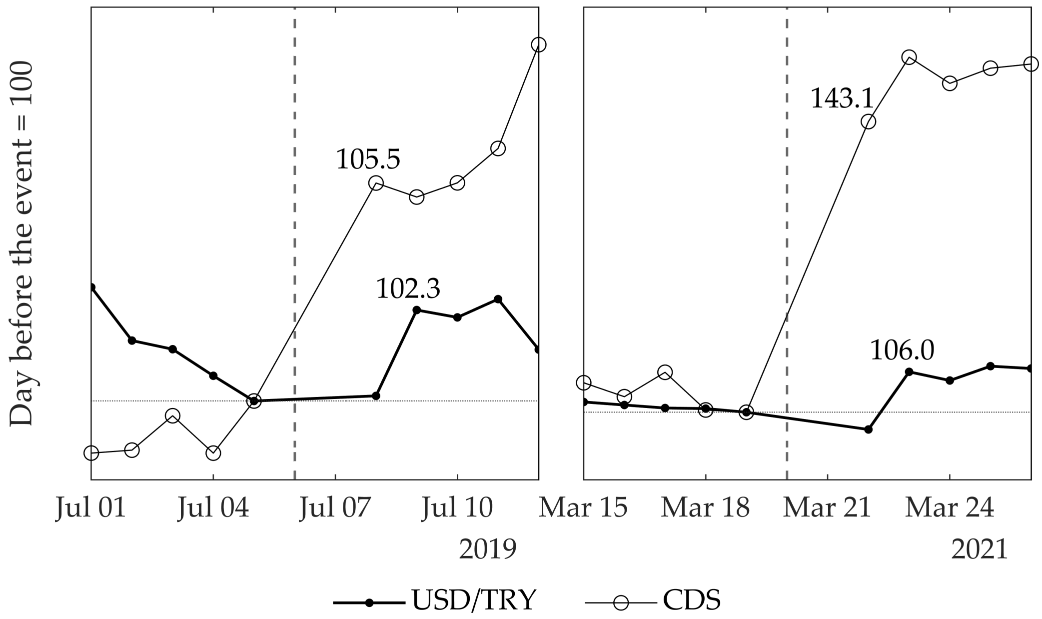
Figure 4: CBRT net foreign exchange reserves

Note: The last observation is from June 2024. This measure is also net of off-sheet liabilities such as swaps. Source: EVDS

Secondly, exchange rate shocks can convey the impact of shocks originating from monetary policy events, which cannot be fully captured by using the policy rate alone. This limitation arises, to begin with, due to frequent changes in the policy rule, such as the appointment of five different CBRT chairs and four policy regime shifts over the past five years.

Further, some non-policy events are essential for monetary policy stance and are not reflected in the policy rate. Notably, two chairs were unexpectedly dismissed on July 6, 2019, and March 20, 2021, due to their hawkish stances on interest rates. The latter dismissal followed a 200 basis point increase in policy rates on March 19, 2021. If one were to rely solely on policy rates to represent the monetary policy stance, these events might appear as either ineffective or indicative of tightening. However, these events triggered significant increases in the risk premium and, consequently, in the exchange rate, as Figure 5 shows. Thus, exchange rate shocks capture a distinct dimension of monetary policy events.

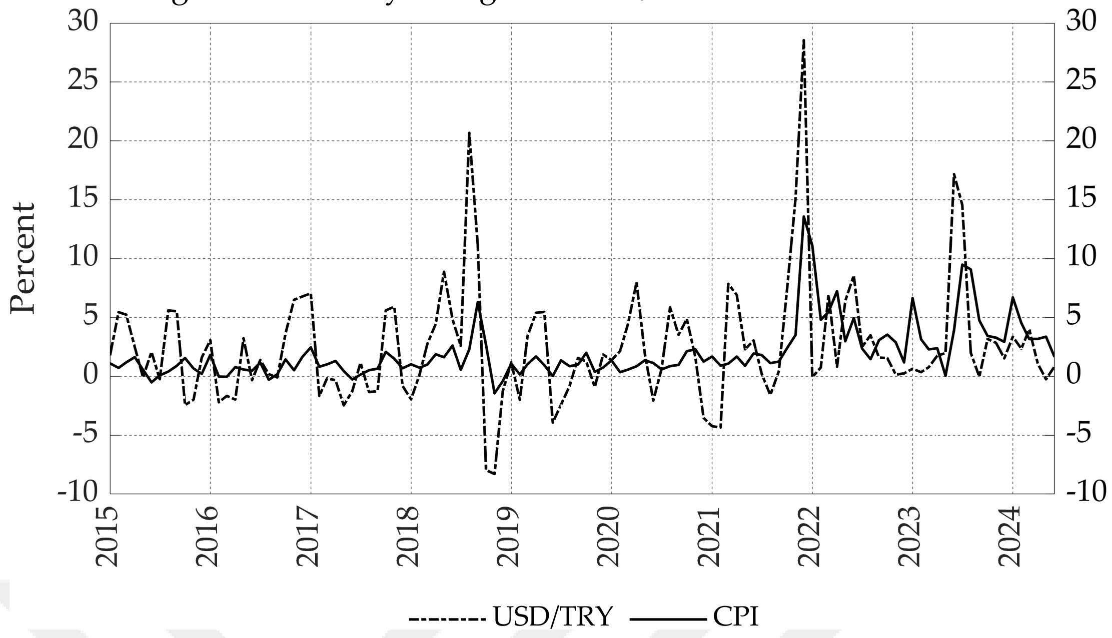
Figure 5: Non-policy events, CDS spreads, USD/TRY exchange rate



Note: Dots represent daily USD/TRY exchange rates, circles represent daily CDS spreads for 5-year Turkish government bonds, and vertical dashed lines indicate event days. All series are normalized to 100 the day before each event. Y-axes are omitted for brevity. Weekend data are excluded. Source: EVDS, Bloomberg.

Incorporating the exchange rate as a variable in the VAR system necessitates the use of monthly data. This requirement arises because exchange rate shocks impact inflation within a single quarter. For example, the significant fluctuations in the USD/TRY exchange rate in August 2018, December 2021, and June 2023, as depicted in Figure 6, demonstrate that the exchange rate pass-through to inflation generally occurs with a one- or two-month lag. Therefore, using monthly data is essential to capture the interdependencies more accurately.

Figure 6: Monthly changes in USD/TRY and CPI inflation



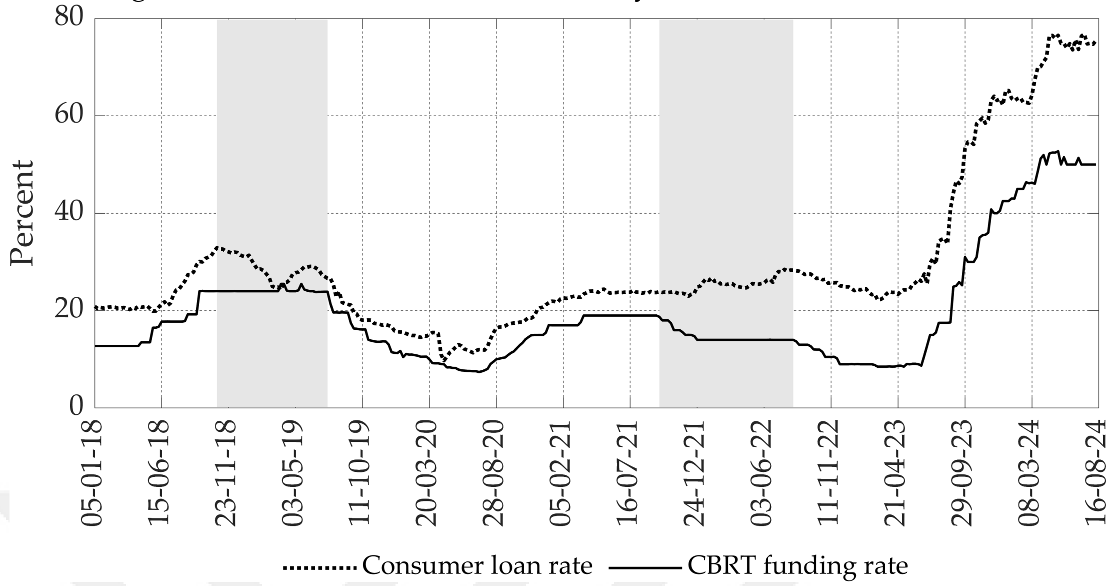
Note: The last observation is from June 2024. Source: EVDS

2.2 Consumer loan rates

Interest rates of consumer credits capture another aspect of the monetary policy stance. Gürkaynak et al. (2023) presents a comprehensive discussion of the anomalies involving how CBRT policy rates do not transmit to the credit interest rates usually, which Figure 7 demonstrates in some periods. Specifically, the consumer loan rates increased even after consecutive cuts to the CBRT funding rate between September 2021 and August 2022, a period when inflation in Türkiye diverged sharply from global trends. This discrepancy renders the policy rate less useful for analysis. Instead, ex-ante real consumer credit interest rates are more directly linked to aggregate demand. As loans become perceived as cheaper, consumers are likely to increase their spending, thereby boosting aggregate demand and, in turn, raising the inflation rate.

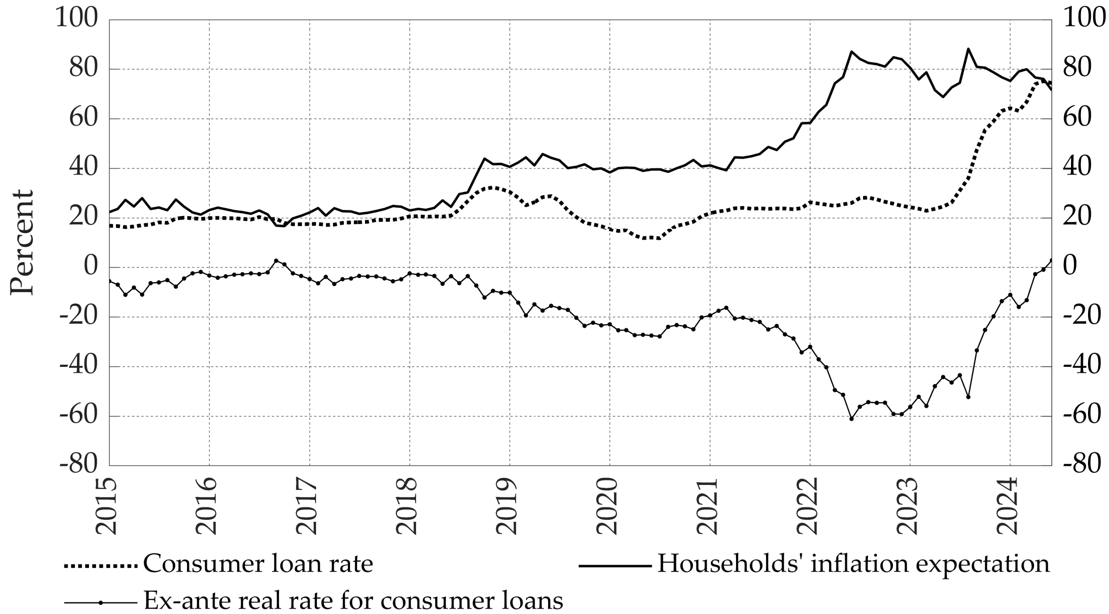
Indeed, as shown in Figure 8, the ex-ante real rates for consumer loans, which were already negative, declined further to minus 60 percent. This sharp decline may have led to a surge in borrowing, which, in turn, could have driven prices

Figure 7: Breakdowns in the monetary transmission mechanism



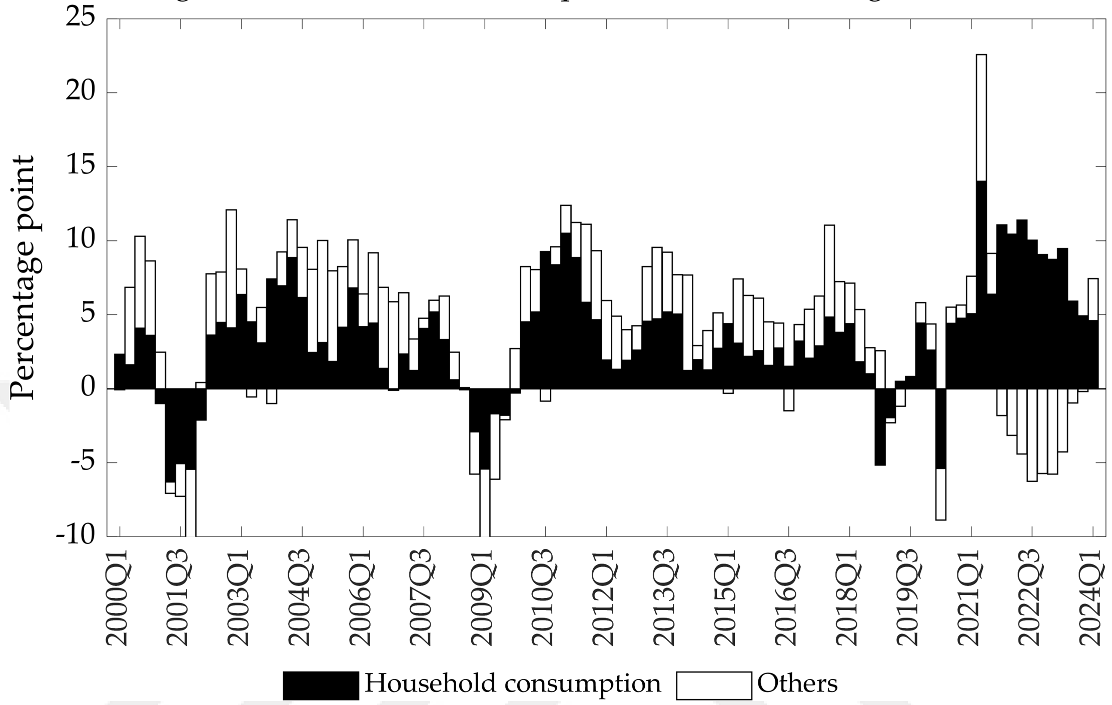
Note: During the periods highlighted by gray bands, the two interest rates do not exhibit their usual correlation. The time series frequency is weekly, with the date format on the x-axis set to dd-mm-yy. Source: EVDS

Figure 8: Consumer loan rate and households' inflation expectation



Note: The last observation is from June 2024. The dashed line shows the weighted average of personal, vehicle, and housing credits. Source: EVDS upward by boosting aggregate demand. Additionally, recent GDP growth has been almost entirely driven by consumption, as illustrated in Figure 9, further supporting this hypothesis.

Figure 9: Household consumption in annual GDP growth



Note: "Others" is calculated as the annual GDP growth minus the contribution of household consumption. Source: Eurostat.

To incorporate this variable into the analysis, I calculate ex-ante real consumer loan rates by subtracting household inflation expectations (see Section 2.4) from nominal consumer loan rates.

2.3 Wages

This section explains the rationale for excluding vacancy/unemployment from the analysis, deviating from the BB model. It also discusses the use of minimum wage changes as a proxy for general wage level changes and why these changes are considered inflationary pressures.

Turkish inflation debates often do not focus on labor market tightness to the same extent as it does in the U.S., as Bernanke and Blanchard (2023) discuss.

Instead, the subject of inflation discussions in Türkiye is whether increases in the minimum wage contribute to inflation. This difference stems from how wage levels are determined in Türkiye.

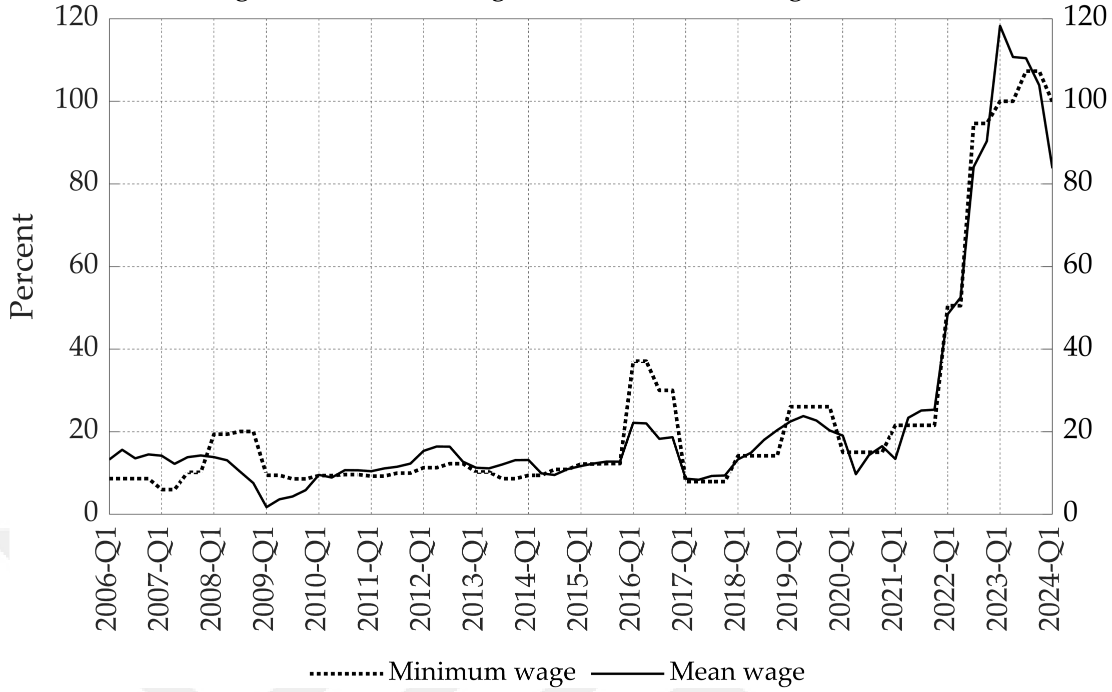
The Turkish government sets the minimum wage at the end of each year and occasionally revises it mid-year, as was the case in July 2022 and 2023. With 55 percent of Turkish employees earning either the minimum wage or within 20 percent of it (DİSK-AR, 2024), decisions regarding the minimum wage have a significant impact on the overall wage level in the country.

Based on the BB methodology, we can test whether labor market dynamics influence wage determination by using vacancy/unemployment rates as indicators of labor market tightness, which could lead to wage inflation. I use monthly job vacancy data from İŞKUR, averaged quarterly, and unemployment data from Turkstat for the regression analysis. Additionally, I select GDP per hour worked from Eurostat as the productivity measure. Table 1 shows that the vacancy/unemployment variable is not a statistically significant predictor of wage level changes.

Note that the explanatory power of the regression is substantially lower when we exclude the period from 2022Q1 to 2024Q1, likely due to the confounding effects of high inflation on wage levels and inflation expectations during that time. Regardless, we can conclude that labor market conditions do not determine the wage level in Türkiye.

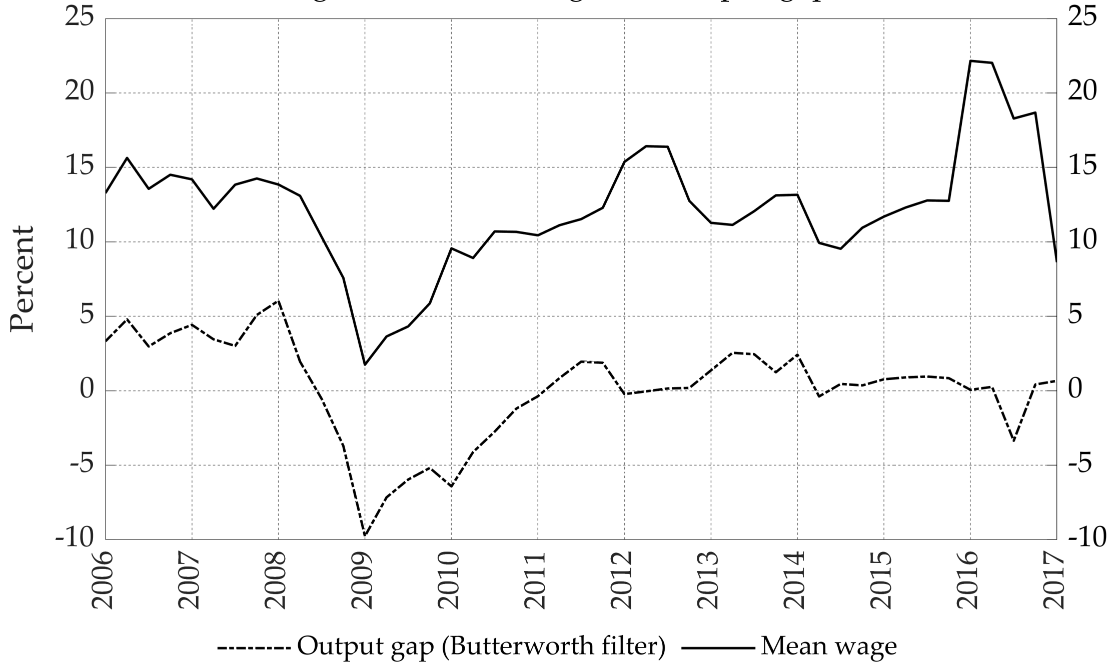
Instead, in 2015-2024, minimum wage and mean wage increases have been strongly correlated, as shown in Figure 10. Before 2015, the mean wage did not follow changes in the minimum wage but was instead largely pro-cyclical, as illustrated in Figure 11. This pattern is consistent with the findings of Aldan and Gürcihan-Yüncüler (2016), who explain that real wages in Türkiye, apart from the acyclical minimum wages, were highly pro-cyclical from 2006 to 2015.

Figure 10: Mean wage and minimum wage raises



Note: Mean wage is the compensation of employees in GDP by income approach divided by the number of employed persons. Source: Ministry of Labor and Social Security, EVDS

Figure 11: Mean wage and output gap



Note: Mean wage is the compensation of employees in GDP by income approach divided by the number of employed persons. The output gap is calculated using the Butterworth filter following Ipek and Kısacıkoğlu (2024) Source: EVDS

Table 1: BB's wage regression with Turkish data

	Sample period	
	2009Q2-2024Q1	2009Q2-2021Q4
Dependent variable:	w_t	w_t
w_{t-1}	-0.80***	-0.22*
	(0.09)	(0.10)
$\mathrm{v}u_{t-1}$	0.80	0.43
	(0.65)	(0.52)
π^e_{t-1}	0.02***	0.01*
	(0.00)	(0.00)
$prod_{t-1}$	0.04	0.07
	(0.10)	(0.05)
c	-0.09	-0.06
	(0.16)	(0.07)
R^2	0.83	0.20
Observations	60	51

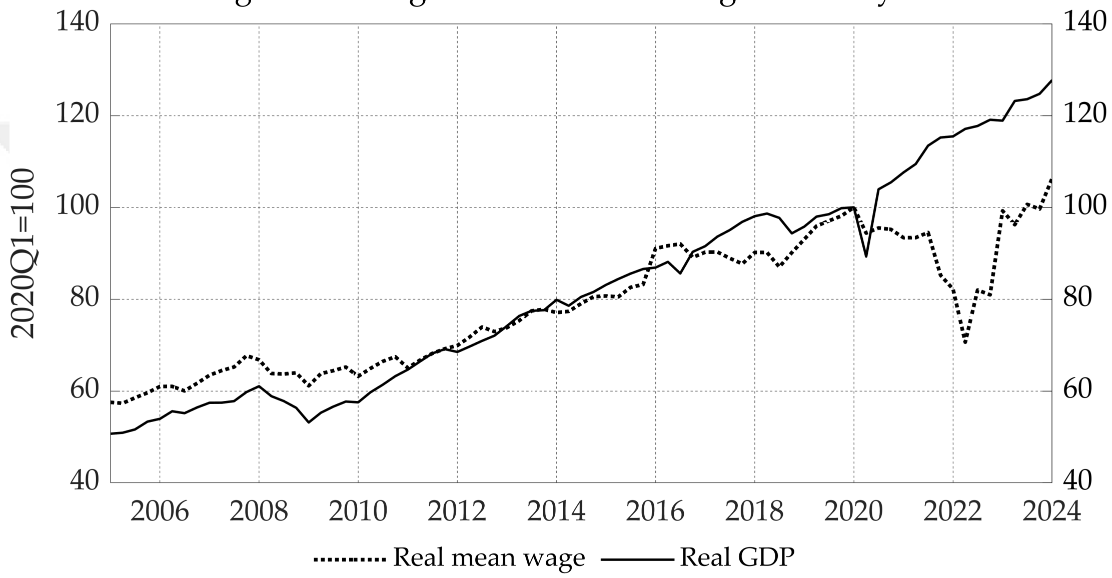
Note: The dependent variable w_t in the regression in Table 1 represents the change in the mean wage of a worker, calculated as the compensation of employees in GDP by the income approach, divided by the number of employed persons. See Table A.3 for a description of the data. Standard errors are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hence, minimum wage changes serve as a proxy for mean wage changes, and 2015 marks a structural break for an analysis involving wages, as in this study.

The question remains whether increases in the minimum wage significantly impact inflation. Yüncüler and Öğünç (2015) found that wages account for 33.3 percent of total costs in the service sector and 23.6 percent in the total non-farm sectors. Consequently, when wages rise, the resulting increase in total production costs is substantial. This finding leads me to hypothesize that wage increases contribute to inflationary pressures.

Furthermore, Figure 12 illustrates the trend in real wage levels. Real wages declined sharply after the pandemic, reflecting the contraction in real GDP. However, while real GDP eventually returned to its pre-pandemic trend, real wages continued to decline before experiencing a rapid recovery toward pre-pandemic levels. This sharp rebound may have contributed to rising consumer prices by increasing both aggregate demand and production costs. Therefore, it is essential to include real wages in the analysis to assess whether the recovery in wages, following a prolonged decline, played a role in driving price increases from 2022 onwards. As the minimum wage is a proxy for the mean wage, the real minimum wage changes, which I am incorporating into the analysis, can also approximate the real mean wage changes.

Figure 12: Progress of real mean wage in Türkiye



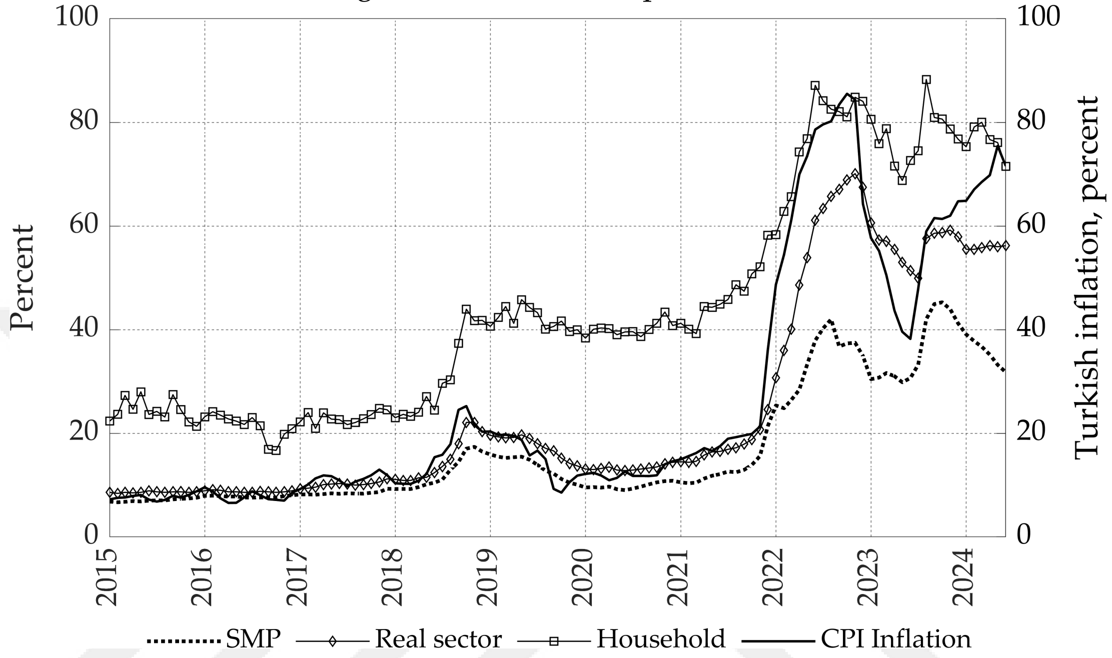
Note: The sample period is 2005Q1-2024Q1. The real mean wage is deflated with the GDP deflator. Both variables are indexed with the base 2020Q1=100. Source: EVDS, Eurostat

2.4 Inflation expectations

As in the New Keynesian model (Clarida et al., 1999), forward-looking firms set prices based on anticipated future marginal costs. In the Turkish context, Gülşen and Kara (2021) and Koç et al. (2021) emphasize that inflation expectations are crucial for understanding Turkish inflation dynamics. Both studies demonstrate the nonlinear relationship between expectations and variables such as inflation and exchange rates. Specifically, inflation expectations respond more strongly to inflationary shocks when the shock is larger, as seen, e.g., during the exchange rate shock in August 2018 (Koç et al., 2021).

CBRT surveys various economic agents monthly: Selected market participants (mainly from the financial sector), real sector, and households. The bank only recently started to publish the last two, which differ remarkably from the expectations in the Survey of Market Participants (SMP), as Figure 13 shows.

Figure 13: Inflation expectations



Note: The last observation is from June 2024. Source: EVDS

Household expectations have consistently been higher and more volatile than those of other groups. Additionally, market participants and the real sector only began to diverge at the end of 2021, a period marked by a sharp increase in the exchange rate and annual inflation rate. Respondents of the Survey of Market Participants (SMP), primarily drawn from the financial sector, appear more optimistic compared to those in the real sector. Furthermore, since the introduction of the new policy framework aimed at disinflation in June 2023, SMP respondents have shown greater confidence in the program, while inflation expectations in the real sector have remained more rigid.

For the main results, I choose real sector inflation expectations as they are price setters, but I also present the results using inflation expectations from

SMP.[1] Lastly, I will take the first difference of the inflation expectation series to make the series stationary (see ADF test results in Table A.4).

2.5 Import prices

Increasing supply chain pressures and energy prices characterize the post-pandemic era. Figure 14 demonstrates how prices Turkish importers face and global supply chain pressures climbed in this period. Following Erduman et al. (2020)'s finding that imported inputs comprise 18 percent of production in Türkiye, and Türkiye's energy import dependency being about 70 percent (see Figure A.3), I hypothesize that the global cost-push shocks might have spilled over to Turkish prices.

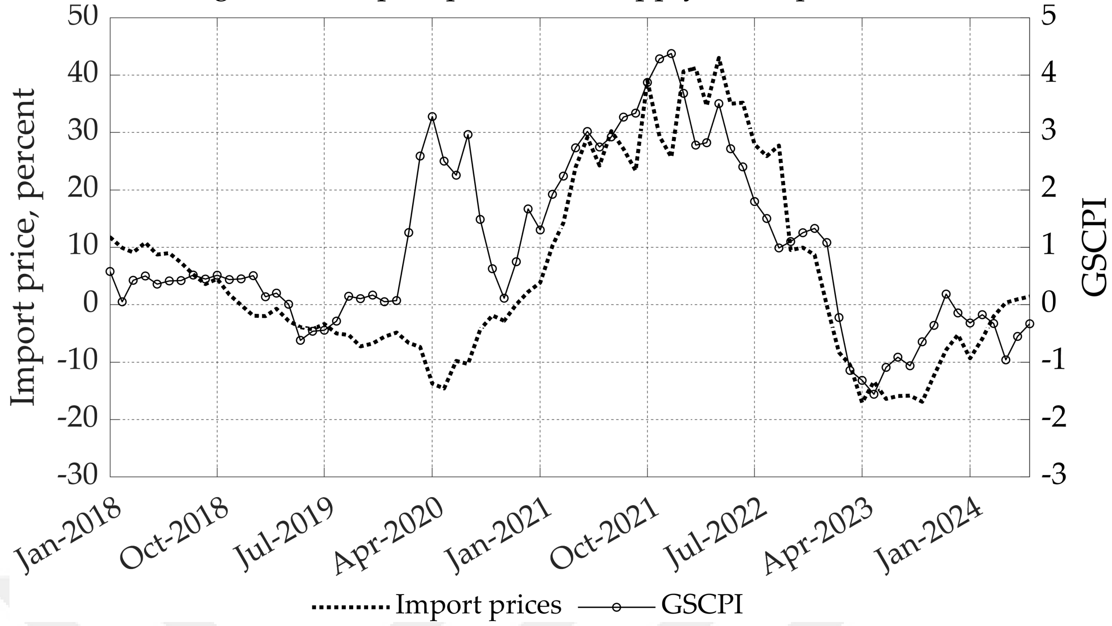
The overall import prices are the transmission channel of supply chain disruptions and it involves imported energy prices. Indeed, Figures 3 and 14 show that import prices, global energy prices, and supply chain pressures highly correlate. Thus, incorporating overall import prices into the analysis would be plausible. To that end, I use the import unit value index that Turkstat calculates, covering the cost, insurance, and freight (CIF) of the imported goods.

2.6 Digression: Inflation series

An analysis of inflation requires reliable measures of inflation. In this section, I examine the reliability of the official inflation series since concerns have been raised about whether Turkstat may understate inflation rates (e.g., Yılmaz, 2024). To evaluate these concerns, I calculate inflation from Turkstat's granular data and compare Turkstat's inflation rates to alternative measures.

[1] Household expectations are indirectly incorporated into the analysis by subtracting them from consumer loan rates as described in Section 2.2

Figure 14: Import prices and supply chain pressures



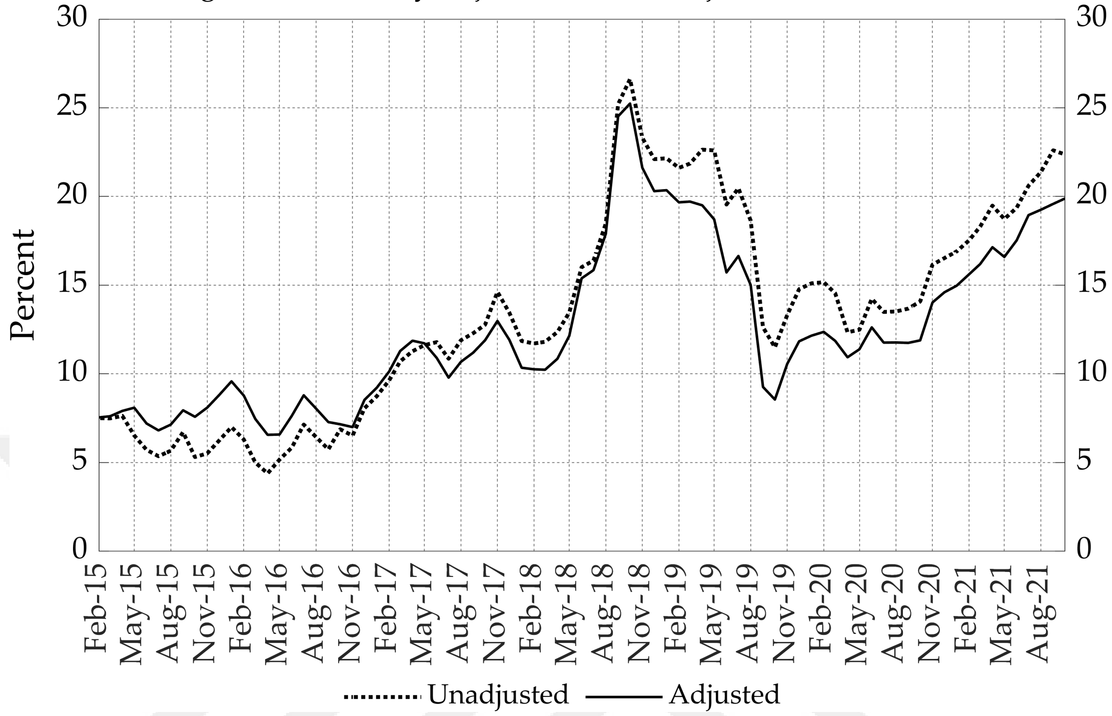
Note: Import price changes are calculated from the Import Unit Value Index, which reflects prices in the U.S. dollar. Source: Turkstat and NY Fed

Like other statistical institutes, Turkstat adjusts collected prices to account for changes in the quality of items. For instance, if a car undergoes technological improvements and its price rises accordingly, this increase is not considered inflation by the institute. This process, known as quality adjustment, is not publicly disclosed because it involves sensitive information about specific brands being tracked, and revealing this information could compromise the accuracy of price monitoring. Nonetheless, the granular data on item prices and weights in the consumption basket enable independent researchers to calculate a quality-unadjusted version of the price index using the Laspeyres method:

$$P_t = \frac{\sum_{i=1}^{n} p_{i,t} q_{i,0}}{\sum_{i=1}^{n} p_{i,0} q_{i,0}} \times 100 \tag{2.1}$$

In Equation 2.1, $p_{i,t}$ denotes the price of an item i at time t, and $q_{i,0}$ stands for the item i's weight in the consumption basket at the base period $t = 0$. Using this formula, one can calculate P_t, the price index in t, and subsequently derive the inflation rate to compare with the official inflation rate. Figure 15 presents the discrepancies between the growth rates of P_t and Turkstat's CPI inflation.

Figure 15: Quality adjusted and unadjusted CPI series



Source: Turkstat

While we should not expect the two indices to always align perfectly due to quality adjustments, unpublished imputations of seasonal item prices and other quality-related factors also create discrepancies between calculated and published indices (Turkstat Metadata). These discrepancies should generally follow a pattern or remain constant over time. Moreover, most quality adjustments should be offset by quantity adjustments (e.g., smaller packages of higher quality goods), as shown by Menz et al. (2023) in the euro area context. However, since August 2018, the discrepancies have consistently been positive, supporting concerns about potentially understated inflation figures.

Further examination of the expenditure groups suggests that imputations or factors beyond quality adjustments cannot fully explain the observed discrepancies, as these influences would typically appear consistently over time. Figure 16 illustrates the discrepancies between the calculated and published indices for the total CPI and specific sub-expenditure groups, such as clothing and electricity, gas, and other fuels. Notably, there were substantial discrepancies in April 2019 and September 2021, highlighted by the gray bars.

The second method for assessing the robustness of Turkstat's CPI is by comparing it with alternative price level measures. Two such measures are the GDP deflator, calculated by Turkstat, and the Cost of Living Index (CLI) for wage earners, compiled by the Istanbul Chamber of Commerce (ICOC). Figure 17a compares the annual growth rates of the GDP deflator and the CPI. Since the GDP deflator weighs consumption items differently from the CPI basket, some differences between the two series were observed between 2006Q2 and 2020Q2, although these differences generally hovered around zero. However, after 2020Q2, the discrepancy became consistently positive and significantly larger.

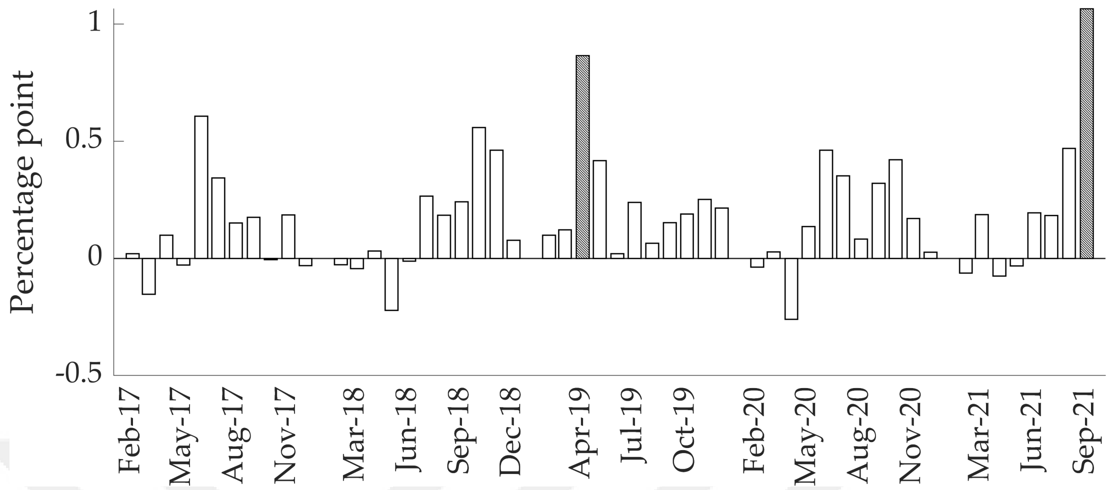
Similarly, the CLI inflation closely tracked Turkstat's inflation measure until March 2022, when annual inflation surpassed 60 percent, as shown in Figure 17b. After this point, the two measures began to diverge[2]. While the consumption baskets used in the ICOC Cost of Living Index and GDP deflator may not be as comprehensive or consumption-weighted as Turkstat's, the distinct breaks in alignment during certain periods are problematic concerning the reliability of the CPI.

For the main results, I use CLI for wage earners calculated by ICOC, considering the pieces of evidence presented above and the frequency of selected variables.

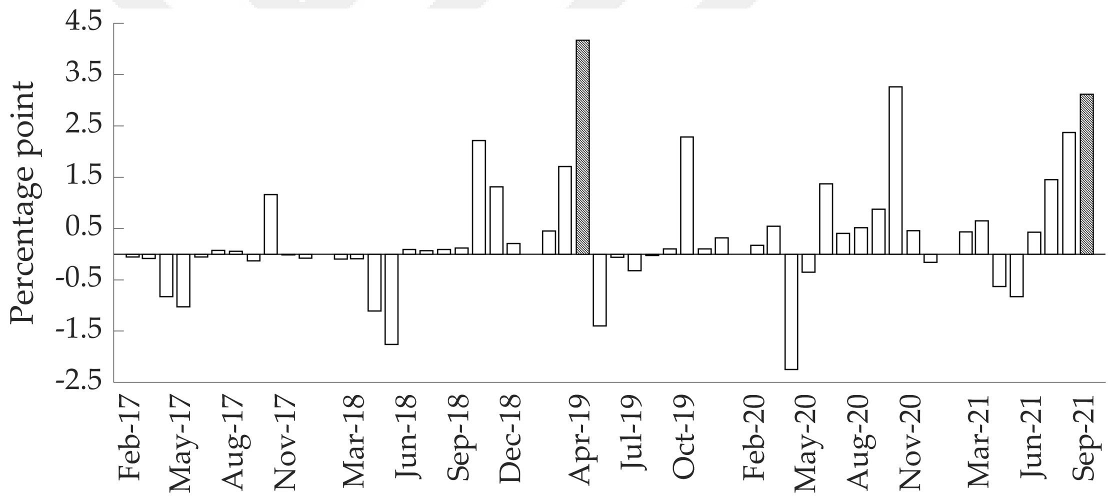
[2]See Figure A.2 in the appendix for the discrepancy in monthly changes.

Figure 16: Discrepancy in expenditure groups

(a) Discrepancy in total CPI



(b) Discrepancy in clothing



(c) Discrepancy in electricity, gas, and other fuels

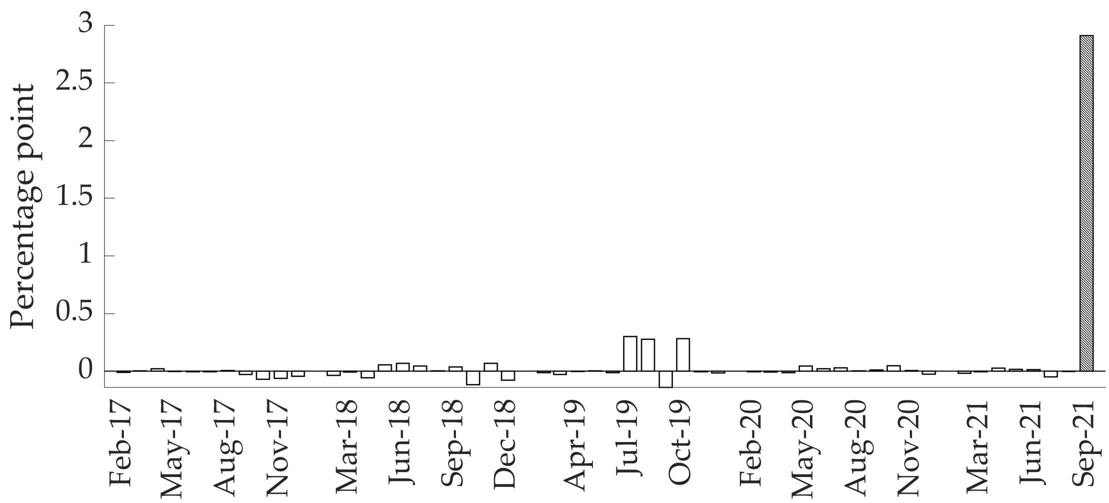
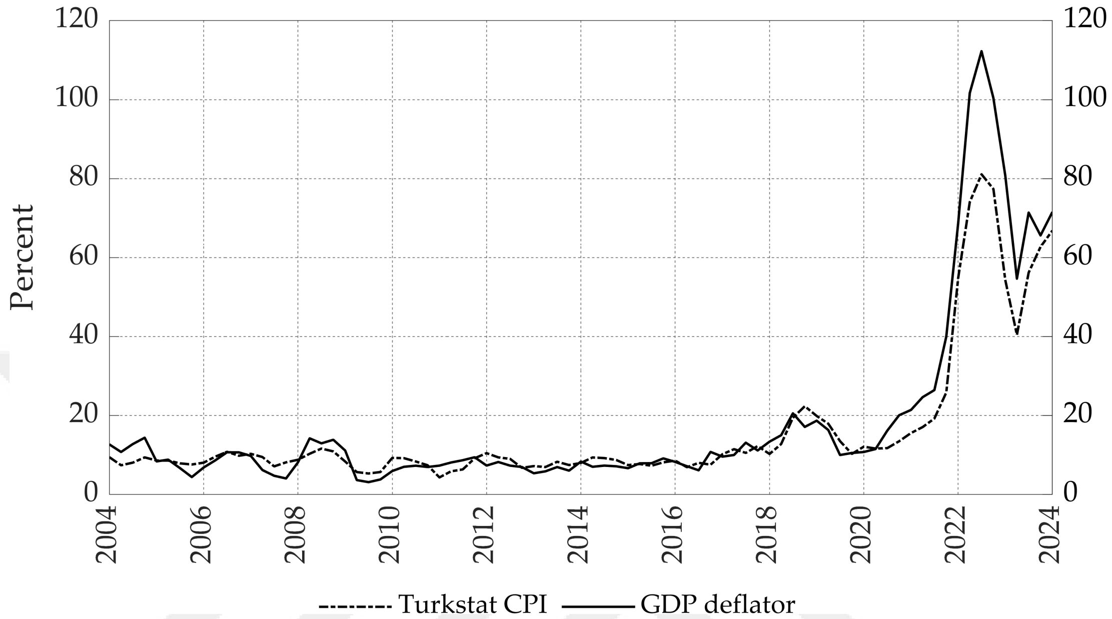
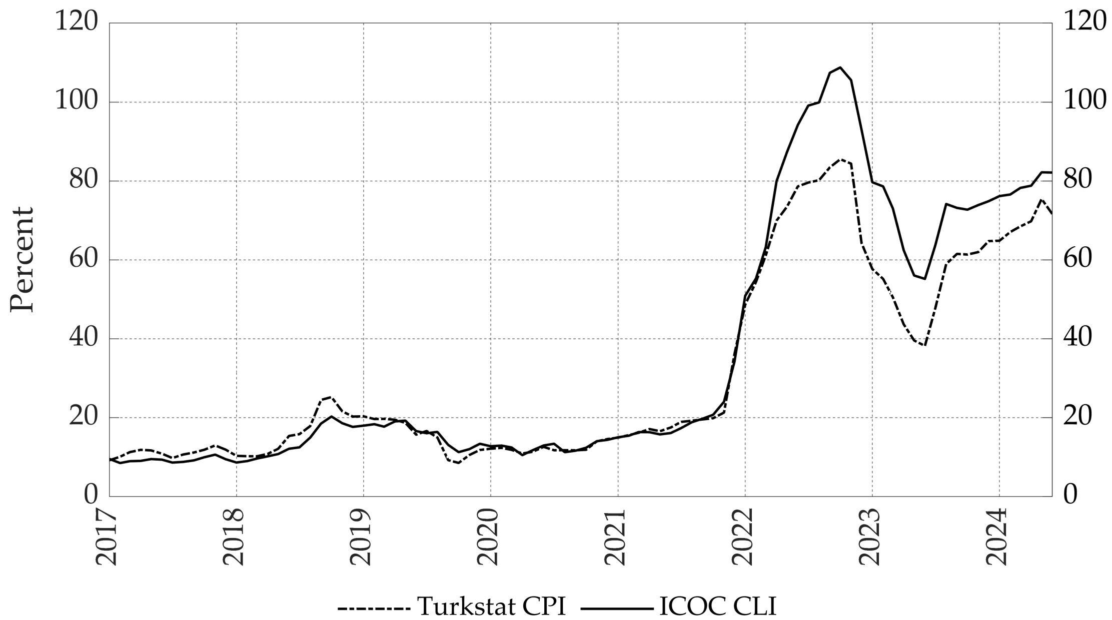


Figure 17: Discrepancy between inflation measures

(a) GDP deflator and CPI



(b) ICOC CLI and Turkstat CPI



Last observation in Panel (a) is from June 2024, and in Panel (b), it is from 2024Q1. Source: Turkstat, EVDS, Eurostat

CHAPTER 3

DATA AND METHODOLOGY

This chapter describes the data used in the analysis and the methodology of Bayesian VAR with stochastic volatility.

3.1 Data

I construct a monthly data set comprised of alternative measures of inflation and an extensive set of variables.[3] Table 2 presents the relevant descriptions.

The sample period spans February 2015 to June 2024, determined by the structural change in the real wages from being cyclical to determined by government decisions. The time series are incorporated as monthly changes into the analysis due to the fact that the augmented Dickey-Fuller test fails to reject that annual inflation series have no unit root (see Table A.4).

[3] See Table A.3 for the quarterly data set's description.

Table 2: Monthly data description

Variable	Definition
Inflation	Consumer Price Index, Turkstat
	Cost of Living Index for wage earners, ICOC
Inflation exp.	Annual inflation expectations of market participants, 12-month ahead, EVDS
	Annual inflation expectations of real sector, 12-month ahead, EVDS
	Annual inflation expectations of households, 12-month ahead, EVDS
Exchange rate	USD/TRY, average of buying and selling prices, EVDS
	Average of USD/TRY and EUR/TRY exchange rate, average of buying and selling prices, EVDS
Import prices	Foreign trade import unit value index by classification of BEC (2015=100), based on U.S. Dollar, Turkstat
Minimum wage	Net minimum wage, Ministry of Labor and Social Security
Cons. loan rates	Consumer loan, TRY, Personal + Vehicle + Housing, including real person overdraft account, flow data, EVDS

Note: All series are employed as monthly changes. Minimum wage and consumer loan rates are deflated by the Cost of Living index calculated by ICOC.

3.2 Methodology

This study employs a Bayesian vector autoregression with stochastic volatility, where structural shocks are identified using sign restrictions to estimate the historical decomposition of inflation. The model includes six variables and allows for twelve lags to capture the effects over one year in monthly data. This section provides an overview of the methodology.

Following the notation in Kilian and Lütkepohl (2017), let y_t be a vector composed of six variables, including monthly changes in inflation and in the explanatory variables mentioned in the previous chapter, whose data-generating process is approximated by the following SVAR model:

$$B_0 y_t = \nu + B_1 y_{t-1} + \ldots + B_{12} y_{t-12} + w_t \tag{3.1}$$

where B_0 captures the contemporaneous impact of each variable on the others, $B_1, \ldots, B_{12}$ are vectors of coefficients, ν is the constant term and w_t represents mutually uncorrelated white noises, namely the unobservable structural shocks. These six series of structural shocks drive the variables in y_t, with a variance-covariance matrix $\sum_w = \mathbb{E}[w_t w_t']$. The reduced-form representation of the SVAR model in Equation 3.1 can be obtained by premultiplying each side by B_0^{-1}:

$$y_t = B_0^{-1}\nu + A_1 y_{t-1} + \ldots + A_{12} y_{t-12} + u_t \tag{3.2}$$

$$\text{where } u_t = B_0^{-1} w_t \text{ and thus } \Sigma_w = B_0 \Sigma_u B_0' \tag{3.3}$$

and u_t is standard normally distributed reduced form errors and $A_i = B_0^{-1} B_i$ for $i \in \{1, \ldots, 12\}$, which is an estimable equation. To recover the structural shocks, w_t, one can impose restrictions on B_0^{-1}, which is a 6×6 matrix. Following the approach in the literature (e.g., Uhlig, 2005), B_0^{-1} can be randomly iterated and filtered using sign restrictions. Then, the structural shocks, w_t, can be extracted using Equation 3.3. Subsequently, the Wald decomposition of the VAR(12) model yields the following results.

$$y_t = w_t + \phi^1 w_{t-1} + \phi^2 w_{t-2} + \ldots + \phi^j w_{t-j} + \ldots \tag{3.4}$$

Here, $\phi^j = \frac{dy_t}{d\varepsilon_{t-j}}$ is a 6×6 matrix representing the impulse response functions, which indicate how each variable is affected over time in response to a shock. These functions are particularly crucial for my study as they serve as the primary tools for calculating how structural shocks propagate to inflation over time, effectively providing the historical decomposition of inflation. Thus, estimating these impulse response functions allows us to derive the historical decomposition, which can be expressed as:

$$\hat{y}_t = \sum_{s=0}^{t-1} \phi^s w_{t-s} \tag{3.5}$$

3.2.1 The Bayesian approach

As discussed in Kilian and Lütkepohl (2017), in the standard frequentist VAR framework, the true model parameters are assumed to be fixed but unknown, while the data are considered stochastic. Coefficients are typically estimated using ordinary least squares. In contrast, Bayesian estimation treats the data as fixed and the model parameters as stochastic. In this approach, parameters are assumed to follow a prior distribution, which is updated based on the observed data. With each new data point, the moments of the posterior distributions converge toward specific values.

The Bayesian approach to estimating my model is particularly preferable given the small sample size and the time-varying nature of the dynamics. As discussed in Section 2.3, the changes in wage dynamics from 2015 onwards leave only 113 data points to use, while the coefficient matrices B alone contain 72 parameters to estimate. Additionally, it is hard to argue that the data-generating process for the Turkish inflation time series remains constant over time, necessitating a time-varying analysis[4]. The first issue reduces the number of data points, while the second increases the number of parameters to estimate, further decreasing the degrees of freedom. A frequentist approach would not provide reliable estimates under these conditions.

Bayesian VARs mitigate this issue by expanding the information set with prior distributions for parameters, therefore increasing the efficiency of estimation despite the small sample size as exemplified in Nakata and Tonetti (2015). By the same account, adopting a Bayesian approach allows for efficiently incorporating a stochastic volatility structure into the model.

Incorporating stochastic volatility concerns Σ_u from Equation 3.3. In particular, this matrix varies over time in this framework.

$$\Sigma_u = F\Lambda_t F' \tag{3.6}$$

where F is a lower-triangular matrix from a Cholesky decomposition, and Λ_t is a diagonal matrix with time-varying variance entries that follows an autoregressive process:

$$L_t = \gamma L_{t-1} + \epsilon_t \text{ where } L_t = \log \Lambda_t \text{ and } \epsilon \sim N(0, \sigma_\epsilon) \tag{3.7}$$

The persistence parameter γ captures the inertia of the volatility of residuals. The estimation starts with $\gamma = 1$, allowing for randomness, and then updated with each new data point, such as other parameters. This framework allows

[4]Assuming a time-invariant distribution leads to unreasonable results, especially in residuals (see Figure A.1).

me to capture the different regimes in the data, where the residuals are drawn from different distributions. Hence, adopting stochastic volatility improves the estimation of impulse response functions, which is crucial for my results, as explained in the previous section.

The Bayesian approach to the estimation of VAR parameters involves several steps. Denoting the VAR parameters by B and Σ_w, the posterior distributions are obtained by applying the Bayes' rule:

$$\pi(B, \Sigma_w \mid y) \propto f(y \mid B, \Sigma_w)\pi(B)\pi(\Sigma_w) \tag{3.8}$$

It remains to substitute the likelihood function and the prior distributions for the parameters into Equation 3.8. The algorithm employed in this study uses multi-layer priors. It means that there are prior distributions for model parameters, and their moments are treated as random variables so that they also have prior distributions governed by hyperparameters. However, this hierarchical structure of priors makes an analytical solution to the model impractical to derive.

For a numerical solution, the Gibbs sampler algorithm, which is a Markov Chain Monte Carlo (MCMC) method, draws random samples from the conditional posterior distributions given the current values of all other parameters (see Casella and George, 1992, for more detail). Starting from OLS estimates of parameters, the Gibbs sampler iterates by resampling over and over from the conditional posteriors until they converge. Then, these distributions are used in the final estimation of parameters that are of interest.

Using multi-layer priors allows the model to adapt based on the data, which might seem counterintuitive or like it undermines the purpose of having a prior in Bayesian analysis. However, in the context of hierarchical priors, this approach actually aligns well with the Bayesian principles. For instance, the coefficient's posterior distributions shrink with each Bayesian update with a new data point. However, this shrinkage depends upon the prior distributions of the coefficients. Using multi-layer priors with hyperparameters allows adapting the degree of shrinkage based on data. This flexibility provides both estimating coefficients efficiently and avoiding overfitting, which could occur if priors were overly influenced by the data.

Adapting stochastic volatility and hierarchical priors frameworks, I estimate the posterior distributions by Bayesian VAR using the BEAR toolbox created by Dieppe et al. (2016), which also includes detailed derivations.

Lastly, note that $y_t \neq \hat{y}_t$ in Equation 3.5. This indicates that historical decompositions do not exactly sum to the observed data due to the nature of the Bayesian approach. Consider the Wald decomposition in Equation 3.4. In the frequentist case, the sum of contributions equals the observed value by construction because the structural shocks, w_t, are point estimates. In contrast, the Bayesian approach generates posterior distributions for w_t, and historical decompositions are typically calculated using the medians of these posteriors. Consequently, depending on the skewness and variance of the posteriors, the sum of contributions may not match the actual value.

3.2.2 Identification

This section explains the sign restrictions imposed on the entries of the B_0 matrix from Equation 3.1, as presented in Table 3. Note that all restrictions are imposed only for the contemporaneous month.

Firstly, as discussed in Chapter 2, I assume inflation is positively influenced by exchange rates, inflation expectations, import prices, and real wage increases, while being negatively affected by ex-ante real consumer loan rates.

Table 3: Sign restrictions

	Shocks					
Variable	Inflation	Inflation exp.	Exchange rate	Import prices	Real cons. loan rate	Real min. wage
Inflation	+	+	+	+	-	+
Inflation exp.		+	+			
Exchange rate			+			
Import prices		0	0	+		
Real cons. loan rate	0	-	0		+	+
Real min. wage	-		0	0		+

Note: An entry with +/- denotes the variable's positive/negative response to the specific shock. An empty cell denotes an unrestricted response.

Structural inflation shocks are identified by their mechanical negative impact on real wages. The contemporaneous response of the real consumer loan rate is assumed to be zero, as price shocks announced the next month cannot immediately influence expectations or bank loan rates.

Secondly, inflation expectation shocks reduce ex-ante real consumer loan rates without impacting import prices, as importers typically operate under pre-set contracts. The same logic applies to exchange rate shocks, which are also assumed to have no immediate effect on loan rates or wages, as these are not directly related and may be slow to react.

Finally, import price shocks are distinguished from wage shocks by assuming that real wages are only affected indirectly through developments in the subsequent months. Wage shocks are assumed to boost consumer loan demand, thereby raising interest rates. Hence, these restrictions uniquely identify the shocks in the system, allowing me to proceed to the results.

CHAPTER 4

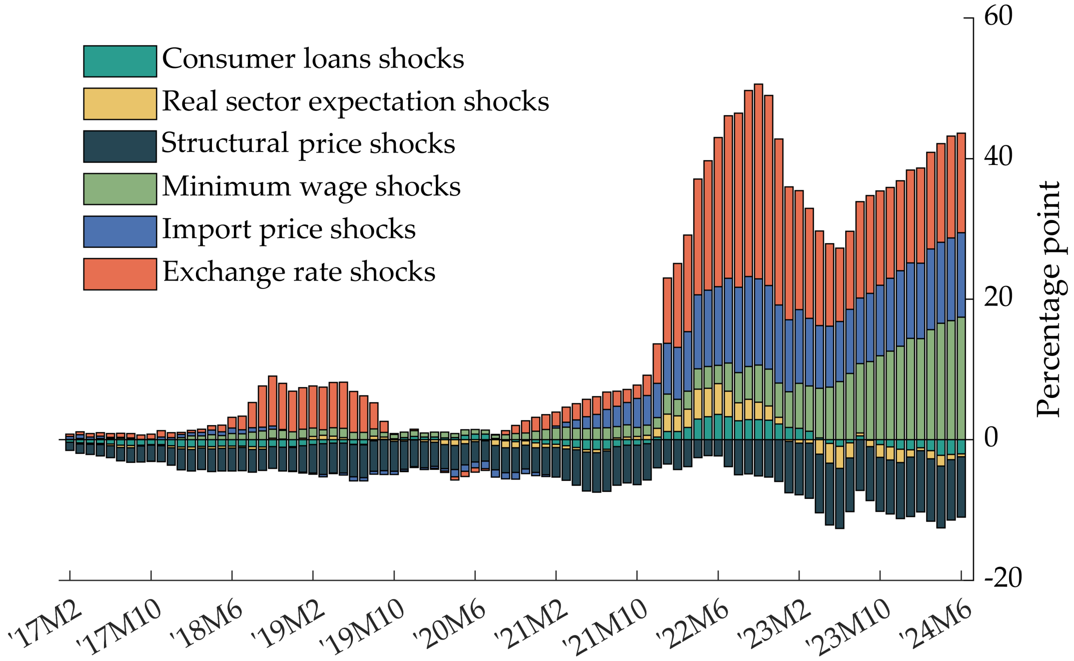
RESULTS AND DISCUSSION

This chapter presents the results of the analysis. First, I discuss the results of the historical decompositions, and then, I show that exchange rate movements stem from predominantly domestic factors.

Figure 18 illustrates the main results, showing the contributions of various shocks to inflation, specifying both their magnitude and timing. The impact of import price shocks aligns with global post-pandemic inflation trends, with imported inflation rising in 2021 and peaking in 2022. However, unlike other economies where inflation mostly subsided in 2023, Türkiye's imported inflation persisted, a pattern that diverts when financial sector expectations are considered instead of those from the real sector (see Figure A.4). In terms of magnitude, the imported inflation in Türkiye is comparable to post-pandemic inflation in the euro area and other Emerging European economies, as Figure 19 shows.

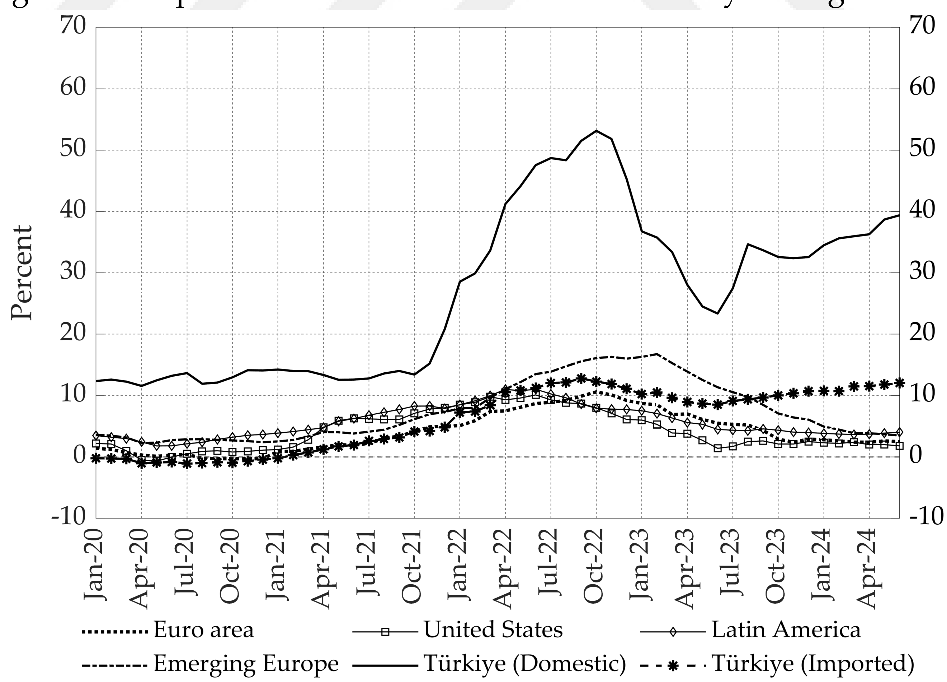
Regardless of data choice, historical decompositions indicate that most of the inflation in Türkiye during the post-pandemic era was driven by domestic factors. The shocks, other than import prices, comprise at least 78 percent of the inflation from November 2021 onwards, when Turkish inflation began to sharply diverge from its trend.

Figure 18: Historical decomposition of Turkish inflation



Note: The bars show deviations from the steady state. See Appendix B for the transformation of monthly contributions to annual. Refer to Section 3.2.1 for the reasoning that the sum of contributions does not precisely sum up to the observed values.

Figure 19: Imported and domestic inflation in Türkiye and global trends



Note: The last observation is from June 2024. Emerging European and Latin American inflation rates are GDP-weighted averages (Table A.1 lists included countries). Sources: Eurostat, national statistics offices, and central banks.

Figure 18 also shows that inflation reaccelerated after May 2023, primarily due to domestic factors such as exchange rate and minimum wage shocks. As was depicted in Figure 6, there were large spikes in the exchange rate changes in June and July 2023, the results show that they hasten the exchange rate contribution to inflation. Further, the sharp increases in real wages, which was shown in Figure 12, further fueled inflation in 2023.

Conversely, inflation expectations and consumer loan rates appear to have had a limited impact in terms of triggering inflation, acting more as transmission mechanisms rather than root causes. However, this observation regarding inflation expectations is sensitive to the inclusion of an additional restriction on the response of exchange rates to inflation expectation shocks (see Figure A.5). If we additionally assume that savers shift their deposits to USD to protect against anticipated inflation and rising demand for USD, the non-linear component of inflation expectations is found to exacerbate inflation from late 2021 through 2022. Still, their contribution considerably diminishes in 2023. Without the additional sign restriction, the net effect is even slightly negative from 2023 onwards.

The significant contributions from exchange rate shocks, and from inflation expectations when the additional sign restriction is applied, can be linked to monetary policy events. These increasing contributions coincide with the period of consecutive policy rate cuts by the CBRT from September 2021 to February 2023. Following this period, the influence of inflation expectations declines, mirroring the reduced impact of exchange rate shocks, as shown in the results from both specifications. Further, the exchange rate is highly sensitive to monetary policy events, as exemplified in Figures 5 and A.6, and inflation expectations are primarily formed by exchange rate changes (Gülşen and Kara, 2021). Thus, the evidence strongly indicates that domestic policy decisions were the primary drivers of inflation during this episode.

Moreover, structural price shocks appear to reduce annual inflation below its steady state. While one possible explanation is that unexpected inflation lowers real wages over the year, thus dampening aggregate demand, the persistently negative contributions remain puzzling. This represents a key limitation of the analysis, and addressing this issue is left for future study.

Lastly, one could argue that the exchange rate shocks do not only reflect domestic monetary policy choices. To test this argument, I regress USD/TRY to the Nominal Broad U.S. Dollar Index, which is constructed from six exchange rates between the currencies of U.S. main trade partners.[5] As the U.S. dollar index does not get affected by Turkish lira movements, the exogeneity assumption of the right-hand side variable holds in this regression. I used the monthly changes in both series and the broader sample period available. The results are presented in Table 4 below.

Table 4: U.S. Dollar index and USD/TRY

Dependent variable: USD/TRY Sample period: 2006M2-2024M7	
Nominal Broad U.S. Dollar Index	1.36*** (0.22)
Constant	0.01*** (0.00)
Observations	222
R-squared	0.17

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

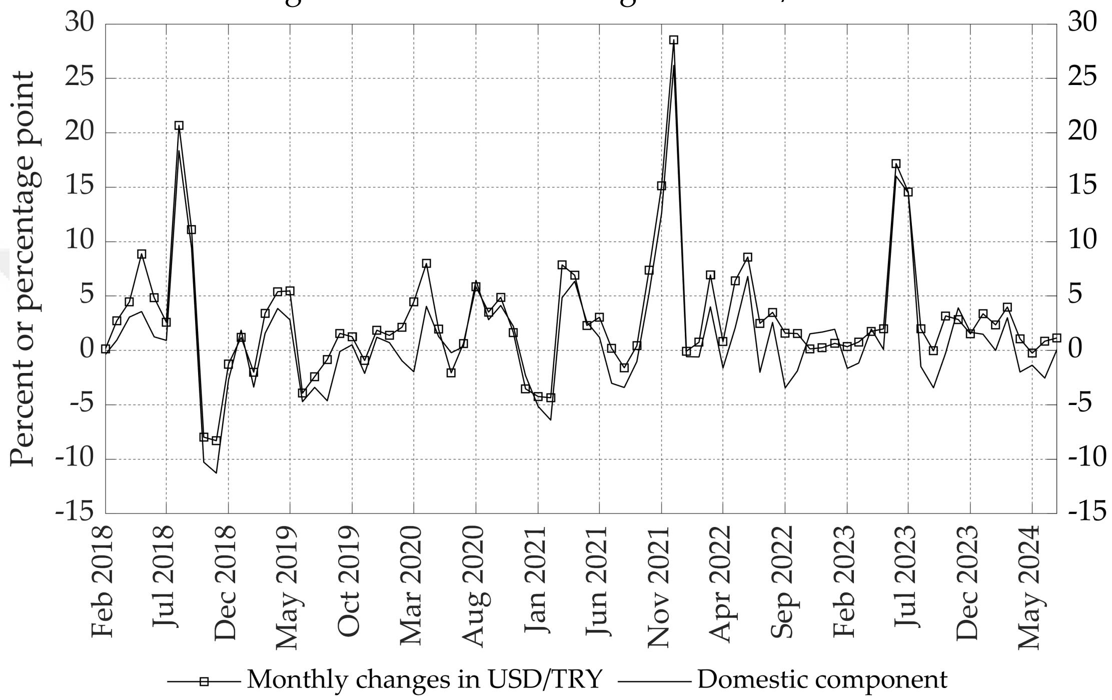
The result in Table 4 shows that external factors explain only 17 percent of the variation in the exchange rate. Moreover, the residual from this regression,

[5]It is calculated by the following formula:

$$\text{DXY} = 50.143 \times \text{EURUSD}^{-0.576} \times \text{USDJPY}^{0.136} \times \text{GBPUSD}^{-0.119} \times \text{USDCAD}^{0.091} \times \text{USDSEK}^{0.042} \times \text{USDCHF}^{0.036}$$

namely the exchange rate movement disentangled from external factors, is not so different from USD/TRY fluctuations, especially for the distinct spikes as shown in Figure 20, showing that the contribution of exchange rate shocks to inflation stems from predominantly domestic factors. The main results remain robust against using this residual instead of USD/TRY changes in the analysis.

Figure 20: Domestic changes in USD/TRY



Note: The domestic component is the residual of the regression presented in Table 4.
Source: EVDS

CHAPTER 5

CONCLUSION

This study presents a quantitative exercise to investigate Turkish inflation dynamics within the global post-pandemic context, suggesting that post-pandemic inflation in Türkiye was predominantly driven by domestic factors, particularly those related to monetary policy, such as exchange rates and inflation expectations. These findings build on the work of Gürkaynak et al. (2015) and Gürkaynak et al. (2023), who attributed Türkiye's high inflation to domestic monetary policy choices. While their analysis concluded in the third quarter of 2021, this study extends the sample period to June 2024, demonstrating that their conclusions remain valid. Additionally, from 2023 onward, significant real wage increases have substantially contributed to inflation.

Therefore, the post-pandemic inflation in Türkiye can be divided into two distinct episodes: the first, from November 2021 to May 2023, was characterized by a sharp rise in inflation driven mainly by domestic factors with some global influences. The second episode, beginning in June 2023, saw inflation reaccelerate, driven almost exclusively by domestic factors.

These findings, however, serve only as a preliminary exploration of the dynamics of Turkish inflation. A more comprehensive analysis is reserved for future research.

REFERENCES

Adal, H. (2024, June 27). No Mid-year Minimum Wage Increase On Turkey's Agenda. Bianet. Accessed: 2024-07-28. 4

Aldan, A. and H. B. Gürcihan-Yüncüler (2016). Real Wages And The Business Cycle In Turkey. Working Paper 16/25, CBRT. 12

Bańbura, M., E. Bobeica, and C. M. Hernández (2023). What drives core inflation? The role of supply shocks. Technical Report 2875, ECB Working Paper Series. 4

Bernanke, B. S. and O. Blanchard (2023). What Caused The U.S. Pandemic-Era Inflation? Working Paper 86, Brookings Institution. 3, 11

Bernanke, B. S. and O. Blanchard (2024). An Analysis Of Pandemic-Era Inflation In 11 Economies. Working Paper 86, Brookings Institution. 1, 3

Bianchi, F., R. Faccini, and L. Melosi (2023, 05). A Fiscal Theory of Persistent Inflation. *The Quarterly Journal of Economics 138*(4), 2127–2179. 1

Casella, G. and E. I. George (1992). Explaining the gibbs sampler. *The American Statistician 46*(3), 167–174. 28

Clarida, R., J. Gali, and M. Gertler (1999, December). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature 37*(4), 1661–1707. 15

Dao, M. C., P.-O. Gourinchas, D. Leigh, and P. Mishra (2024). Understanding the international rise and fall of inflation since 2020. *Journal of Monetary Economics*, 103658. 1

Dieppe, A., R. Legrand, and B. van Roye (2016). The BEAR toolbox. Technical Report 1934, ECB Working Paper. 29

DİSK-AR (2024, July 1). Asgari Ücret ve vergi raporu. İstanbul. 12

Erduman, Y., O. Eren, and S. Gül (2020). Import content of turkish production and exports: A sectoral analysis. *Central Bank Review 20*(4), 155–168. 4, 17

Gülşen, E. and H. Kara (2021). Policy performance and the behavior of inflation expectations. *International Journal of Central Banking 17*(4), 179–224. 3, 6, 15, 33

Gürkaynak, R., Z. Kantur, A. Taş, and S. Yıldırım-Karaman (2015). Monetary Policy In Turkey After Central Bank Independence. *İktisat, İşletme ve Finans 30*(356), 9–38. 4, 36

Gürkaynak, R. S. (2024). Post-Covid Inflation In Emerging Europe. Working paper, Brookings Institution. 1, 41

Gürkaynak, R. S., B. Kısacıkoğlu, and S. S. Lee (2023, 08). Exchange rate and inflation under weak monetary policy: Turkey verifies theory. *Economic Policy 38*(115), 519–560. 4, 9, 36

Ipek, M. S. and B. Kısacıkoğlu (2024). Euro Area Output Gap. Available at `https://sites.google.com/site/burcinkisacikoglu/home/research`. 13

Kara, H. and C. Sarıkaya (2021). Enflasyon dinamiklerindeki değişim: Döviz kuru geçişkenliği güçleniyor mu? Working Paper 2121, Koç University-TÜSİAD Economic Research Forum. 6

Kara, H., F. Öğünç, and Çağrı Sarıkaya (2017, May). Inflation Dynamics In Turkey: A Historical Accounting. Technical Report 17/03, CBRT Economics Notes. 3

Kilian, L. and H. Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Themes in Modern Econometrics. Cambridge University Press. 25, 26

Koç, U., F. Öğünç, and M. U. Özmen (2021). Türkiye'de enflasyon sürecinde beklentilerin rolü: Dinamikler son dönemde değişti mi? Working Paper 21/02, CBRT. 3, 15

Medina, J. P. and J. M. Wlasiuk (2024). Inflation Dynamics In Latin America: Lessons From The COVID And Other Episodes. Working paper, Brookings Institution. 1, 41

Menz, J.-O., E. Wieland, and J. Mehrhoff (2023). Estimating the impact of quality adjustment on consumer price inflation. ECB Working Paper 2023/2773, European Central Bank. 19

Nakata, T. and C. Tonetti (2015). Small sample properties of bayesian estimators of labor income processes. *Journal of Applied Economics 18*(1), 121–148. 27

Uhlig, H. (2005). What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of Monetary Economics 52*(2), 381–419. 26

Weber, I. M. and E. Wasner (2023). Sellers' inflation, profits and conflict: why can large firms hike prices in an emergency? *Review of Keynesian Economics 11*(2), 183–213. Open access. 1

Yeldan, A. E., A. H. Köse, and K. Boratav (2023). Türkiye'de Derinleşen Yapısal Kriz Eğilimi Ve Kâr İtilimli Enflasyonun Dinamikleri. *İktisat ve Toplum Dergisi 158*, 8–30. 4

Yüncüler, H. B. G. and F. Öğünç (2015, January). Firm cost structure and cost-push factors of inflation. Technical Report 15/03, CBRT. 14

Yılmaz, K. (2024, July). Türkiye'de enflasyon. [https://sarkac.org/2024/07/turkiyede-enflasyon-2/; accessed 18-August-2024]. 17

APPENDIX A

Table A.1: Lists of countries

Latin America	Emerging Europe
Bolivia	Albania
Brazil	Bosnia-Herzegovina
Chile	Bulgaria
Columbia	Croatia
Costa Rica	Hungary
Dominican Republic	Kosovo
Ecuador	Macedonia
Guatemala	Montenegro
Mexico	Poland
Paraguay	Serbia
Peru	
Uruguay	

Note: Latin American countries are selected based on Medina and Wlasiuk (2024), with the exception of some small countries for which data are not publicly available. The sample presented here consists of 85.4% of the Latin American sample of IMF. Emerging European countries are selected according to the criteria outlined in Gürkaynak (2024).

Table A.2: Imports and household consumption

Years	Imported Consumption	Total Consumption	Imported Share of Consumption (%)
2013	63.7	1,113.7	5.7
2014	71.4	1,235.2	5.8
2015	83.7	1,404.0	6.0
2016	90.7	1,551.9	5.8
2017	112.6	1,826.5	6.2
2018	118.7	2,100.1	5.7
2019	120.6	2,441.8	4.9
2020	171.2	2,846.9	6.0
2021	221.3	3,983.4	5.6
2022	514.2	8,563.6	6.0
2023	1,149.5	15,539.7	7.4

Note: The values in the second and third columns are in millions of Turkish lira. Import values were originally published in USD and have been converted to lira by multiplying by the monthly average exchange rates. The replication code is available on the author's webpage. Source: Turkstat, EVDS.

Table A.3: Quarterly data description

Variable	Definition
Compensation of employees	Total compensation of employees, seasonally adjusted at current prices by income approach gross domestic product value and percentage change, Turkstat
Number of employees	Employment, seasonally adjusted main labor force indicators, Turkstat
	Unemployment, seasonally adjusted main labor force indicators, Turkstat
Job vacancies	Job vacancies, 3-month average, Turkish Employment Agency
Inflation exp.	Annual inflation expectations of market participants, 12-month ahead, 3-month average, EVDS
GDP	GDP and main components (expenditure), seasonally and calendar adjusted data, chain linked volumes, index 2015=100, Eurostat
Hours worked	Index of total actual hours worked in the main job by sex and age group (2021=100) - quarterly data, Eurostat

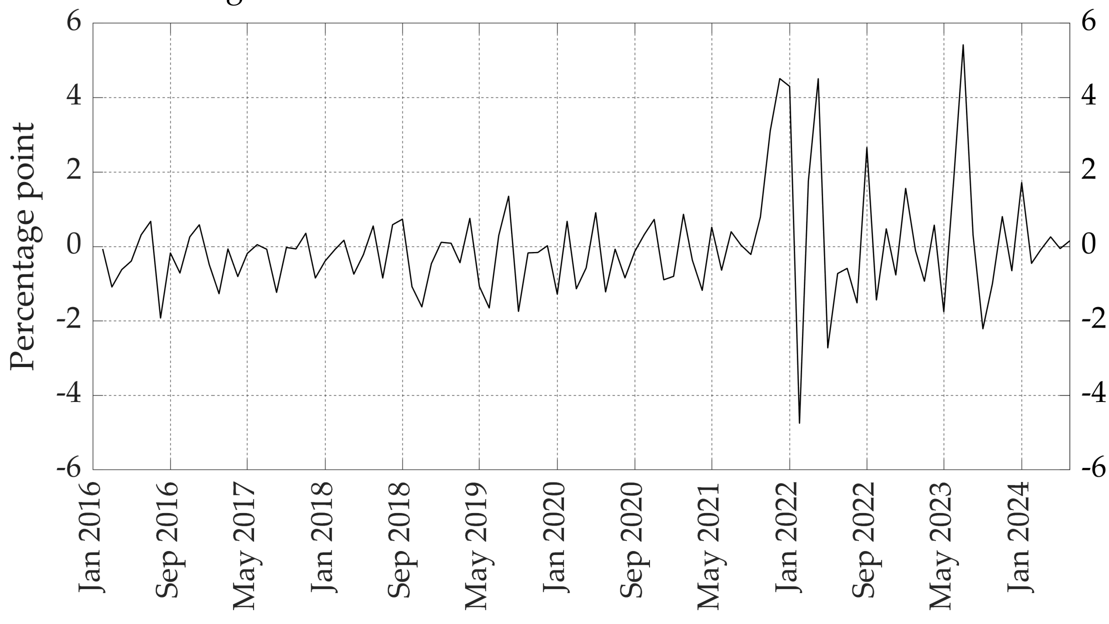
Note: Job vacancy data are only available on the Turkish version of the web page.

Table A.4: Dickey-Fuller test results

Variable	Sample	Obs	Lags	Z(t)	CV (1%)	CV (5%)	CV (10%)
Turkstat CPI	All Data	246	0	0.137	-3.461	-2.880	-2.570
	Date > Jan 2015	114	0	-0.402	-3.505	-2.889	-2.579
ICOC CLI	All Data	246	0	0.425	-3.461	-2.880	-2.570
	Date > Jan 2015	114	0	-0.143	-3.505	-2.889	-2.579
SMP inf. exp.	Date > Jan 2015	114	0	-0.584	-3.505	-2.889	-2.579
Real sector inf. exp.	Date > Jan 2015	114	0	0.269	-3.505	-2.889	-2.579
Household inf. exp.	Date > Jan 2015	114	0	-0.583	-3.505	-2.889	-2.579

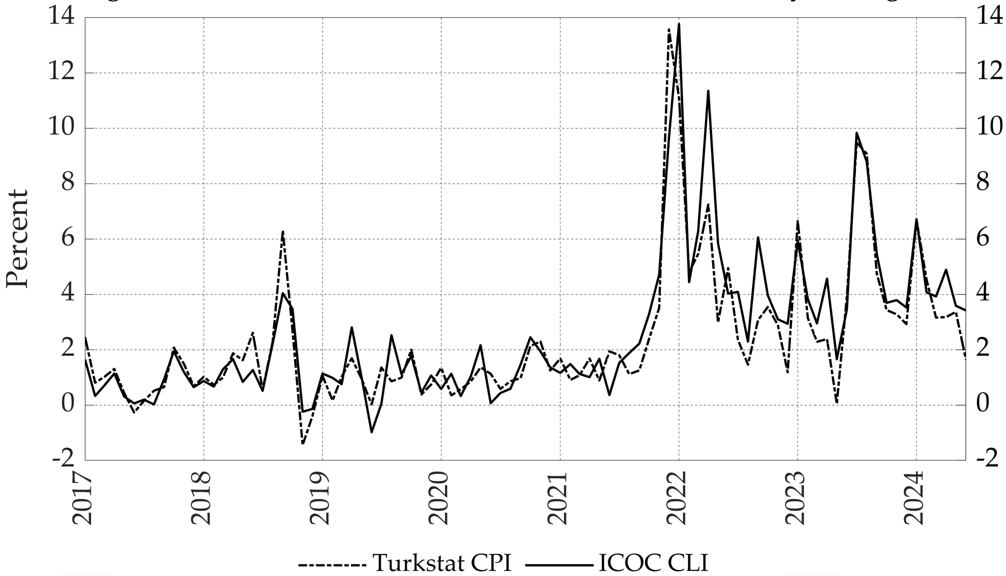
Note: Z(t) represents the test statistic. CV stands for critical value, which Z(t) must fall below to reject the unit root hypothesis at the specified confidence level.

Figure A.1: Residuals from a time-invariant model



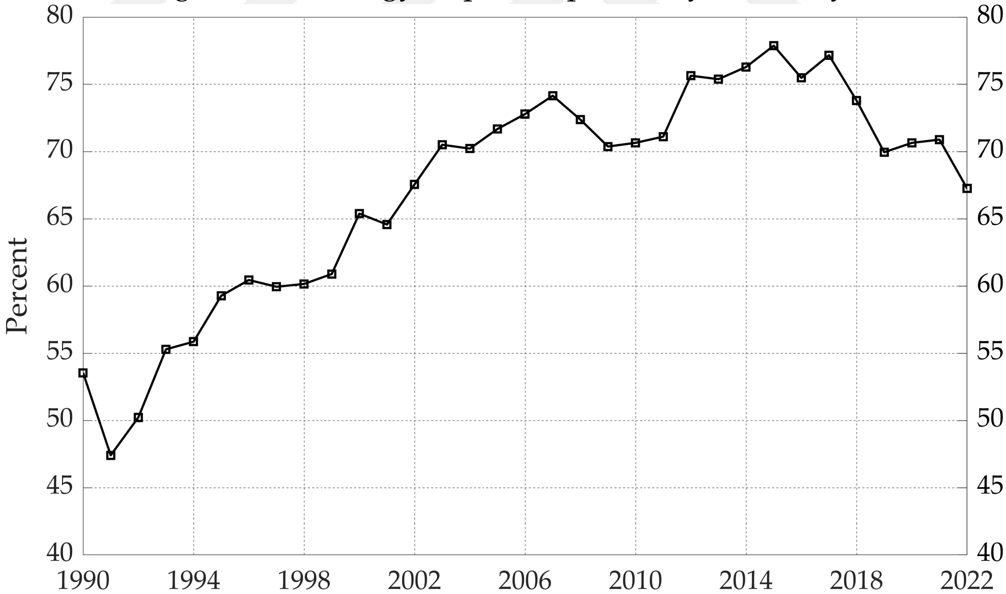
Note: Residuals estimated with the same model whose results are shown in Figure 18 except for the time-invariant distribution assumption for the reduced-form residuals.

Figure A.2: Turkstat CPI and ICOC CLI in monthly changes



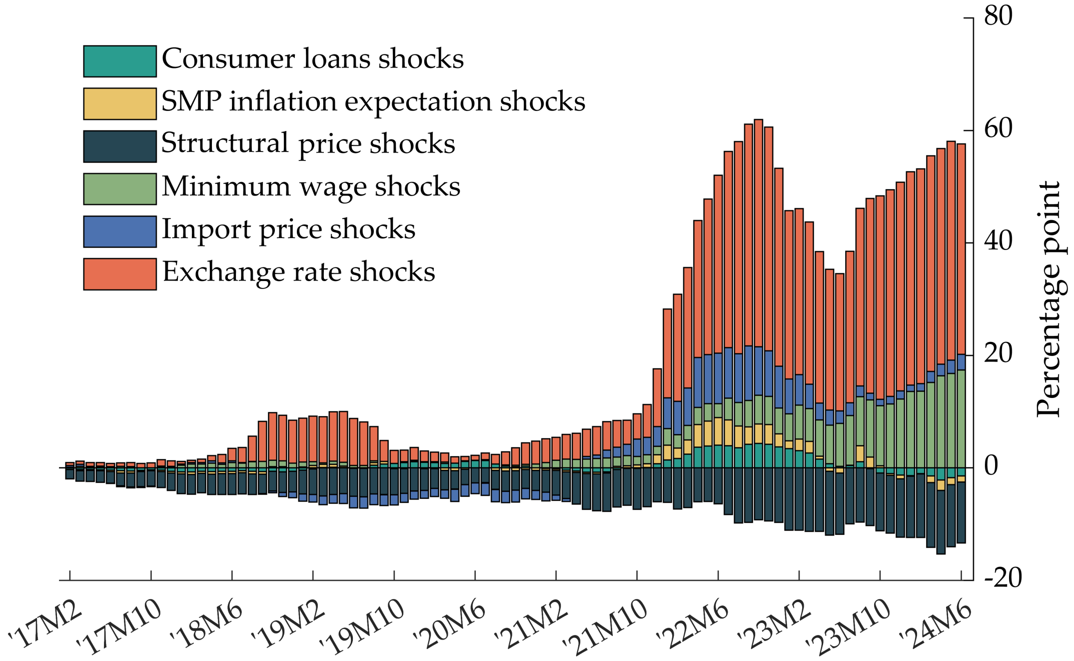
Source: EVDS

Figure A.3: Energy import dependency of Türkiye



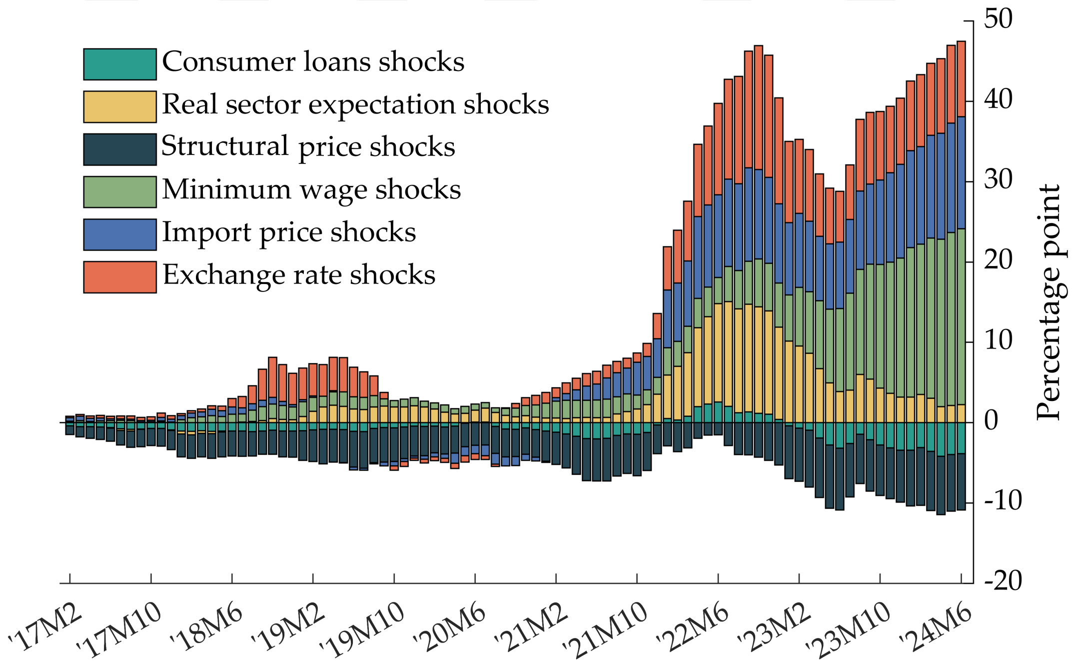
Source: Eurostat

Figure A.4: Alternative results with inflation expectations of financial sector



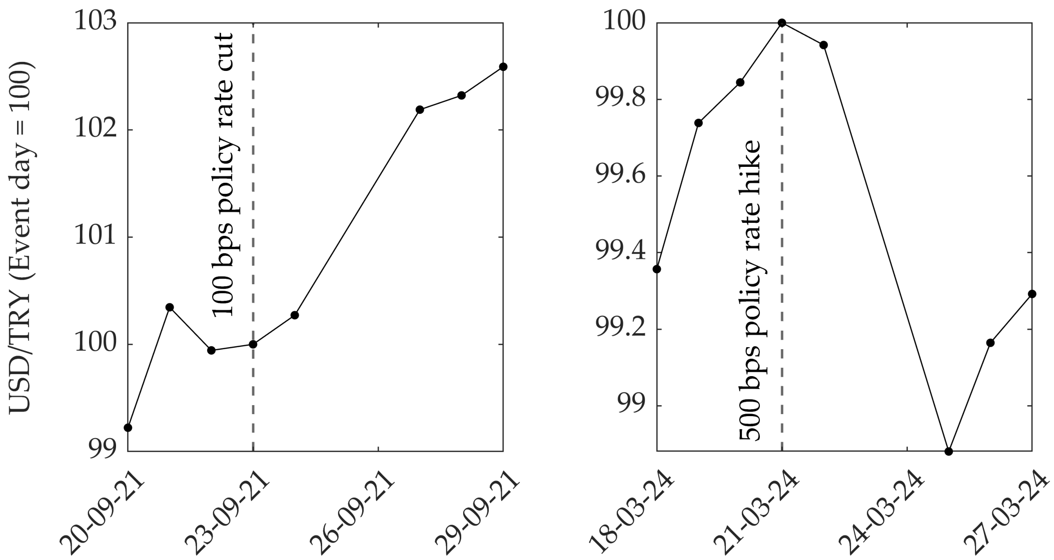
Note: See Appendix B for the transformation of monthly contributions to annual. Refer to Section 3.2.1 for the reasoning that the sum of contributions does not precisely sum up to the observed values.

Figure A.5: Alternative results with an additional restriction on exchange rate response



Note: See Appendix B for the transformation of monthly contributions to annual. Refer to Section 3.2.1 for the reasoning that the sum of contributions does not precisely sum up to the observed values.

Figure A.6: Policy rate changes and USD/TRY exchange rate



Note: Dots represent daily USD/TRY exchange rates, and vertical dashed lines indicate event days. The exchange rate is normalized to 100 for the policy day. Weekend data are excluded. The date format in the X-axis is dd/mm/yy. Source: EVDS

APPENDIX B
TRANSFORMATION OF SHOCK CONTRIBUTIONS: MONTHLY TO ANNUAL

The following steps will convert shock contributions to inflation from monthly to annual:

1. Set the index level to 100 in January 2015.
2. Calculate each variable's contribution to the index in February 2015 by determining what the index level would have been if only that variable had contributed to the price index for that month.
3. Repeat the second step for all subsequent months.
4. Aggregate the total contribution of each variable to the index over the past twelve months.
5. Calculate the ratio of each variable's contribution to the annual change in the index level.
6. Multiply each ratio by the annual percentage change in the index to determine the contribution of each variable to the yearly change in inflation.