COST-PUSH OR INDEXATION: AN EMPIRICAL EVALUATION OF THE WAGE-PRICE PASS-THROUGH IN UKRAINE

by

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Abstract

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Identifying the specific determinants of inflation dynamics is essential for maintaining price stability in forward-looking monetary policy. Theoretical literature identifies labor market tightness as a fundamental driver of inflation, primarily through the wage transmission channel. In Ukraine, these dynamics are influenced by unprecedented structural shifts in labor supply and productivity.

This thesis empirically estimates the structural dynamics of the wage-price pass-through in Ukraine and evaluates the relative significance of labor costs as a determinant of core inflation. The analysis employs a Bayesian Vector Autoregression framework applied to a reconstructed dataset spanning the 2011–2025 period. Structural shocks are identified using recursive ordering and sign restrictions to isolate the independent impact of domestic labor market innovations. The findings reveal a modest positive price response to growth in labor costs with a peak impact after three quarters. However, this transmission remains secondary to the demand and currency channels, indicating that an indexation mechanism, rather than a cost-push effect, predominates in the Ukrainian economy. These results contribute to the literature by providing an initial empirical estimation of the wage-price pass-through in Ukraine while accounting for the unique data constraints of the wartime period.

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My deepest thanks go to the Armed Forces of Ukraine for their service and sacrifice, which made this work possible. Finally, I thank my parents for their endless faith and emotional support throughout this journey.

AI USE DECLARATION

During the preparation of this thesis, Generative AI (Gemini) was used as a supplementary tool to:

- support grammar correction and improvement of sentence clarity in Chapters 1-6 of this thesis;
- idea brainstorming on a) backcasting techniques b) robustness checks;
- coding for a) data transformations, b) backcasting models, c) charts.

Any suggestions produced by the AI tool were critically evaluated and substantially modified by the author before being incorporated into the thesis.

The tool was not used to generate research findings, produce literature summaries used directly in the thesis, create citations, or conduct any form of data analysis. All research questions, theoretical framing, methodology, analysis, interpretation of results, and conclusions were developed independently by the author. The author takes full responsibility for the originality, validity, and academic integrity of the work presented in this thesis.

LIST OF ABBREVIATIONS

AI. Artificial Intelligence.

AIC. Akaike Information Criterion.

BIC. Bayesian Information Criterion.

BVAR. Bayesian Vector Autoregression.

CESEE. Central, Eastern, and Southeastern Europe.

CPI. Consumer Price Index.

ECB. European Central Bank.

ER. Exchange Rate.

EU. European Union.

FEVD. Forecast Error Variance Decomposition.

FPE. Final Prediction Error.

FX. Foreign Exchange.

GDP. Gross Domestic Product.

HD. Historical Decomposition.

HP. Hodrick–Prescott (Filter).

HQ. Hannan–Quinn Information Criterion.

IMF. International Monetary Fund.

IRF. Impulse Response Function.

NBU. National Bank of Ukraine.

OLS. Ordinary Least Squares.

PFU. Pension Fund of Ukraine.

PPI. Producer Price Index.

SC. Schwarz Criterion.

SSM. State Space Model.

SSSU. State Statistics Service of Ukraine.

ULC. Unit Labor Cost.

US. United States.

VAR. Vector Autoregression.

Chapter 1

INTRODUCTION

The full-scale war in Ukraine has introduced unprecedented shocks to the national labor market. Significant labor market disruptions have been caused by mass migration, labor force displacement, and continuous conscription (Anastasia et al. 2022). Despite an economic downturn, these labor shortages make it difficult for businesses to recruit and retain employees, driving costs increasing. The efficiency of inflation-targeting policies may be challenged by this mismatch, which could lead to substantial inflationary pressures. Thus, the main research question of this thesis is: Is the transmission of labor cost shocks to core inflation significant in Ukraine, and how has the magnitude of this transmission evolved over time and under the regime of wartime labor supply shocks?

A common belief in economics is that prices reflect the costs of production for firms plus a markup. Since labor costs make up a large part of total production costs, they should, in theory, directly affect the price level. Therefore, a change in labor costs should lead to changes in the inflation rate. Evidence from number of existing studies shows that price response is usually moderate and depends on the state of the economy and the type of shock affecting it. The specific "supply-side" nature of Ukraine's current labor shock provides a different perspective on this relationship.

Despite the theoretical relevance of the wage-price pass-through, empirical evidence remains limited, particularly regarding changes in dynamics of the link under wartime conditions. The suspension of official statistics and the extreme volatility of macroeconomic indicators since 2022 present significant challenges for structural analysis. Therefore, it is necessary to determine whether domestic

labor costs exert an independent influence on prices or if external shocks and falling aggregate demand have diminished their impact.

This thesis contributes to the literature by providing the first empirical estimate of the wage-price pass-through in Ukraine. By constructing a novel dataset that proxies missing official wage statistics with high-frequency job portal data, this study fills a critical gap, offering policymakers an evidence whether labor cost dynamics represent a latent risk to price stability or if inflation remains primarily determined by the demand and exchange rate channels.

To empirically measure these dynamics, this thesis uses a Bayesian Vector Autoregression model, with recursive identification (Cholesky decomposition). The baseline model consists of three endogenous variables: real GDP, real unit labor costs, and core CPI. The robustness of the results is also checked using a different ordering and proxy data sources.

The analysis identifies a transmission path where the structural impact of labor costs peaks positively within two to three quarters and subsequently reverses into a negative CPI response after nine months. While this relationship remains an independent feature of the Ukrainian economy even when controlling for currency volatility, the findings indicate that the wage-price pass-through is currently secondary to the dominant influence of exchange rate dynamics and aggregate demand contractions. Furthermore, the evidence identifies significant second-round effects and adaptive expectations, where price shocks drive substantial nominal wage adjustments. Finally, the research highlights a structural shift during the 2024–2025 period, where labor supply constraints have transitioned unit labor costs into a rising inflationary driver.

The remainder of this thesis is organized as follows. Chapter 2 reviews the theoretical foundations and empirical evidence from global and regional studies. Chapter 3 outlines the BVAR methodology and the recursive identification

strategy used to isolate shocks. Chapter 4 details the data construction, specifically the novel integration of official statistics with high-frequency wage proxies. Chapter 5 presents the empirical results, applying Bayesian VAR estimation, structural correlations, and an analysis of impulse responses and variance decompositions to quantify the magnitude of the wage-price pass-through and evaluate its structural evolution across peacetime and wartime regimes. Finally, Chapter 6 concludes with policy implications and discusses research limitations.

Chapter 2

LITERATURE REVIEW

Studies on wage-price dynamics can generally be grouped into two categories. The first category includes a theoretical framework investigating causality and the direction of influence. The second category includes empirical studies assessing whether the link exists in economies, whether this link has changed, whether it is state-dependent and what factors may influence the connection between wage and price movements. I provide a general review of the modern view of such a connection and summarize empirical papers with a focus on estimation results of observed studies.

One of the fundamental debates regarding the relationship between labor markets and inflation centers on the direction of causality: does wage growth drive price inflation (cost-push), or do prices drive nominal wages (cost-of-living adjustment, or indexation)? On one side, the post-Keynesian view argues that causality runs from wages to prices, as firms set prices by adding a markup over labor costs. Under this framework, if wages rise faster than productivity, inflation is the expected outcome. On the other hand, Neoclassical theory suggests the opposite, as it views nominal wages as a variable that adjusts after prices change, as workers bargain to sustain their purchasing power. Consequently, economic theory does not provide a single answer, implying that the direction of the wage-price link is not tied directly but depends on the specific mechanism – whether supply shocks or demand adjustments are dominating in the economy.

The markup pricing rule, as part of the New Keynesian views, provides the explanation for how labor costs translate into consumer prices. As defined in, for example, Blanchard and Galí (2007), firms in imperfectly competitive markets set

their prices (P) by adding a specific markup (μ) on top of their marginal costs (MC), which can be shown by the following formula:

$$P = MC \times (1 + \mu) \quad (1)$$

In this equation, the marginal costs are the expenses that the firms incur to produce one more unit, which includes the cost of labor, the cost of raw materials, and the rent paid to capital. The "markup" is the profit that the firms earn, but this is not fixed. Its size may vary depending on the nature of the market and the state of the business cycle. For example, firms may be forced to reduce their markup in the case of a recession to attract customers. Thus, we have a transmission mechanism, which works as follows: if the wage rate increases, causing marginal costs to rise, the firms will be forced to raise their prices if they are unable to reduce their markup.

Wages do not drive inflation on their own. The relevant factor for inflation is the relative wage in relation to the efficiency of the worker. As can be seen in the structural analysis of the inflation process in the economy, as done by Galí and Gertler (2000), the key driver of inflation in the New Keynesian model is not the "raw" wage level. The key driver of inflation in the economy is the Real Marginal Cost. The Real Marginal Cost is directly proportional to the Real Unit Labor Costs:

$$ULC = (W \times L)/Y = W/(Y/L) \quad (2)$$

Where *W* is nominal wages, *L* is labor, *Y* is real GDP. This means that if the nominal wage rises by 10%, as long as labor output rises by 10%, the cost of production for a single item will still be the same. The company does not have to raise prices to cover the cost of higher wages because it will have more items to sell. Inflation will be driven by a situation in which wages grow at a rate that exceeds labor output.

Labor cost inflation contains predictive information about future price inflation. The relationship between the labor market and inflation is currently represented by the so-called New Keynesian Phillips Curve, which relates inflation to inflation expectations and the unemployment gap:

$$\pi_t = \beta E_t \pi_{t+1} - \kappa(u_t - u_t^n) + \textit{Supply shocks} \tag{3}$$

where π_t is inflation, $E_t\pi_{t+1}$ is inflation expectations, and $(u_t - u_t^n)$ is the unemployment gap, κ is the slope coefficient, β is the discount factor, and "Supply shocks" is a combination of external factors that shift curve directly.

As highlighted by Heise et al. (2020), the overall sensitivity of inflation to unemployment (the slope κ) can be mathematically decomposed into two distinct stages:

$$-\kappa \equiv \underbrace{\frac{d\pi_t}{du_t}}_{\text{Slope of price Phillips Curve}} = \underbrace{\frac{d\pi_t}{dw_t}}_{\text{Wage-Price pass-Through}} \times \underbrace{\frac{dw_t}{du_t}}_{\text{Slope of wage Phillips Curve}} \tag{4}$$

This process suggests that in order to generate inflation, two things could happen: first, low unemployment could cause wages to rise (Wage Phillips Curve), and

second, firms could decide to pass these rising costs onto consumers (Wage-Price Pass-Through). This process, however, is distorted by structural frictions. As Tobin (1972) argues, if wages are downward rigid, then negative demand shocks mean real wages are above the marginal product of labor; firms cannot cut wages to restore equilibrium, so they lay people off instead. Downward Nominal Wage Rigidity (DNWR) creates an asymmetry where wages rise easily during shortages but refuse to fall during recessions, keeping the $\frac{dw}{du}$ component sticky on the downside. In addition, when the central bank loses credibility, the expectations term ($E_t\pi_{t+1}$) can become unanchored. Then, workers demand higher wages in anticipation of future prices, and firms increase prices in anticipation of future wages, and so on in a wage-price spiral.

However, despite the theoretical significance of labor costs, the findings of the studies regarding the strength and nature of the wage-price pass-through have been inconclusive. Although the traditional studies employed simple Granger causality tests to verify the "direction" of the relationship (as done in the study by Hu and Toussaint-Comeau (2010)), more recent studies have started to incorporate more complex models to estimate the magnitude of the effect. The traditional model used for this purpose nowadays is the Vector Autoregression model, as evident from the extensive usage of the model by Bobeica et al. (2019), Hahn (2020), and Peneva and Rudd (2017), among others. Other recent models include the Local Projections model used by Heise et al. (2020) and Ampudia et al. (2024), and the Structural Vector Error Correction Model used by Leutert et al. (2025) for the case of small open economies.

The literature in the US suggests that wage growth does affect inflation, but this is limited, slow, and volatile in nature. The literature based on US data, such as Peneva and Rudd (2017), and Heise, Karahan, and Şahin (2020), indicates that the role of growth in labor costs in explaining inflation is very limited, particularly

after the Great Recession. The low wage and price inflation pass-through in the US is attributed to factors such as the weakening bargaining power of workers, the rise in concentration, and the pricing strategies employed by firms. Firms tend to offset the increase in labor costs by reducing their markups.

In the EU, the wage–price pass-through exists but is heterogeneous across countries and time, and generally weaker than predicted by standard Phillips curve models. ECB and IMF studies (Bobeica et al., 2019; Boranova et al., 2019) find that wage growth contributes to inflation, but the relationship weakened after the global financial crisis. De Luigi et al. (2019) show that pass-through differs substantially across euro area countries and sectors, with services displaying stronger effects than manufacturing. This heterogeneity is explained by institutional differences such as wage bargaining systems, labor market rigidities, and varying exposure to international competition. In addition, globalization and lower inflation expectations have reduced firms' willingness to pass higher costs into prices.

For Central, Eastern, and South-Eastern Europe (CESEE) economies, wage–price pass-through is stronger than in advanced economies, but still incomplete and highly sensitive to external conditions. De Luigi et al. (2019) study indicates that wage growth in CESEE countries tends to translate into higher inflation more quickly than in the US or core EU economies. However, the estimated pass-through differs substantially across countries and periods. Importantly, the study shows that the link between ULC growth and inflation weakened after the global financial crisis, when many CESEE economies experienced prolonged periods of low inflation or deflation.

The empirical literature on wage–price pass-through relies on a common set of core variables, but their measurement, transformation, and role in the model differ substantially across studies. The main explanatory variable is typically unit

labor cost growth. It is usually defined as labor compensation adjusted for productivity, but implemented using different data sources and aggregation levels. Inflation is generally measured by core CPI, PPI, or GDP deflator. Labor market slack introduced in estimation model as HP-filtered unemployment gap in Boranova et al. (2019). It is considered that external price pressures help separate domestic wage effects from imported inflation. For that purpose, Peneva and Rudd (2017) introduced in the model import price inflation, while, for example, De Luigi et al. (2019) used oil prices and nominal exchange rate. Long-term inflation expectations measured as the deviation of long-term inflation forecasts of professional analysts from central bank's target are included in the model by Boranova et al. (2019). Some studies also incorporated institutional factors such as market concentration, corporate profitability, import penetration, etc.

Despite its theoretical importance, empirical evidence for the wage-price pass-through remains inconsistent across different regions and methodologies. Methodologically, the literature has evolved from simple Granger causality tests toward more complex econometric frameworks, such as various VAR models, to better quantify the magnitude of the effect. Regional studies suggest that the transmission is limited and volatile in the United States, significantly heterogeneous within the European Union, and comparatively stronger—though sensitive to external factors—in CESEE economies. Furthermore, while the literature relies on a consistent set of core variables, researchers employ different measurement and transformation techniques and often control for specific institutional factors.

A significant research gap persists, however, as there is currently no empirical estimation of these dynamics for the Ukrainian economy, nor has the stability of the pass-through been analyzed under a wartime regime. This thesis addresses these deficiencies by providing the first empirical evaluation of the wage-price

pass-through in Ukraine using a Bayesian Vector Autoregression framework. By using a reconstructed dataset that includes the period following the 2022 full-scale invasion, this research identifies the characteristics of the domestic inflation regime under conditions of massive macroeconomic shocks.

Chapter 3

METHODOLOGY

To analyze the dynamic relationship between labor costs and price inflation, this study employs a Bayesian Vector Autoregression (BVAR) model. While standard Reduced-Form VARs are widely used in macroeconomics for their ability to capture complex interdependencies without imposing restrictive structural assumptions, they suffer from the "curse of dimensionality". As the number of variables or lags increases, the number of parameters to be estimated grows quadratically, which may often lead to overparameterization and questionable out-of-sample forecasting accuracy.

The foundational framework for this study is the Vector Autoregression (VAR) model, popularized by Sims (1980) as an alternative to large-scale, over-identified structural econometric models. Unlike univariate models, a VAR treats every variable in the system as endogenous, allowing for the capture of complex dynamic interdependencies between macroeconomic aggregates.

However, despite its flexibility, there is a major limitation of the standard VAR model, estimated using Ordinary Least Squares, which is sometimes referred to as the "curse of dimensionality". As argued by Stock and Watson (2001), the number of parameters to be estimated $(n^2p + n)$, where p is the number of variables and n is the number of observations, increases quadratically with the number of variables.

To overcome these limitations, Doan et al. (1984) proposed an alternative approach, namely Bayesian Vector Autoregression. Unlike other vector autoregressions, which are based on the frequentist approach and treat parameters as fixed, unknown constants, the BVAR model is based on an alternative approach, namely Bayes' Theorem, where information available from the data (called

likelihood function) and prior information available from the researcher (called prior distribution) are combined.

The BVAR model reduces "noise" from the data and retains "signals" through "shrinkage", i.e., moving coefficients towards a prior mean (usually zero), and allows for a richer set of variables and longer lag structures than is possible with an OLS model, thus creating a more stable and robust framework for analyzing labor cost pass-through (Miranda-Agrippino and Ricco 2018).

Formally, the structural system is defined as:

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \quad (5)$$

Where:

Y_t is the vector of endogenous variables: $[GDP, ULC, CPI]$.

A_0 is the 3×3 matrix of contemporaneous coefficients.

ε_t is a vector of white noise error terms with a covariance matrix Σ.

The problem is that we cannot estimate equation (5) directly. We can only estimate the Reduced-Form VAR:

$$Y_t = c + \sum_{i=1}^{p} B_i Y_{t-i} + e_t \quad (6)$$

The link between the two is the error term. The observed residuals (e_t) are a linear combination of the true structural shocks (ε_t), defined by the matrix A_0:

$$e^t = A^{-1}\varepsilon_t \tag{7}$$

To recover the structural shocks (ε_t) from the observed errors (e_t), I apply a recursive identification scheme – Cholesky decomposition. This method imposes a restriction that the matrix A_0^{-1} is lower-triangular. This mathematical restriction implies a strict causal ordering of how shocks transmit through the economy within a single quarter (t). Based on the small open economy framework (following Bobeica et al., 2019), the variables are ordered from "most exogenous/slow-moving" to "most endogenous/fast-moving": $GDP \rightarrow ULC \rightarrow CPI$.

Following the framework established by Bobeica et al. (2019), variables are ordered according to their contemporaneous responsiveness within a single quarter: real GDP is placed first because output adjustments are constrained by real-economy frictions; unit labor cost is ordered second, reflecting the fact that nominal wages adjust within the quarter but are subject to contracting lags; and core CPI is placed last, as firms maintain the flexibility to re-price goods and services immediately in response to both demand and cost innovations. While this hierarchy provides a theoretically grounded baseline, the sensitivity of the findings to this specific recursive structure is further evaluated through an alternative ordering as a robustness check.

Based on the recursive ordering, the observed residuals for each variable are decomposed as follows:

$$\varepsilon_{GDP,t} = \alpha_{11}\eta_{GDP,t} \tag{8}$$

$$\varepsilon_{ULC,t} = \alpha_{21}\eta_{GDP,t} + \alpha_{22}\eta_{ULC,t}$$

$$\varepsilon_{CPI,t} = \alpha_{31}\eta_{GDP,t} + \alpha_{32}\eta_{ULC,t} + \alpha_{33}\eta_{CPI,t}$$

The defining characteristic of the BVAR approach is the choice of the prior distribution. Following the work of Litterman (1986) and the specific implementation in Bobeica et al. (2019), this study employs the Minnesota Prior.

The core intuition of the Minnesota Prior is that most macroeconomic variables are well-approximated by a random walk process. Therefore, the prior centers the distribution of the coefficients around a random walk for non-stationary variables (in levels) or around zero for stationary variables (such as growth rates or output gaps).

The main modelling decision in a BVAR is the selection of hyperparameters that control the degree of shrinkage. Using the hierarchical framework proposed by Giannone et al. (2015) and implemented by Kuschnig (2021) in R package called "BVAR", I set up priors to better capture the potential labor price pass-through. The model utilizes the hierarchical prior selection framework, which treats parameters like λ and α as random variables to be estimated from the data itself, rather than fixed values. This approach is vital because it allows the model to "decide" how much importance to give to the labor cost signal versus the prior assumptions.

I follow the Kuschnig (2021) for parameters set up recommendations. For the primary tightness parameter, λ, I have specified a mode of 0.2 with a standard deviation of 0.4 to ensure the prior remains sufficiently diffuse to capture the emerging labor-price pass-through signals. Given that the variables in the system are already expressed in year-on-year growth rates, the prior mean b is set to zero to assume mean-reversion rather than an explosive random walk in growth levels. Furthermore, a diffuse prior with a variance of 10^7 is assigned to the constant term to accommodate the high average inflation rates characteristic of the Ukrainian wartime regime. To account for the potentially long transmission window of second-round effects, the model is specified with five lags. The lag decay parameter, α, is set to 2 to ensure that the prior variance decreases for higher lag orders, which prevents 15-month-old history from exerting undue influence on current forecasts. The posterior distribution is simulated using the Metropolis-Hastings algorithm through 50,000 iterations, with the initial 25,000 draws discarded as burn-in to eliminate any influence from starting value bias. I employ an adaptive scaling mechanism that targets an optimal acceptance rate between 25% and 45%. The stability of the resulting Markov chains is visually confirmed via trace plots exhibiting a stationary distribution, while unimodal posterior densities for the hyperparameters suggest that the hierarchical priors were successfully updated by the data.

Chapter 4

DATA

The empirical analysis of this thesis is based on a comprehensive dataset, covering the period from 2010 to 2025. The dataset includes mixed-frequency indicators from different sources, namely, the National Bank of Ukraine (NBU), State Statistics Service of Ukraine (SSSU), robota.ua national online job portal, and administrative data from the Pension Fund of Ukraine (PFU). Using different sources of information allows filling in gaps in official national accounts and private sector developments, especially for labor market indicators, due to the effects of the full-scale invasion in 2022. This is important for ensuring the continuity of the required time series for subsequent Bayesian Vector Autoregression estimation.

4.1. Inflation and Output

The main macroeconomic variables are represented by the series of consumer price inflation and economic output. Consumer price series are represented through the Core CPI (CPI) data, which is provided by the NBU. Economic output is represented through the series of Real GDP (GDP), at constant 2021 prices, sourced from the SSSU. The use of Core CPI, rather than Headline CPI or GDP Deflator, is consistent with the literature (e.g., Peneva and Rudd (2017)), and allows the model to identify underlying inflationary pressures, which are driven by labor costs, while ignoring effects of volatile CPI components.

The variables listed in Table 1 serve as the raw inputs for constructing the final series used in the structural model. Specifically, the raw index of Core CPI and the levels of Real GDP are seasonally adjusted and transformed into year-over-year growth rates to ensure stationarity.

Table 1. Summary of variables used and their sources

Variable name	Definition	Period	Source
CPI	Core Consumer Price Index, pct m-o-m	2010M01-2025M12	NBU
ER	Average monthly exchange rate	2010M01-2025M12	NBU
Wage_t	Average monthly nominal wage	2010M01-2022M01, 2025M01-2025M12	SSSU
$\mathrm{Wage}_t^{\mathrm{PFU}}$	The average salary (income) in Ukraine, from which insurance contributions are paid and which, in accordance with the Law of Ukraine "On Compulsory State Pension Insurance," is considered for calculating pensions.	2010M01-2025M12	PFU
$\mathrm{Wage}_t^{\mathrm{robota.ua}}$	Average monthly of weekly median offered salary on the online job portal robota.ua.	2018M02-2025M12	robota.ua
GDP	Gross Domestic Product of Ukraine in 2021 constant prices	2010Q1-2025Q3	SSSU
L_t	Employed aged 15-70 (cumulative, thousands person)	2010Q1-2021Q4	SSSU
L_t^{PFU}	Number of employees out of total insured persons	2016Y-2024Y, 2025M01-2025M12	PFU
Flow_t	Net change of employed and layoffs of insured persons	2017M05-2025M12	PFU

4.2. Deriving Unit Labor Cost

The derivation of a unit labor cost series is a central challenge of this research due to the suspension of official wage statistics by the SSSU following the 2022 full-scale invasion. To maintain the 2011–2025 sample period, this study reconstructs the labor cost series by merging official historical records with high-frequency proxy data from national job portal (robota.ua). This approach is necessary to provide the model with the "labor" component of the marginal cost equation, allowing for an empirical test of the pass-through during the wartime regime.

However, the use of proxy wage data introduces specific limitations that must be considered when interpreting the results. First, job portal data typically exhibits a selection bias, as it reflects "offered" wages rather than "paid" wages and tends to over-represent sectors with higher turnover or digital presence, such as services and IT. Consequently, the proxy may overstate wage growth during periods of labor scarcity or fail to capture the stagnation in traditional industrial sectors. Second, measurement issues related to the informal economy—which historically represents a significant portion of Ukrainian labor compensation—may lead to an underestimation of the absolute level of labor costs. These factors imply that while the identified structural shocks remain valid for detecting the direction and timing of the pass-through, the magnitude of the coefficients should be viewed as an estimation based on the visible portion of the formal and digital labor market.

To correctly capture the cost-push channel of transmission, the dataset contains labor market indicators that cover nominal income and employment levels. The nominal wage series is constructed using information on Average Monthly Wages from the SSSU dataset (Wage_t), Insurance-Based Income from PFU ($\mathrm{Wage}_t^{\mathrm{PFU}}$), and median offered salaries from the online platform robota.ua ($\mathrm{Wage}_t^{\mathrm{robota.ua}}$) (see Figure 1 below for a visual presentation). The reason for inclusion of the

robota.ua data is to use it for the level reconstruction of the SSSU nominal wage series during periods of missing official statistics.

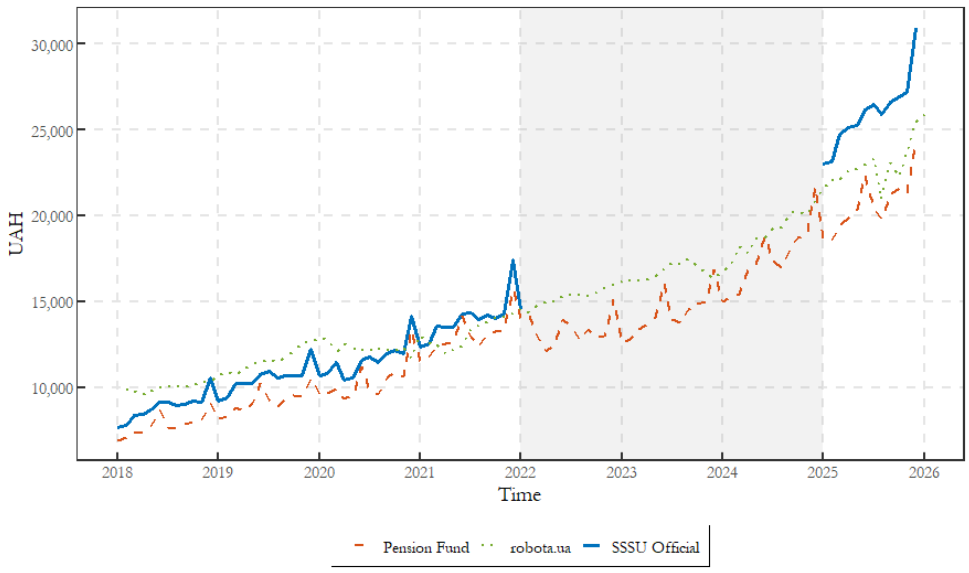


Figure 1. Nominal wage data sources

Apart from the wage series, another important task is the construction of the employment series, which is used in the calculation of labor productivity and unit labor costs. The key series to represent the labor input is the SSSU Employment level (L_t), which includes individuals aged 15-70 years. However, because of the full-scale invasion, the suspension of the labor survey resulted in the need for the incorporation of administrative series from the Pension Fund of Ukraine (L_t^{PFU}) and the Net change of insured persons (Flow_t). The key role of the SSSU series is to represent the historical benchmark required to represent the Ukrainian labor market, but the series from the PFU is considered a high-frequency proxy that is capable of capturing the changing employment trends in the period between 2022 and 2025.

However, before running the model, there were a number of steps taken to clean the data and correct the gaps that were originated because of the war. These steps included filling in the "holes" in the wage data, using State-Space models to correct the employment data, and extracting a structural trend in productivity using the Kalman Smoother. In addition, because the official SSSU data was cut off in early 2022, administrative data was used to continue the series, and seasonal adjustments were made to the GDP and employment data to remove seasonality in the data.

I reconstructed the missing SSSU nominal wage data for the 2022-2024 period using two econometric methods: a growth-rate regression and a State-Space Model (SSM). First, I used an OLS regression on pre-war data to model the relationship between official wages (Wage_t) and Pension Fund wages ($\mathrm{Wage}_t^{\mathrm{PFU}}$):

$$\Delta \ln(\mathrm{Wage}_t) = \beta_0 + \beta_1 \Delta \ln\left(\mathrm{Wage}_t^{\mathrm{PFU}}\right) + \beta_2 \Delta \ln\left(\mathrm{Wage}_t^{\mathrm{robota.ua}}\right) + \varepsilon_t \quad (9)$$

While job portal data (robota.ua) was also tested, it was statistically insignificant (the estimation summary is reported in Appendix A Table 6 named as **Model 1**), so the final projection relied on the PFU signal (**Model 2**):

$$\Delta \ln(\mathrm{Wage}_t) = \beta_0 + \beta_1 \Delta \ln\left(\mathrm{Wage}_t^{\mathrm{PFU}}\right) + \varepsilon_t \quad (10)$$

After predicting these growth rates, I converted them into levels starting from January 2022 (resulted series is plotted on Figure 2):

$$\mathrm{Wage}_t = \mathrm{Wage}_{t-1} \cdot \exp\left(\Delta \ln \widehat{Wage}_t\right) \quad (11)$$

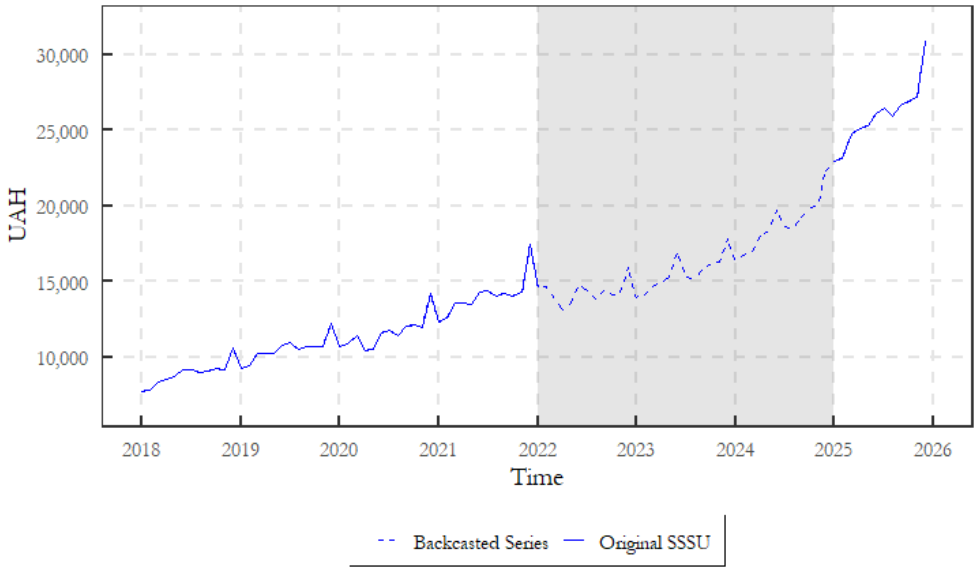


Figure 2. Backcasting of SSSU nominal wage series with Model 1

To achieve a more accurate reconstruction than simple regression, I used a State-Space Model with Kalman Smoothing. This model breaks down the logged SSSU wage into several hidden components: a local linear trend (level μ_t and slope ν_t), a seasonal component (γ_t), and exogenous proxies from the Pension Fund ($\text{Wage}_t^{\text{PFU}}$) and job portals ($\text{Wage}_t^{\text{robota.ua}}$). The mathematical system is the following:

$$\ln(\text{Wage}_t) = \mu_t + \gamma_t + \beta_1 \ln\left(\text{Wage}_t^{\text{PFU}}\right) + \beta_2 \ln\left(\text{Wage}_t^{\text{robota.ua}}\right) + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2) \quad (12)$$

$$\mu_{t+1} = \mu_t + \nu_t + \eta_{\mu,t}, \quad \eta_{\mu,t} \sim N\left(0, \sigma_{\eta_\mu}^2\right)$$

$$\nu_{t+1} = \nu_t + \eta_{\nu,t}, \quad \eta_{\nu,t} \sim N\left(0, \sigma_{\eta_\nu}^2\right)$$

$$\gamma_{t+1} = -\sum_{j=1}^{11} \gamma_{t+1-j} + \omega_t, \quad \omega_t \sim N(0, \sigma_\omega^2)$$

The Kalman Filter moves forward through time, making a guess for the next month's wage and then correcting that guess when it sees new PFU data. Second, the Kalman Smoother runs backward from the end of 2025 to the start of the gap in 2022. Because it looks at the data from both sides, it can estimate the missing values in 2022-2024 much more smoothly than a regular forecast. It also accurately handles the December bonuses effects (see Figure 3 below for a reconstructed series).

This approach is better for a wartime economy, not just because it does not make assumptions about a constant relationship between variables, but also because the "trend" and "slope" can shift in response to changing conditions in the economy. This series is a more accurate estimate of official Ukrainian wages during the period in which SSSU surveys were suspended.

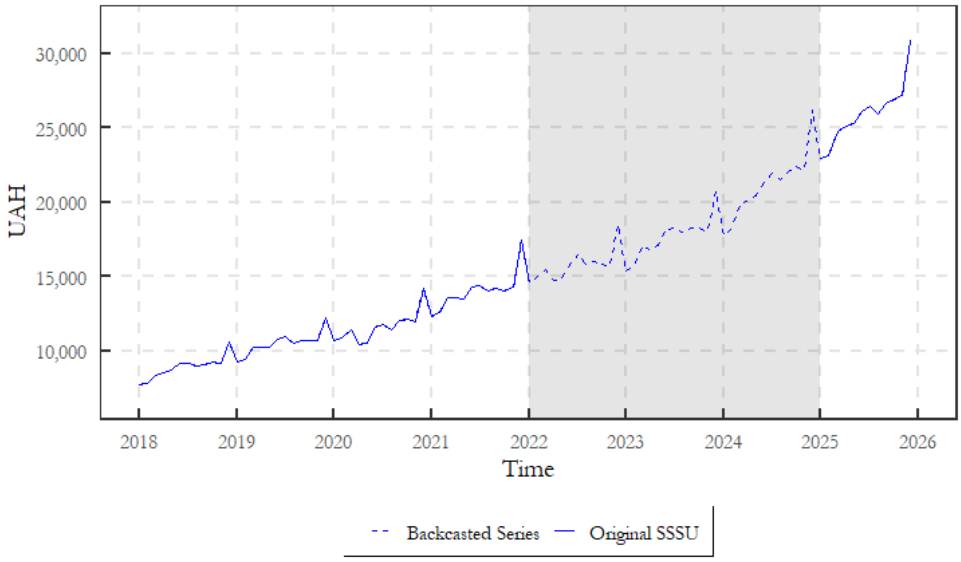


Figure 3. Backcasting of SSSU nominal wage series with Model 2

The statistical validity of the State-Space approach is also confirmed by the variances of the hidden variables. Indeed, as shown in Appendix A Table 5, Seasonal Variance is much higher than Slope Variance. This is economically logical because it shows that the most important changes in wages are driven by seasonal patterns (in particular, the large bonuses paid every December), rather than sudden changes in the long-term growth rate. The very small slope variance also suggests that, after controlling for seasonal shocks, the growth of wages in Ukraine is relatively stable. The Kalman Smoother approach allows for a much more realistic "bridge" between 2022 and 2024 than a regression-based model would suggest.

I used a State-Space Model to reconstruct the employment series because the available administrative data had different frequencies and measurement gaps. The Pension Fund employee counts (L^{PFU}) were only available as annual observations (specifically, every December) between 2016 and 2024, only becoming monthly in 2025. In contrast, the Net Flow data (hires minus layoffs) was available monthly

starting in May 2017. The data is plotted on Figure 4 below. The model used to combine these is:

$$L_t^{PFU} = \mu_t + \beta \cdot \text{Flow}_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{13}$$

$$\mu_{t+1} = \mu_t + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

The main problem is that the monthly flows do not exactly equal the change in the total number of employees for several institutional reasons. First, the flows do not capture "natural" exits such as retirements, which are not necessarily registered as being "fired." Second, some people may have been put on unpaid vacations, especially during the war, maternity, or sick leaves. This means that while they are formally employed, they may not necessarily be registered as social insurance payers in a given month, but they are not registered as "fired" in the flow data.

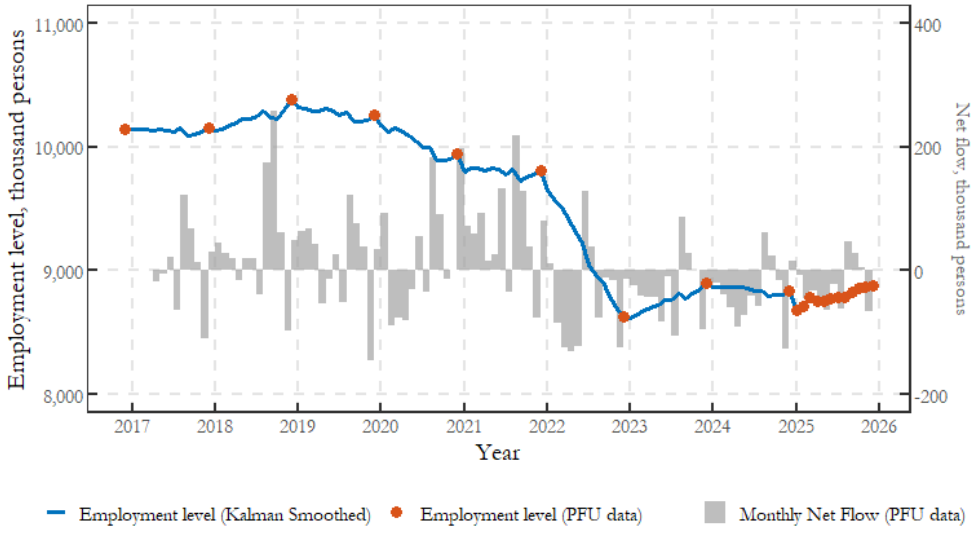


Figure 4. Backcasting of PFU employment series

However, with the help of the Kalman Smoother, I was able to use the high-frequency monthly flows to "fill in" the months between the December annual observations, accounting for the discrepancies observed. Following this, after extracting the smooth monthly signal (μ_t), I linked this to the official SSSU level using the bridge ratio (R_t):

$$Ratio_t = \frac{L_t}{\widehat{\mu_t}} \tag{14}$$

I used linear interpolation with a "carry-forward" method to keep the ratio stable during the war to fill in these gaps. The last reconstructed employment series is the result of combining the smoothed PFU signal with the ratio. This is an important step because it creates a steady stream of jobs from 2010 to 2025. It uses the official historical level and also keeps track of how the PFU series moves in real time during the war. This is the series I will use to figure out how productive the workers are and, in the end, the Unit Labor Costs.

To correctly represent ULC, we need to account for labor productivity. Since it is not the volatile macroeconomic variable by nature, I separated the long-term structural trend of productivity growth from short-term changes and the effect of the war in 2022. There are three steps in this stage: seasonal adjustment, interpolation, and state space filtering.

I used official SSSU data and the reconstructed monthly series averaged by quarter to make a quarterly series of employment. Then, I used the X-13ARIMA-SEATS method to seasonally adjust both real GDP and employment series. The ratio of these seasonally adjusted series was used to calculate labor productivity:

$$A_{t,\mathrm{SA}} = \frac{GDP_{t,\mathrm{SA}}}{L_{t,\mathrm{SA}}} \tag{15}$$

I aligned the quarterly productivity with the center of each quarter and applied a cubic spline interpolation to forecast the months in between. To obtain the structural component of this interpolated series, I applied a Local Linear Trend model with a state space approach and added an intervention term to map wartime period:

$$\ln\left(A_{t,\mathrm{Interp}}\right) = \mu_t + \delta \cdot \mathrm{War_Dummy}_t + \epsilon_t,\ \epsilon_t \sim N(0, \sigma_\epsilon^2) \tag{16}$$

$$\mu_{t+1} = \mu_t + \nu_t + \eta_t, \quad \eta_t \sim N\left(0, \sigma_\eta^2\right)$$

$$\nu_{t+1} = \nu_t + \zeta_t, \quad \zeta_t \sim N\left(0, \sigma_\zeta^2\right)$$

The war dummy shows the immediate change in level that the invasion caused. It lets the Kalman Smoother account for the 2022 drop as a separate break in the data. This approach results in more reliable estimate of trend growth before and after the war, which can be seen on Figure 5 below.

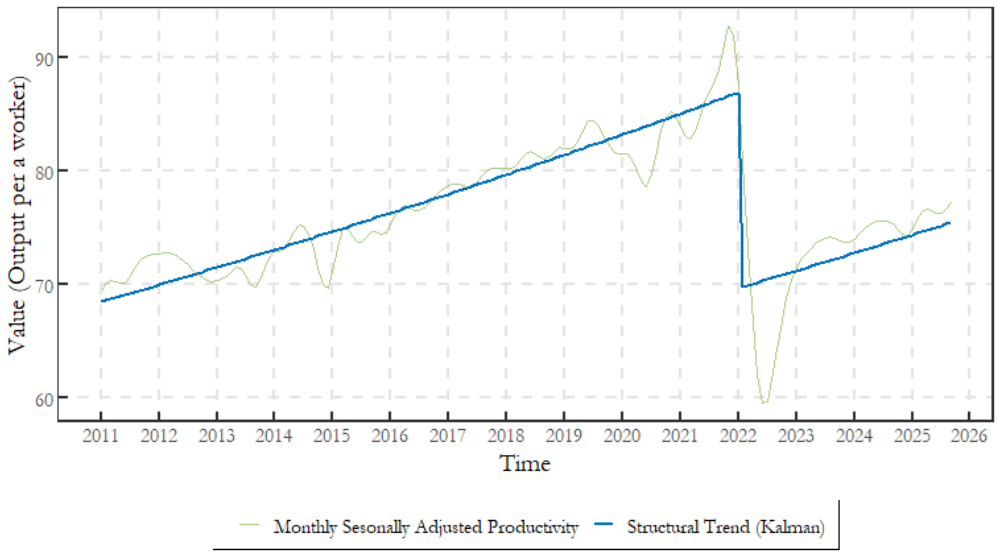


Figure 5. Estimated labor productivity trend

After extracting the smoothed structural trend ($\widehat{\mu_t}$), I calculated the Unit Labor Costs by dividing the seasonally adjusted with X-13ARIMA-SEATS nominal wage by the estimated trend:

$$ULC_t = \frac{Wage_{t,SA}}{\exp(\widehat{\mu_t})} \tag{17}$$

Finally, all the variables, including ULC and Core CPI, were expressed in their rate of change over the year (see Figure 6). This aligns with the existing literature, with the procedure followed from Bobeica et al. (2019). This series of ULC constitutes the link between the labor market and inflation in the BVAR model, with the structural trend and seasonal adjustments enabling the model to capture real cost-push effects that are not driven by direct productivity shocks or seasonal patterns.

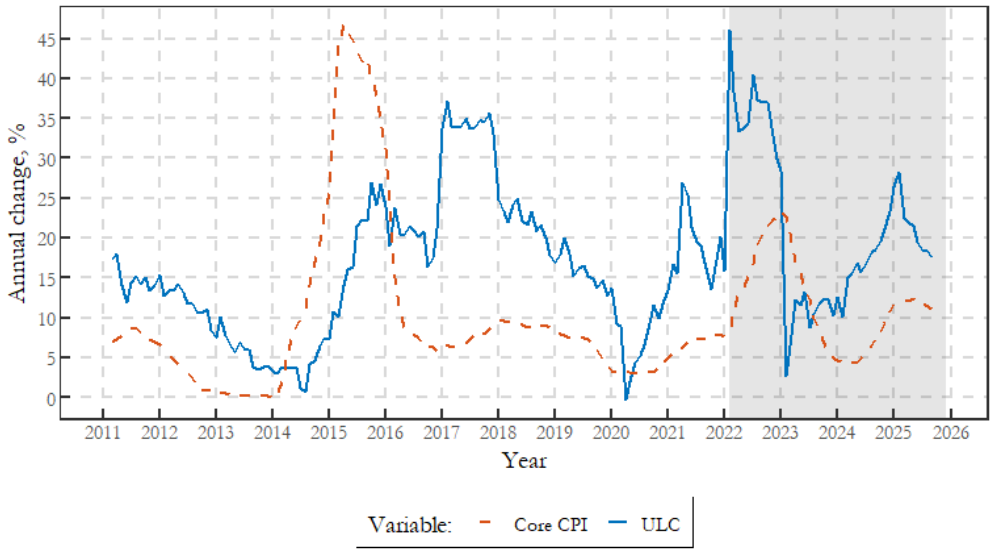


Figure 6. Estimated Unit Labor Costs and Core CPI

4.3. Stylized facts of the data

The summary statistics of the quarterly series indicate a high volatility of key macroeconomic variables, which is one of the defining characteristics of the Ukrainian economy over the estimation period. As presented in Table 2 below, Core Inflation has a standard deviation of 9.83%, which is nearly equal to its mean of 10.28%. Furthermore, Real GDP growth has recorded a massive swing of over 42 percentage points, moving from its pre-war peak of 6.6% in 2021Q4 to its wartime trough of -36.6% in 2022Q2. This massive variance is far higher than what is observed in stable economies such as EU, where inflation and economic growth are observed to move within a narrow band of 2-4%. This is due to repeated structural shocks faced by Ukraine, including the 2014-2015 crisis, the COVID-19 pandemic, and the 2022 full-scale invasion. In terms of methodology, these "fat tails" of the distribution of macroeconomic variables justify the use of a Bayesian VAR. This is because the shrinkage properties of the BVAR and the use of Minnesota prior prevent the model from overreacting to these extreme outliers and

ensure that the final impulse responses are based on structural economic relationships rather than statistical artifacts.

Table 2. Summary of statistics of key variables

Variable	**Obs.**	**Mean, %**	**Std. Dev.**	**Min, %**	**Max, %**
Real GDP growth	59	-1.19	9.59	-36.59	19.25
ULC growth	59	17.27	9.25	1.97	38.23
Core inflation	59	10.28	9.83	0.19	45.87

Note: All variables are expressed as year-on-year percentage growth rates.

The resulting series clearly demonstrate that the relationship between output and labor costs in Ukraine has changed significantly through three structural regimes in the past 15 years (see Figure 7 below). The period begins with a relatively balanced regime up until 2013, followed by a significant change in 2022, and finally a new alignment in 2024-2025. Through examining the relationship between GDP, ULC, and Inflation, we are able to clearly demonstrate how labor costs have developed from a secondary factor to a factor possibly determining inflation levels. This clearly justifies the focus of this study on examining the structural changes in 2022, as it is clearly evident that a fundamental change has occurred in the generation of cost-push inflation.

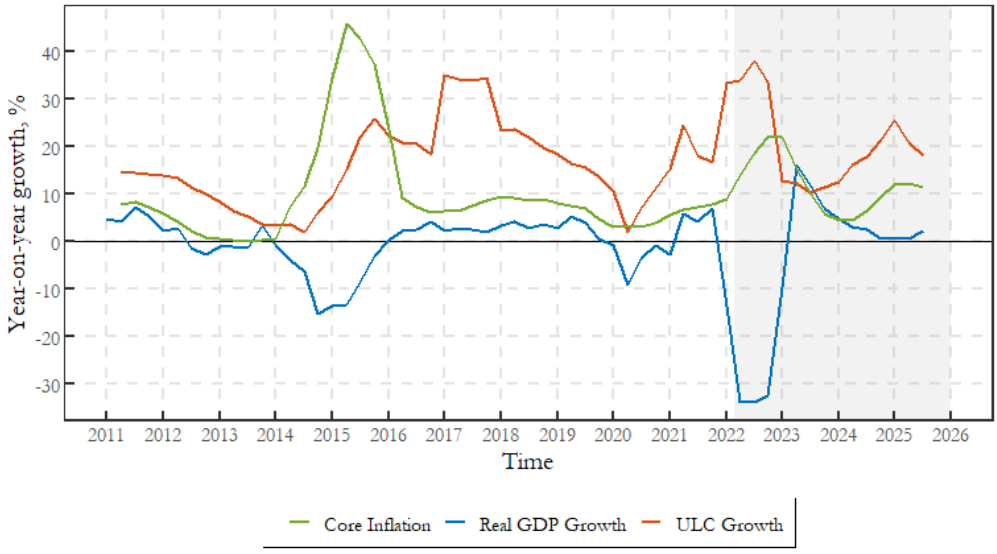


Figure 7. Key variables of the baseline model

Throughout the early 2010s, Ukraine continued its growth at a moderate rate with inflation rates in the low single digits, as witnessed in Q3 2013 when it hit a minimum of 0.19%. The crisis of 2015 witnessed the first significant increase in Core Inflation of 45.87%, but this was mainly driven by currency factors. Of interest is that as ULC growth increased to 25.9% by late 2015, it lagged behind price growth and therefore seemed to be catching up with the new price level. In January 2017, Ukraine's government doubled its minimum wage from 1,600 UAH to 3,200 UAH. This "shock" therefore pushed up the entire wage scale. This is because it was a one-off administrative action and therefore caused a much higher increase in wages compared to the growth in consumer prices. This is a phenomenon observed up until the COVID-19 crisis.

The full-scale invasion in 2022 represents the largest structural break in the data set. The Real GDP Growth plummeted to a historic trough of -36.59%[1](2022 Q2),

[1] according to the SSSU data, while -33.9% from seasonally-adjusted series is used in estimations

while the Unit Labor Costs reached its peak of 38.23% (2022 Q3). This happened because firms could not reduce labor costs as output declined as fast as it did. The productivity collapse meant that the cost of labor per unit of output essentially doubled.

Unlike 2015, Core Inflation's peak of 22.1% in late 2022 lagged behind the Unit Labor Costs peak and appeared as a supply-side driven factor, as labor costs possibly became a push factor. By the end of 2023 and into 2024, there have been signs of adaptation in the economy. For instance, the economy's GDP has grown at a positive rate (peaking at 19.3% in 2023 Q2), thus allowing the economy's productivity to grow. Consequently, the rate of growth in ULC has moderated to 10.3%. The latest economic data (2024 Q4 – 2025 Q3) shows that there has been a secondary increase in the rate of growth in ULC (peaking at 21.4% and 25.7%), coupled with the return of double-digit Core Inflation (11.4%). This suggests that there is a secondary wave of cost-push inflation arising from labor market tightening (possibly due to migration/mobilization effects).

Chapter 5

ESTIMATION RESULTS

In this chapter I present the estimation results of the BVAR model, which was constructed to estimate the wage-price pass-through in the Ukrainian economy. The presentation of the results is hierarchical, moving from preliminary statistical analysis of the link to the structural identification of macroeconomic shocks.

The results are organized as follows. First, I examine the lead-lag relationship between labor costs (ULC) and core CPI using cross-correlation functions and recursive Granger causality tests. The next section contains estimation results of the BVAR with specification, that was discussed in the methodology section along with respective model diagnostic. The core findings are presented through impulse response functions, which trace dynamic impact of a shock on a variable. Here I mainly focus on the responses of core CPI to ULC shock and vice versa. This is supplemented by the forecast error variance decomposition, which quantifies the relative importance of labor cost shocks compared to other structural drivers in explaining inflation volatility over different time horizons. After that, I perform historical decomposition to see the estimated labor cost effect on the timeline. Finally, I execute various robustness checks to challenge the specification, model parameters, as well as assessing identification issue.

5.1. Preliminary lead-lag analysis

5.1.1. Cross-correlation analysis

Cross-correlations allow for simple examination of a lead-lag structure of 2 series. It is the initial diagnostic tool to identify the timing of the transmission. I analyze the connection between ULC and core CPI in such manner by looking at their

cross-correlations. If labor costs are leading the CPI, then strong correlation is expected between ULC in quarter *t* and CPI in some k-th quarter after *t*. In the case of wage catching up with inflation, we expect to see strong correlation of CPI at time *t* and ULC of the period *t-k*.

The results of cross-correlation is shown on the Figure 8 below. Correlation coefficients on the left side (negative lags) indicate that ULC are leading CPI. Specifically, coefficient at lag -1 represents the correlation of ULC at time *t-1* with CPI at a period *t*. Conversely, on the right side (positive lags) correlations of CPI with lags of ULC are shown. The interpretation is the same – lag 1 coefficient is correlation of CPI at time *t-1* with ULC at a period *t*. The red dashed line represents the 95% confidence interval, calculated as $\pm 1.96/\sqrt{n}$, where n is the number of quarterly observations. Based on the sample size (n=58), this threshold is approximately 0.257.

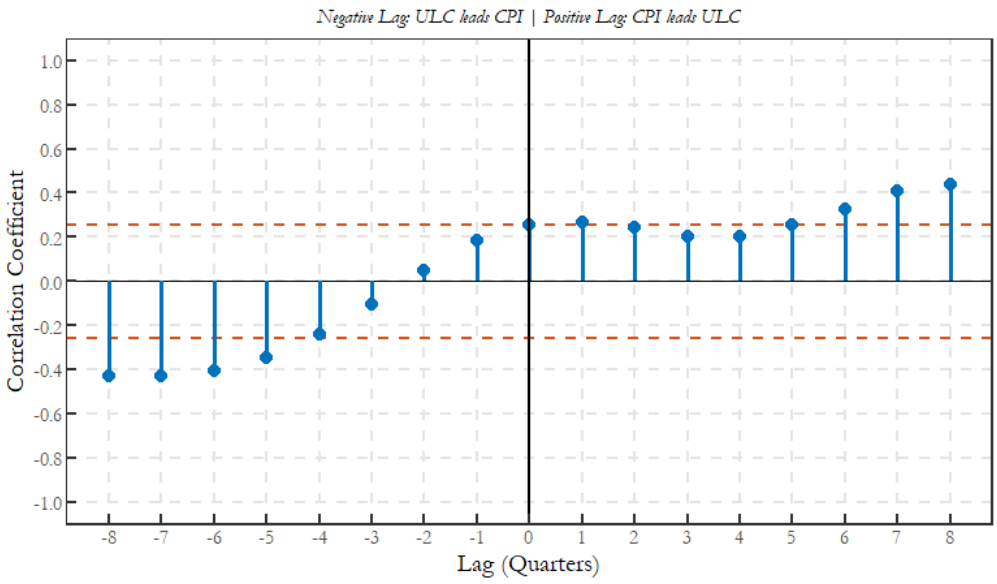


Figure 8. Cross-correlation between labor costs and inflation

Unconditional contemporaneous correlation is relatively weak – 0.25 – and is very close to the significance threshold, indicating that a substantial portion of wage and price adjustments occur within the same quarter. The highest positive correlation in the short term is found at Lag 1 (0.2679), which is statistically significant. This suggests that the signal of prices driving wages may currently be more immediate and statistically visible in Ukraine than the reverse. However, the correlation becomes strongly negative at longer horizons when ULC leads CPI. The strong negative correlations at long negative lags do not imply that higher wages reduce inflation directly; rather, they reflect cyclical adjustment, policy responses, or specific Ukrainian shocks, all of which could generate reversal dynamics in the wage-price relationship. Specifically, one may think of the following sequence: after growth in ULC, which can build inflationary pressure (solely, or together with other shocks), demand collapses or a central bank tightens monetary policy. As a result, inflation lowers in subsequent periods. Another explanation of the negative correlation may come from the business cycle dynamics. Economic boom drives wages up, increasing inflation. Then output slows down and inflation decreases. Finally, Ukraine context could substantially contributed to a negative relationship. For example, FX shock drives CPI almost immediately, while wages adjust slowly. Later inflation drops, while wages are still adjusting up, creating negative link in wage-price relationship. Additionally, the use of year-over-year growth rates introduces overlapping observations, which can mechanically generate oscillatory patterns in cross-correlations.

5.1.2. Granger Causality analysis

It is essential to move beyond simple correlations and establish the predictive direction of the relationship. In this section, I use Granger Causality analysis to

determine if labor cost growth contains statistically significant information that can help forecast future inflation.

Granger causality is an econometric tool used to determine whether one time series is useful in forecasting another. It is important to clarify that "Granger Causality" does not imply "true" causality; rather, it identifies predictive precedence. In our example, a variable ULC is said to "Granger-Cause" core inflation if the past values of ULC provide statistically significant information about the future of core CPI that is not already contained in the past values of CPI itself.

The test operates by comparing two different linear regressions: the restricted model (autoregressive process of CPI itself) and the unrestricted model (which includes past values of both CPI and ULC). The F-test on the coefficients of the ULC provides a p-value. If the p-value is low, I reject the null hypothesis, meaning that ULC does help predict CPI. Otherwise, ULC does not add a predictive value beyond CPI itself.

The Granger Causality test is performed on a recursive basis. The equation is estimated with a starting window of 20 quarters, subsequently adding one quarter at a time. This allows us to see the predictive power over time. Also, an optimal lag selection process is in place. Different lag lengths were tested using various information criteria (reported in Appendix A Table 6), all of which suggested a lag length of two as optimal. Consequently, the recursive Granger causality test is executed using this fixed two-lag specification.

The results are presented in Figure 9 below. Optimal lag length found with grid search is 2. The p-values are consistently high, often exceeding 0.55, for the period of 2017 through late 2021. This means that before the full-scale war, labor costs didn't influence inflation. Inflation was likely driven more by other factors, like shocks to the exchange rate and energy prices. However, things started to change

in the quarter of 2023. As I add data from the wartime to my calculations, the p-value decreases, reaching 0.149 in the third quarter of 2025.

The current value of 0.149 is a little higher than the 5% significance threshold. But what matters for this thesis is the trajectory. The p-value has dropped by 40 percentage points over two years. This is a sign of the change in the link between labor costs and inflation. These results tell us that labor costs may now be a more relevant determinant for inflation trends. This further justifies the use of the BVAR model. The relationship between labor costs and inflation is dynamic and it evolves, which needs to be accounted for. So, we need to employ a Bayesian approach to understand these trends.

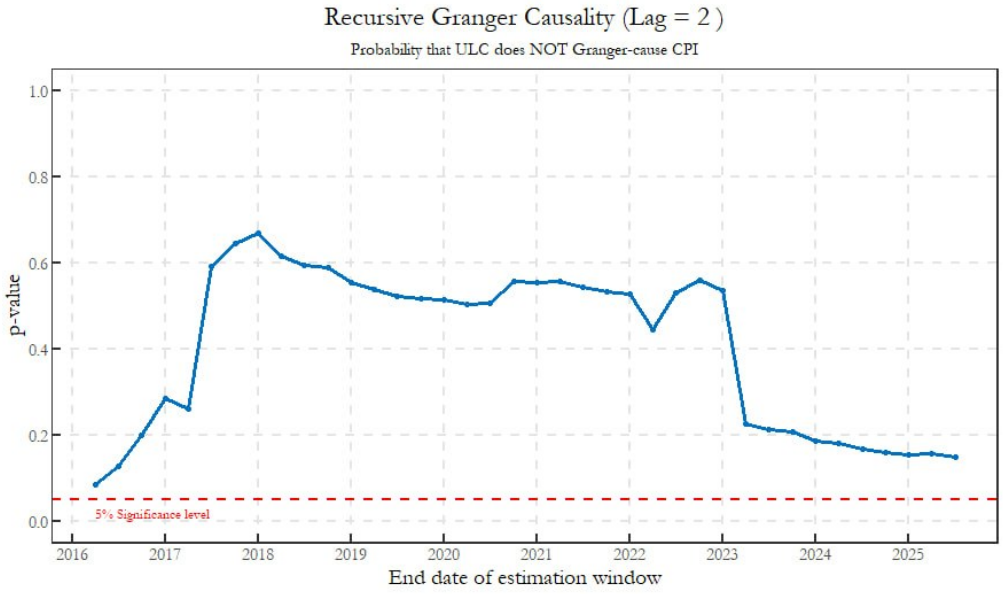


Figure 9. Recursive Granger Causality test results (p-values)

5.2. BVAR estimation and diagnostics

The VAR model is estimated with Bayesian techniques to examine the relationship in more conditional and dynamic manner. The standard frequentist VAR often struggles with "the curse of dimensionality", where adding variables or lags leads to an explosion of parameters that can over-fit the data, especially in a sample of 58 observations. By employing a Bayesian approach, I impose a Minnesota Prior, which shrinks the model toward a parsimonious random walk unless the data provides strong evidence to the contrary. The baseline VAR contains three variables, namely year-over-year growth rates of GDP, ULC and core CPI. The estimation period ranges from 2011Q2 to 2025Q3.

The estimation of the five-lag Bayesian VAR model provides a more granular and statistically better fit for the Ukrainian data, capturing complex transmission dynamics that were previously missing in shorter-lag and simple specifications. The optimization process yielded a hyperparameter λ of 0.289, which is notably higher than the initial prior of 0.2. Following the logic of the Minnesota prior, this increase from initial prior value suggests that there is a strong enough signal coming from the data, allowing to make the degree of shrinkage weaker. When the degree of shrinkage is weaker the relationship between unit labor costs and inflation has influence on the final coefficients. This is greater influence than the random walk prior would normally have. The algorithm is also stable. We can see this because it has an acceptance rate of 25.1 percent over 50,000 iterations. This acceptance rate is between 25 percent and 45 percent. This range is what we want to see for an exploration of the posterior distribution of Minnesota prior.

Median coefficients estimated by the model are provided in Appendix A Table 7. The results advocate for a system dominated by high autoregressive persistence and the existence of hierarchy in the wage-price feedback loop. As seen, the coefficient from CPI_{yoy}-lag1 to ULC_{yoy} is 0.342, making it around ten times larger

than the reverse coefficient of ULC_{yoy}-lag1 to CPI_{yoy}, which equals 0.035. The difference in magnitude provides strong evidence for the second-round effect. It shows that in Ukraine, nominal wages react very sensitively to any previous price shocks, with labor and firms renegotiating contracts based on realized inflation rates. On the other hand, the "cost-push" effect is not so evident in its initial form of wage leading prices because it is more dispersed throughout the five-lag scheme considered. In addition to that, it can be stated with certainty that the persistence of the coefficient of the first lag of CPI, equaling 1.294, implies that inflation rates in Ukraine have a highly self-reinforcing nature, caused by unanchored expectations and supply-side problems. This model provides solid ground for proceeding to impulse response function analysis through structural moving average presentation.

In order to verify that the estimation process is reliable and that the model is stable, diagnostics were conducted. First, convergence of the Markov Chain Monte Carlo method was assessed through trace plots presented in Appendix A Figure 15. They indicate that there is a stable "fuzzy caterpillar" pattern, meaning that the chain successfully sampled the posterior density. This conclusion is reinforced by the Effective Sample Size of the lambda parameter being 4357.85. The latter clearly indicates that the sample of 50,000 iterations gave us enough information for the inference. Moreover, Geweke diagnostic of lambda equaled 0.097, which is nearly zero. As this value falls within the range of -1.96 to 1.96, I can claim that the beginning and the end of the Markov Chain Monte Carlo (MCMC) chain converge to each other.

The density plots in Appendix A Figure 16 provide an insight into how the new information helped in updating the initial priors. In order to assess the goodness-of-fit for the model, I calculated both the Widely Applicable Information Criterion (WAIC) and the Log-Likelihood function. The results showed that WAIC was

equal to 962.24 while the log-likelihood was equal to -432.51. These figures indicate a strong fit for the data within the hierarchical Bayesian framework.

I also checked the structural stability of the system by obtaining the values of the eigenvalues of the companion matrix. The highest absolute eigenvalue is 0.8699, which is clearly less than one. Thus, the model VAR system is stationary, implying that shocks will dissipate and not persist in the long run. Lastly, I did a residual test for GDP, cost of labor, and inflation, and their results are presented in Appendix A Figure 17. There are no spikes in the residuals, indicating that there are no more underlying dynamics present in the data after including five lags.

5.3. Structural impulse response analysis

5.3.1. Response of inflation to labor cost shocks

The estimated impulse response function depicts the dynamics of a one-standard-deviation shock to the economy for up to 15 quarters ahead. As shown in Figure 10, the solid line represents the posterior trace median response of the Core CPI to ULC shock, while the dark-grey and light-grey shaded regions correspond to 68% and 95% credible intervals, respectively. These are indicative of the persistence and statistical significance of the shock. The full set of estimated model impulse response functions is presented in Figure 14 of Appendix A.

The response begins with an instantaneous positive effect, with its magnitude rising to around 0.2 percentage points during the first quarter. The response follows an inverted U shape and reaches its local maximum at approximately 0.4 percentage points during the second quarter. For the early stage (quarters 0 to 3), the 68% credible interval does not exceed the zero boundary, suggesting that the inflationary effect generated by the shock is statistically indistinguishable from zero in the short run.

After reaching the peak in the first year, the inflationary impulse is highly reversed. The median effect crosses the no-effect baseline at the start of the fourth quarter to become negative. The downward trend hits bottom at the eighth quarter when the most significant negative effect reaches about -1.2 percentage points. Structurally, this intermediate deflationary force can be interpreted as the result of the second-round effect of a supply shock in an economy with high inflation rates. With rising costs, households' real incomes fall, leading to a decline in profits. As a consequence, aggregate demand drops, sometimes with an even tighter monetary policy regime. This process has a strong downward pull on the price level. The width of the 95% credible interval during this trough indicates heightened uncertainty, yet the median remains below zero, suggesting a probability of a medium-term correction.

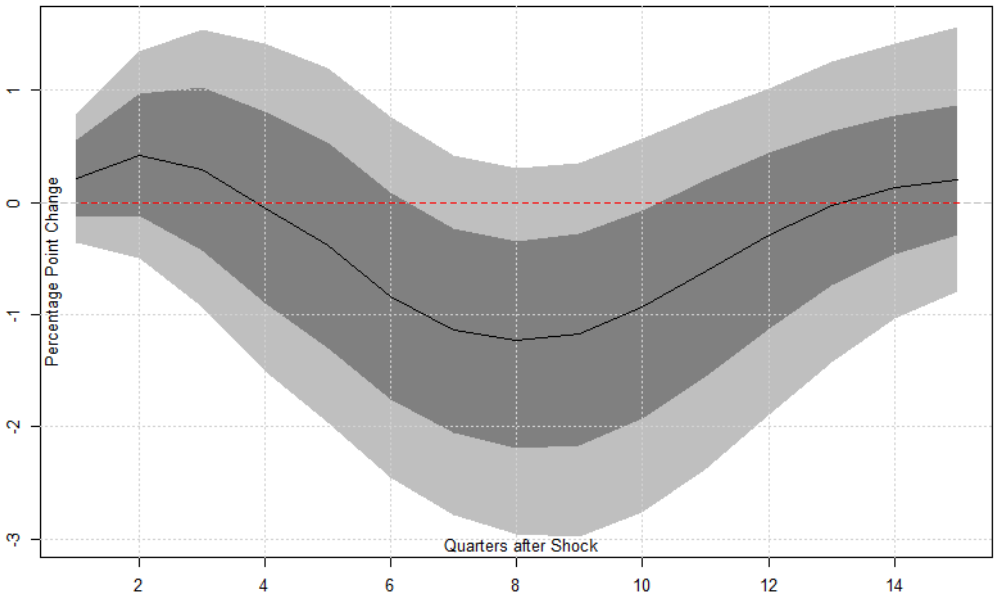


Figure 10. Cholesky decomposition-based impulse response function of price inflation to a shock to labor cost inflation (variables are ordered as GDP-ULC-CPI)

The stability of the baseline findings is evaluated through a series of alternative specifications, with full methodological descriptions and visualizations provided in Appendix B. First, reordering the variables to allow labor costs to impact the system contemporaneously confirms that the "hump-shaped" transmission is not an artifact of the model's recursive structure. Second, applying alternative sign restrictions reveals that while the statistical precision varies, the median path of the wage-price lag remains qualitatively consistent across different identification strategies. Finally, extending the system into a four-variable model to account for the exchange rate demonstrates that labor cost dynamics exert a separate influence on prices that is independent of currency volatility. Collectively, these tests suggest that the identified transmission mechanism, characterized by a short-term inflationary impulse followed by a medium-term demand correction, is a consistent feature of the data across various structural assumptions.

5.3.2. Second-round effects

The impulse response function of ULC to CPI shocks, shown in Figure 11 below, offers a strong empirical confirmation of the indexation mechanism, which is crucial to the second round effect. Whereas earlier we have been looking into the cost-push pass-through, this result shows the reverse causality and provides further support to the notion that price inflation plays an important role in driving future changes in labor cost levels.

The median posterior response of ULC to a structural price shock is positive, robust, and has a hump shape. The highest response occurs at around 1.9 percentage points between Q3 and Q4 after the initial price shock. It takes about a year before reaching the peak in order to show that there is no instant adjustment of nominal wages in Ukraine. Rather, it comes as a result of wage negotiations and the period needed to recognize that real incomes are being eroded. The 95%

credible interval stays above the zero line throughout the first six quarters, confirming the immediate effect of prices on wages. Even the 68% credible interval stays positive for more than two years. Such persistence might signal that an increase in price level could take place for several years in the labor market.

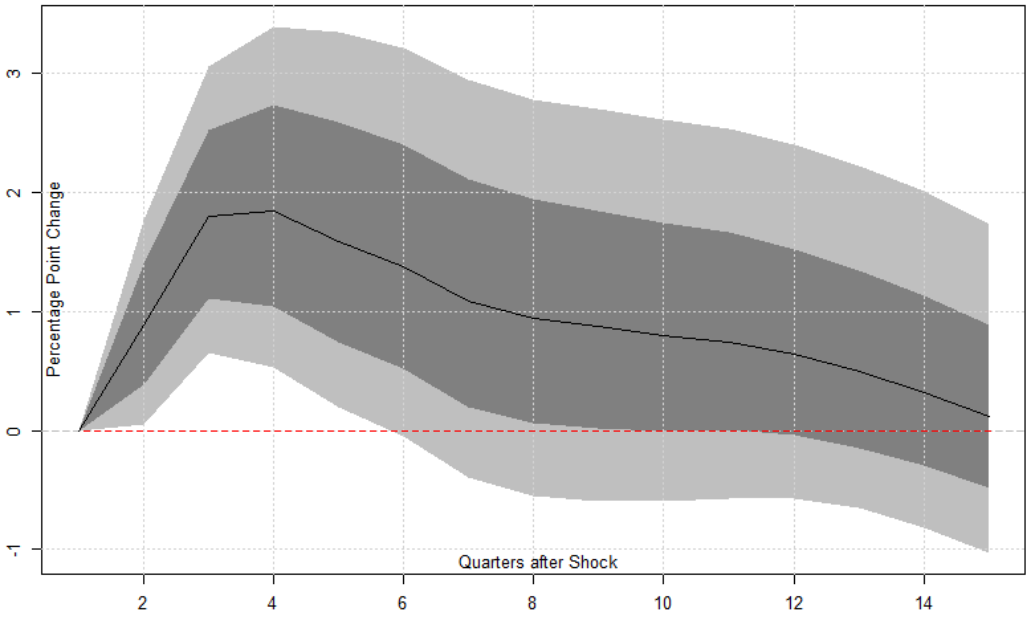


Figure 11. Cholesky decomposition-based impulse response function of unit labor costs to a shock to core inflation (variables are ordered as GDP-ULC-CPI)

5.3.3. Structural correlation analysis

Although the unconditional correlations give an indication of the movement of these variables, they can sometimes obscure the actual structural factors involved. This will be shown in Table 3 below, where the conditional correlations are presented and which reflect the relationship between the ULC and CPI under structural shocks to the economy.

Table 3. VAR-based correlation between unit labor costs and core inflation

Conditional on	**Correlation**	**Lower 68% credible interval**	**Upper 68% credible interval**
All shocks	**0.28**	**0.27**	**0.34**
Y shock	**0.76**	0.24	0.77
ULC shock	**0.82**	0.79	0.82
P shock	**0.80**	0.76	0.88

The correlation coefficient under the "All shocks" assumption has reached a moderate level of 0.28. On its face, the value of the parameter indicates inconsistency in the relationships among the variables. In fact, the overall result is the statistical outcome of structurally different factors that affect output, wages, and prices independently from each other in some cases, such as the influence of productivity on wages and at the same time on the price level. The strength of the relationship is revealed only by separating structural shocks, which brings the correlation coefficient to the 0.76 - 0.82 range.

The maximum correlation has been achieved assuming that the structural factor has a ULC source; therefore, the correlation coefficient equals 0.82. Under the condition of labor market shocks, the ULC and CPI are correlated very closely. Correlation during price shocks at 0.80 supports the results of the "second-round effects" analysis conducted earlier.

5.4. Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) is a tool used to analyze the extent of influence of each structural shock in contributing to the variance of the variables in the model at various time intervals. Although the impulse responses indicate the direction and period of the shock, the FEVD indicates how much variance of a certain variable can be traced to its innovations and the innovations

of other variables in the model. As far as the present study is concerned, the role of the FEVD is to ascertain the strength of the wage-price pass-through, whereby labor cost pressure would emerge as a structural determinant of inflation or a side effect of macroeconomic instability. Figure 12 below visualizes the variance decomposition for Core CPI, and the numerical results are detailed in the subsequent analysis.

Looking at the near-term horizon (Horizon 1), the effects that drive the changes to inflation come from its structural developments, which explain 91.01% of the forecast errors variance. At this early phase, the effect of the shock to labor cost is insignificant, accounting only for 1.06% of the variance. From an objective point of view, the conclusion drawn is that the "first-round" effect on the prices comes mainly from certain structural features like administrative price adjustments, fluctuations in exchange rates, which cannot be explained by the model, or adaptive expectations and is not caused by labor market conditions. The labor market appears "decoupled" from the price level in the very short run, reflecting significant nominal rigidities or menu costs.

In addition, as the forecasting period increases, the structural significance of the wage-price relationship slowly rises. By the one-year point, the effect of ULC shock rises to 2.06%, and by the fourth year, the figure rises further to 12.98%. Although 13% of the structural inflation can be attributed to labor costs, we would recognize that labor costs are not the main contributor to inflation. The rising significance of labor costs throughout the forecasting period shows that the pass-through effect is slow because the labor cost effect does not immediately lead to price spikes but instead has a continuous effect on the inflation baseline.

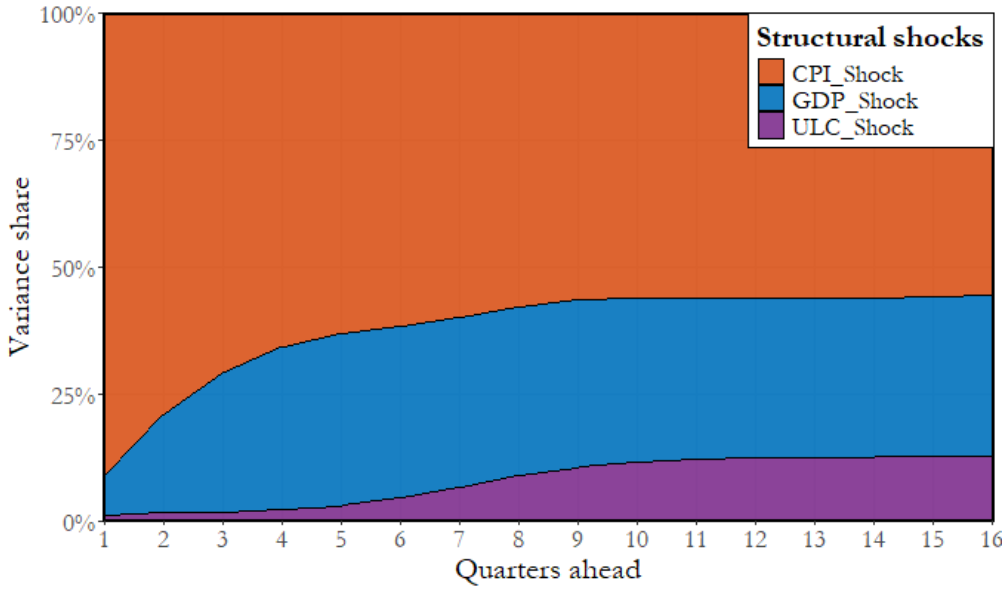


Figure 12. Forecast Error Variance Decomposition of the Core CPI

According to the FEVD findings, inflation persists for a long time and becomes progressively more responsive to output shocks. The labor cost pass-through theory has been validated from the evidence presented as a structural determinant of inflation in the economy. However, with a relatively small proportion of 13% attributed to labor costs at the 16-quarter period, the wage-price spiral is secondary for the structural development of inflation.

5.5. Historical decomposition of CPI dynamics

Historical decomposition (HD) is a backwards structural method of the observed data by decomposing the actual movements of the endogenous variable into the total impact of the structural shocks detected within the VAR model framework. Contrary to the FEVD technique, which presents a forward average variance estimate, historical decomposition enables the assessment of particular economic events on a point-to-point basis. In the current research, Figure 13 will be used to identify the particular time intervals when the effects of the labor costs (ULC

shocks) either intensified or dampened the inflation trend within the 2012-2025 timeframe.

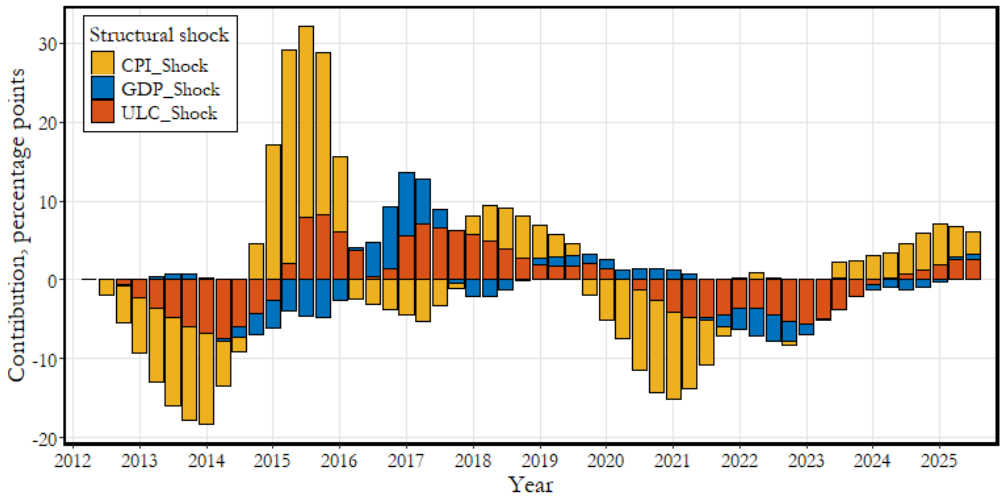


Figure 13. Historical decomposition of the core CPI in the baseline 3-variable model

At the time of the 2014Q1-2015Q2 inflationary spike, Core CPI increased from 0.72% to a peak of 45.87%. As seen in the historical decomposition, the main factor was the CPI shock, which reached its highest contribution of 26.07 p.p. in 2015Q2. Meanwhile, the labor market serves as a second-order propagator. Following the data presented, the rate of ULC contribution increased from 3.41% to 15.44% within the same period. From the perspective of the structural model, although the labor market did not start the shock, it was an important factor for propagation. By 2015Q3, the ULC shock accounted for 7.22 p.p. of inflation and helped maintain high price levels despite the decreased of effects of the primary impulse.

During 2020–2021, both GDP and ULC shocks were major disinflationary factors amid the pandemic shock. In turn, the start of the large-scale invasion in 2022 creates a structural paradox for the economy. Based on the empirical data, the GDP shock experienced a historic reduction by -36.59% in 2022Q2, whereas nominal ULC growth surged to 33.88%. However, despite such nominal wage growth, the historical decomposition demonstrates that the ULC shock was a negative factor for inflation, with its contribution being -5.72 p.p. in 2023Q1.

However, this result needs further explanation. Specifically, in the initial shock of 2022, aggregate demand collapsed along with the weakening of real purchasing power of households. Even with positive nominal wages, this event could be described as demand-destroying.

Among other important results, the critical discovery here is the structural break, which is observable starting in 2024. One can note how the contribution of labor costs started to increase. The ULC shock contributes positively starting with zero in early 2024 and reaches 2.60 p.p. in 2025Q2. This is when the "phase" of demand destruction shifts to cost-push dynamics. Due to the tightness of the labor market amid mobilization and migration, nominal wage changes exceeded productivity growth and hence became inflationary. Importantly, one may also observe a slight positive contribution of the GDP Shock (0.35 p.p.). It means that Ukraine entered the new phase where each slight economic recovery would face constraints in the labor market.

The historical decomposition confirms that the wage-price relationship in Ukraine is episodic. In most cases (e.g., 2012–2023), labor costs were often a stabilizing or secondary factor. However, the current period (2024–2025) represents an effective structural relationship.

The historical decomposition is further refined by comparing the baseline results with the extended four-variable model, which explicitly accounts for exchange rate

dynamics (see Appendix B for full decomposition charts). This comparison reveals that while the baseline model identifies labor costs as a significant contributor to the 2015 and 2025 inflationary episodes, the inclusion of the exchange rate provides a more complex narrative. In the 2015 spike, the four-variable model identifies the currency crisis as the primary catalyst, with ER shocks explaining up to 6.91 p.p. of inflation, thereby reclassifying much of the baseline's idiosyncratic "price shocks" as direct exchange rate pass-through.

The two models reach a consensus regarding the 2022–2023 period, where the collapse in labor demand and real wages functioned as a structural barrier to inflation, contributing approximately -2.04 p.p. to price growth in early 2023. However, a key distinction emerges in the 2025 observations. While the baseline suggests a strong re-emergence of labor-push inflation (+2.60 p.p.), the extended model indicates that this effect is almost entirely overshadowed by currency fluctuations and other supply-side shocks, with the ULC contribution falling to -0.29 p.p. Ultimately, these results suggest that while structural analysis confirms an independent transmission mechanism from labor costs to prices, the realized historical impact of these pressures is frequently secondary to the dominance of the exchange rate and the persistence of collapsed aggregate demand.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

6.1. Conclusions

By applying the Bayesian Vector Autoregression model and analyzing the dynamics of wages and prices during the period between 2011 and 2025, this thesis reveals the causes of the ongoing domestic wage-price cycle. As a result, it becomes evident that various labor market shocks, changes in the exchange rate, and fluctuations in the aggregate demand affect the price level. In general, this empirical investigation offers an insightful structural description of the inflation regime in Ukraine, based on which I may outline three key conclusions.

First, the model reveals a "hump-shaped" transmission delay. As the IRFs indicate, labor market shocks do not directly result in core inflation. Rather, there is a certain time gap between the two processes, amounting to 2–3 quarters, whereas the correction effect of the structural shock occurs at the 8–9-quarter mark. Therefore, it appears that nominal rigidities along with slow-moving wage negotiations, have resulted in persistent inflation pressure, which continues even well after the initial impulses. The inclusion of the exchange rate in the extended model confirms that this pass-through is an independent structural phenomenon rather than a byproduct of currency volatility. Consequently, the 4-variable specification serves as the preferred model for final evaluation, as it provides a more realistic representation of the Ukrainian economy by controlling for the dominant exchange rate channel while still isolating the domestic wage-price link. In such a way, labor cost can serve as a relevant price stability indicator.

Second, the results confirm that second-round effects are strong. Analyzing the so-called "indexation mechanism", where prices drive wages, we can see that the Ukrainian economy has robust feedback loops. Thus, a shock to prices produces a

substantial upward spike in nominal labor costs after a year, peaking at 1.87 percentage points. As a result, inflation expectations in Ukraine are most likely to be adaptive in nature. Given the high structural power of the labor market, workers are willing to claim increased compensation for the decrease in real income levels, which contributes to the wage-price spiral in the absence of strong demand.

Third, I note that wages and prices develop separately. The results from the FEVD and historical decomposition provide a realistic perspective on this issue. Even though labor costs account for around 13% of the long-term variability in inflation, the main structural factors affecting it are supply shock and exchange rate pass-through. Historical assessment shows that the impact of labor costs largely depends on the overall macroeconomic environment. Specifically, the 2022 to 2023 period can be characterized by demand destruction, when low levels of economic activity kept inflation relatively low. However, in 2024 to 2025, there is a structural shift, which means that labor market limitations such as mobilization and migration cause Unit Labor Costs to become an increasingly positive influence on inflation. Despite being only indirectly linked to inflation and having little explanatory power for price growth, labor costs play an important but secondary role due to the dominance of the exchange rate. This indicates that while the wage-price spiral remains a latent risk, its emergence in Ukraine is currently suppressed by the dominance of currency dynamics and the lasting effects of contracted aggregate demand.

However, despite the well-defined nature of the analysis within the BVAR modeling context, there exist several limitations to this study worth mentioning. First, the data on the Ukrainian labor market has been constructed using different sources due to the cessation of official statistics owing to the full-scale war. Second, a relatively limited number of observations along with a structural break in 2022 makes the model incapable of adequately separating the effects of short-term wartime fluctuations from long-lasting changes in economic performance. Third,

while the structural identification approach allows one to capture the effects of shocks in the Ukrainian economy, there may exist other important variables affecting the level of prices in Ukraine that do not fit into the standard macroeconomic model.

6.2 Policy recommendations

Based on these findings, I propose the following recommendations for authorities. Regarding monetary policy, the National Bank of Ukraine should maintain labor-forward targeting. As it takes 2-3 quarters for increases in unit cost of labor to influence prices, the central bank needs to monitor Unit Labor Cost changes. Monetary tightening should be pre-emptive when wage growth significantly outpaces productivity, rather than reacting only after these costs show up in the Core CPI. If the NBU waits for the CPI to spike, it effectively allows 6 months of inflationary momentum to become incorporated to the expectations of the public.

On the other hand, when it comes to fiscal policy, the government needs to deal with productivity issues. Clearly, it is not possible to have nominal wage growth, with no increase in productivity. These imbalances will eventually generate inflationary pressure. Fiscal and structural policies need to emphasize investments in increasing productivity of capital and retraining workers, to match wages to productivity improvements. Addressing labor shortages and inefficiencies remains the best solution to economic recovery and stable prices.

The issue of managing expectations through exchange rate flexibility is crucial as well. Indeed, the robustness checks showed that the exchange rate was still a key determinant of realized inflation. Hence, it makes sense for the NBU to continue following its "managed flexibility" regime in order to provide an additional cushioning mechanism. By shifting some part of external risks onto the exchange

rate, the central bank can lower the frequency of the initial price increases that cause the wage-price spirals observed in this research.

Lastly, it is important to watch out for second-round inflation triggers. It seems that there is a high level of responsiveness of inflation expectations due to the strong transmission between prices and wages. In other words, policymakers should have internal alert thresholds regarding nominal wage changes. Once wage growth surpasses a certain corridor against the target level of inflation and productivity margins, it may serve as a reason to reconsider the policy course.

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APPENDIX. A ESTIMATION RESULTS

Table 4. Backcasting estimation of SSSU nominal wage series

Explanatory variables	**Model 1**	**Model 2**
Intercept	0.0038	0.0030
	(0.0063)	(0.0031)
$\Delta \ln(\text{Wage}_t^{\text{PFU}})$	**0.6950***	**0.7396***
	(0.0794)	(0.0430)
$\Delta \ln(\text{Wage}_t^{robota.ua})$	-0.1855	—
	(0.1813)	
Observations	50	147
R-squared	0.6523	0.6709
Adjusted R-squared	0.6375	0.6686
Residual Std. Error	0.0427	0.0370
F-statistic	44.09*	295.6*

Note: Standard errors are in parentheses. Asterisks (*) indicate significance at the 1% level ($p < 0.01$).

Table 5. State-Space Model nominal wages estimation

Component	**Parameter**	**Estimate**
Level Variance	$\sigma^2_{\eta_\mu}$	5.40×10^{-7}
Slope Variance	$\sigma^2_{\eta_\nu}$	9.36×10^{-9}
Seasonal Variance	σ^2_{ω}	6.91×10^{-6}

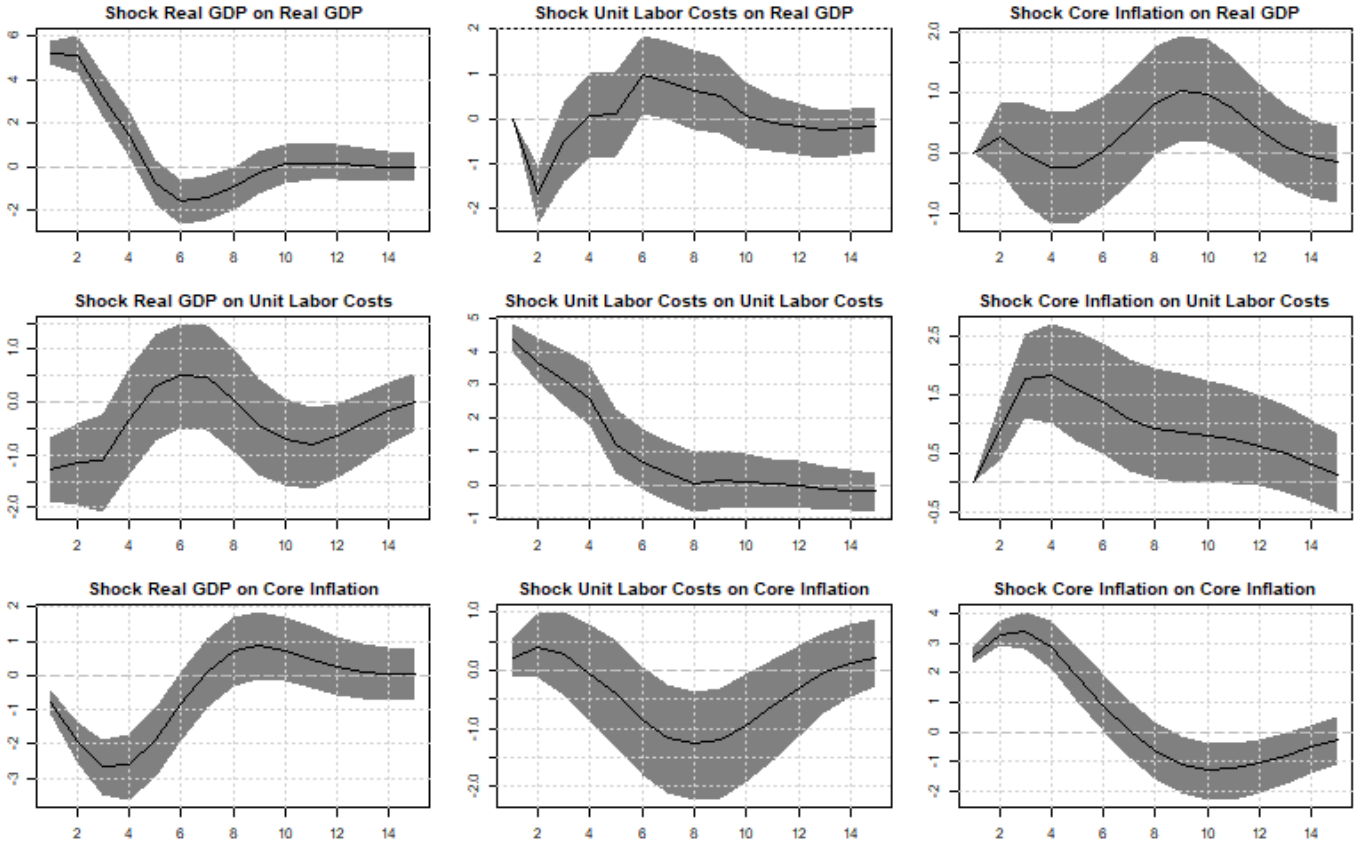


Figure 14. Impulse response functions estimated in the baseline model

Table 6. Information criteria for lag length selection

Lags (p)	**AIC**	**HQ**	**SC (BIC)**	**FPE**
1	6.621	6.709	6.851	751.59
2	5.695*	5.841*	6.078*	298.04*
3	5.831	6.035	6.366	342.16
4	5.787	6.049	6.475	328.71
5	5.777	6.097	6.618	327.68
6	5.701	6.08	6.695	306.76
7	5.752	6.189	6.899	327.29
8	5.874	6.369	7.174	376.44

* Denotes the optimal lag selected by the respective criterion.

Table 7. Median coefficients estimated by the baseline model

	GDP	ULC	CPI
constant	-2.424	1.8	3.07
GDP-lag1	0.904	0.029	-0.172
ULC-lag1	-0.388	0.832	0.035
CPI-lag1	0.096	0.343	1.293
GDP-lag2	-0.201	0.061	0.068
ULC-lag2	0.555	-0.012	-0.136
CPI-lag2	-0.083	-0.037	-0.346
GDP-lag3	-0.067	0.164	0.03
ULC-lag3	-0.142	0.037	0.036
CPI-lag3	-0.009	-0.269	-0.125
GDP-lag4	-0.173	-0.066	0.02
ULC-lag4	-0.074	-0.147	0.03
CPI-lag4	-0.044	0.029	-0.057
GDP-lag5	0.109	-0.001	-0.03
ULC-lag5	0.078	0.062	-0.037
CPI-lag5	0.154	0.184	0.051

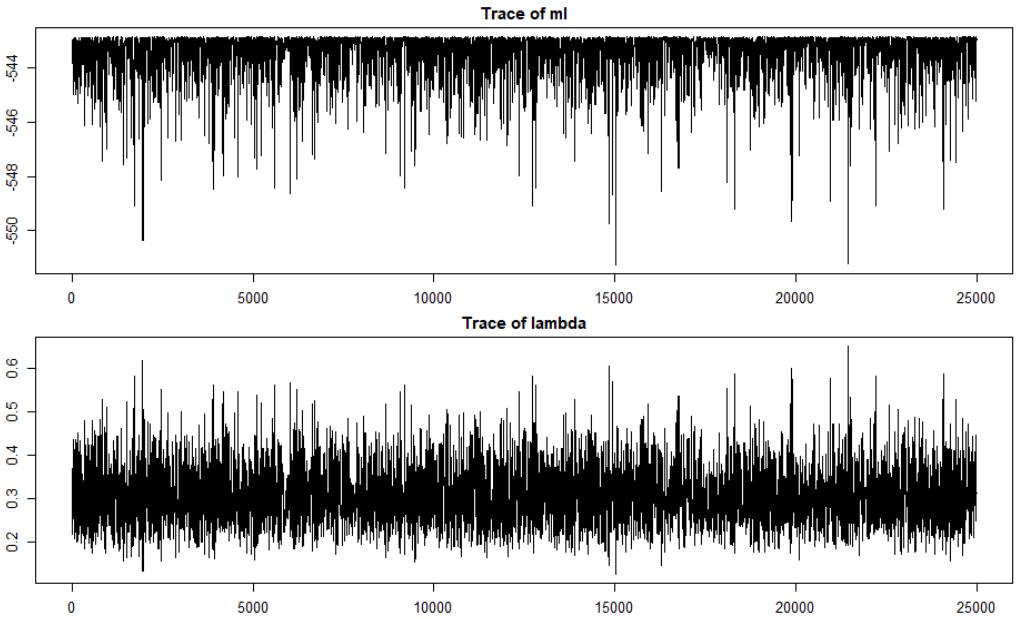


Figure 15. Posterior trace of the Minnesota Prior Tightness and Marginal Likelihood

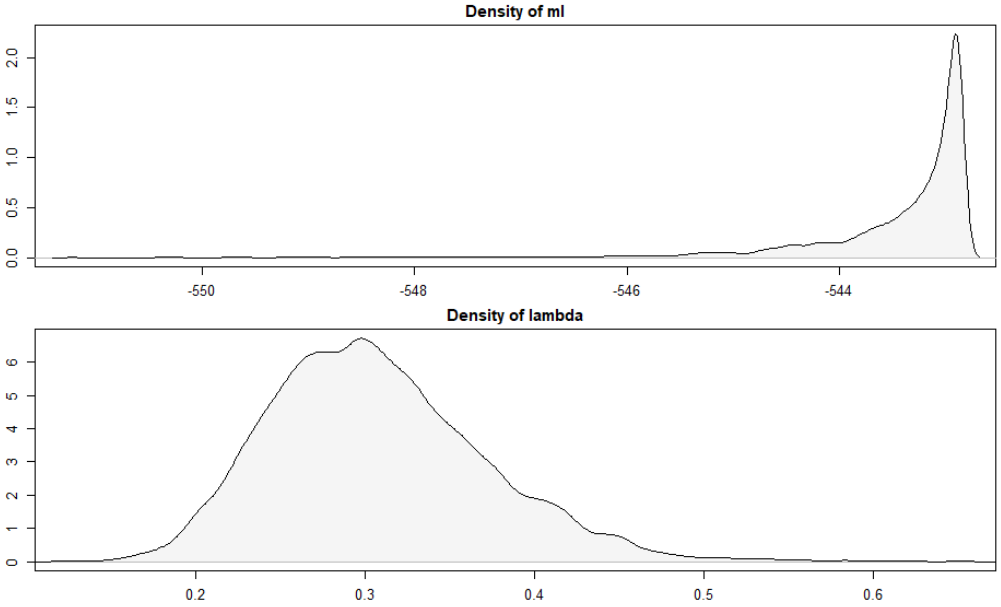


Figure 16. Density plots of the Minnesota Prior Tightness and Marginal Likelihood

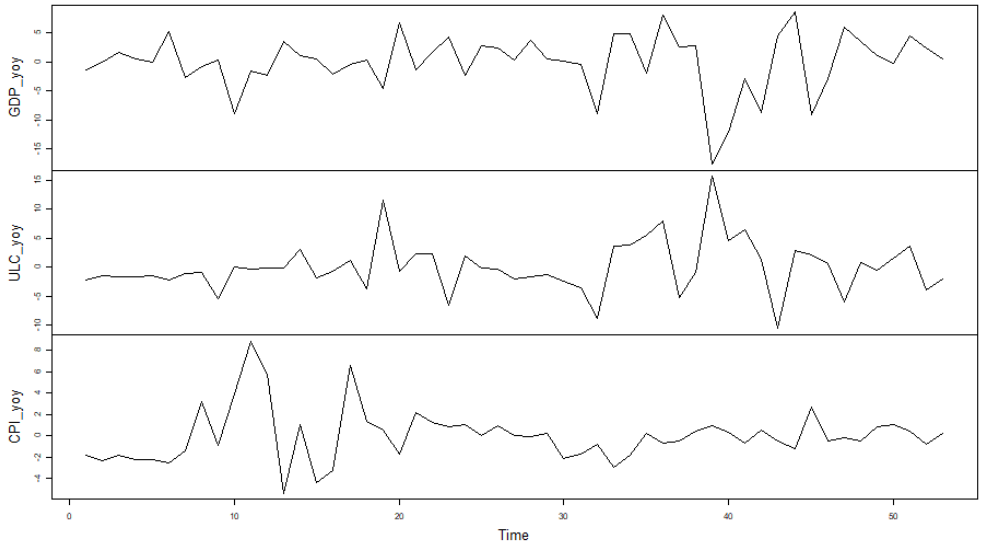


Figure 17. Diagnostic residuals of the baseline BVAR model

APPENDIX. B ROBUSTNESS CHECKS

Robustness check 1: Variable reordering

The key issue when employing structural VAR models lies in the sensitivity of the Impulse Response Function (IRF) to the Cholesky decomposition of the order in which the variables are entered as an input for the sign restriction algorithm. In the baseline model, the variables were ordered as $[GDP_{yoy}, ULC_{yoy}, CPI_{yoy}]$. The robustness check reorders the system to $[ULC_{yoy}, CPI_{yoy}, GDP_{yoy}]$, assuming labor costs can impact all other variables contemporaneously, while output reacts to price and wage shocks only with a lag.

In Figure 18, the reaction of Core CPI to the Unit Labor Cost shock is illustrated for the alternative ordering of variables. Comparing the base case to the robustness test results (see Table 8) one can see a remarkable similarity in qualitative characteristics.

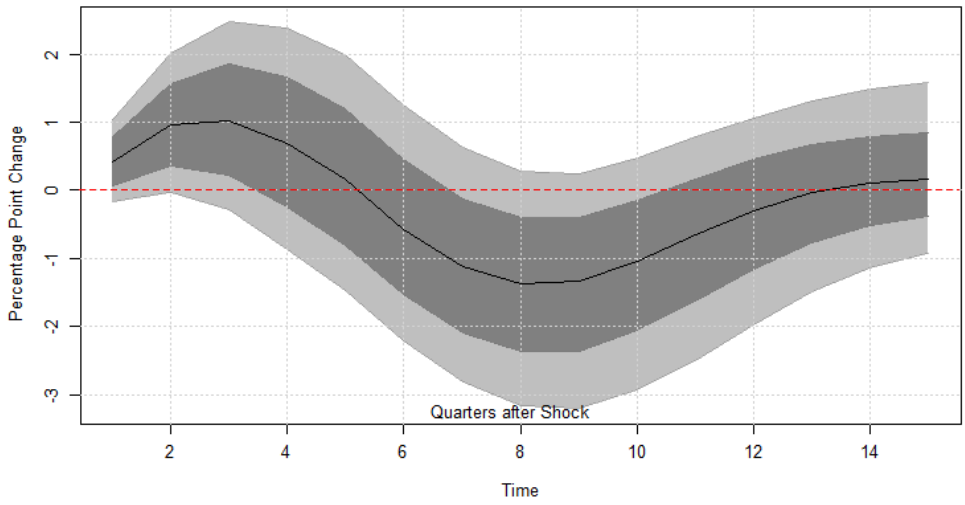


Figure 18. Cholesky decomposition-based impulse response function of unit labor costs to a shock to core inflation in alternative ordering (variables are ordered as ULC-CPI-GDP)

The results of robustness check 1 provide evidence that the core findings of this thesis are not a result of the variable ordering. Though the restructured equation implies a higher pass-through effect, the story is still the same in that structural cost shock triggers inflation and then creates deflationary pressure.

Table 8. Comparison of median responses of ULC shock to Core CPI between the baseline model and the model with alternative ordering

Horizon, quarter	Baseline Median	RC1 Median
0 (contemp.)	0.21	0.42
1	0.42	0.94
2 (peak)	0.29	1.01
8 (trough)	-1.26	-1.39
15 (long-run)	0.21	0.20

Note: RC1 means robustness check 1

Robustness check 2: Sign restriction

The second robustness check assesses the sensitivity of the findings to the choice of structural identification method. In the base case specification, the labor cost innovation remains entirely unidentifiable in order to maintain maximum agnosticism about the empirical evidence. Using the same identification method as Bobeica et al. (2019) in their parsimonious identification approach, demand and supply innovations are identified based on the relationship between output and price levels. In order to implement the third innovation, which is unidentifiable, in such a way that there is no loss of information from the process of pointwise median elimination, a common normalization constraint is imposed on the labor cost variable along the diagonal axis. The identification scheme is presented in Table 9.

Table 9. Sign restriction VAR identification scheme

Variables	Shocks		
	Demand	Supply	ULC
GDP	+	+	•
Core CPI	+	–	•
ULC	•	•	+

Notes: • = unconstrained, + = positive sign, – = negative sign

The results obtained using this alternative identification approach are depicted in Figure 19 below. The median response of Core Inflation in reaction to an impulse of the ULC shows similar behavior to that of other scenarios discussed, in terms of its hump-shaped path. The peak value of the median response equals 0.52 p.p. and occurs in the second quarter. The figure is greater than that from the baseline scenario (0.42 p.p.), but less than that from the recursive reordering specification (1.01 p.p.).

The key takeaway from this robustness test is that there is an evident increase in the credible intervals. At its highest point (quarter 2), the credible interval for 68% confidence range ranges from -2.26 to +2.87. In contrast to the baseline scenario, where the credible intervals were quite narrow around the median, this identification shows high levels of noise. While the credible intervals for the ULC shock are located at the baseline of zero, under the frequentist approach, one would assume that the effect is insignificant since it does not pass the significance level. However, in a Bayesian estimation approach, the similarity in the paths of the median under different identification strategies indicates that the wage-price lag is a robust feature in Ukrainian data.

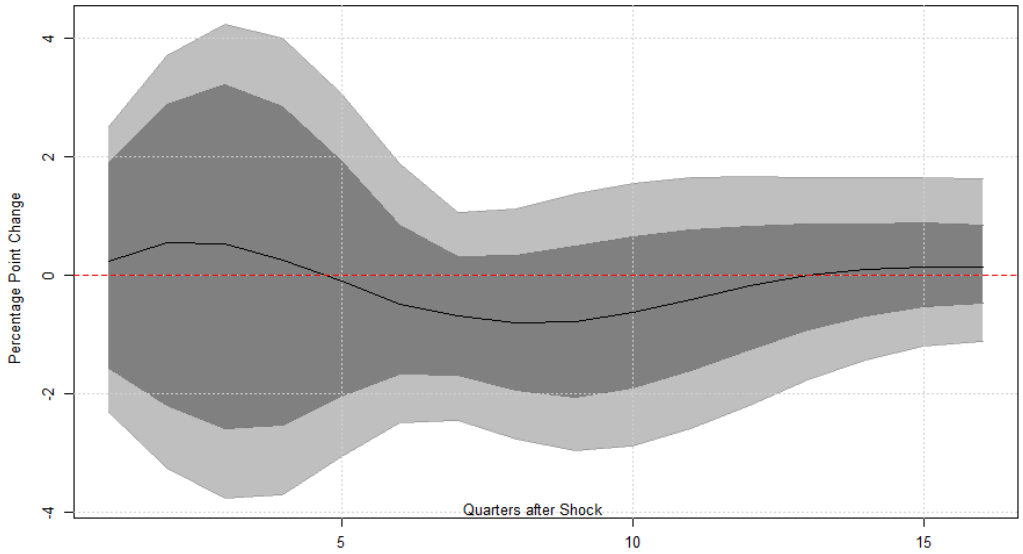


Figure 19. Sign restrictions based impulse response function of unit labor costs to a shock to core inflation

Robustness check 3: Controlling for exchange rate dynamics

One critical issue in the Ukrainian case is the possibility that the noted co-movement between labor cost and price could simply be an illusion generated by a common reaction to exchange rate (ER) shocks. With such a highly dollarized economy and intense pass-through effect from exchange rates to inflation in Ukraine, domestic inflation should also consider the impact of exchange rates when structural analysis is applied.

Accordingly, the basic 3-variable BVAR model is extended into the 4-variable version where the exchange rate enters. Following the standard process of quarterly transformation, the exchange rate enters the model by calculating a yearly growth rate based on the quarterly averages from monthly data for UAH/USD.

The model uses a recursive Cholesky decomposition, where the variables ordering is set as: $[GDP_{yoy}, ER_{yoy}, ULC_{yoy}, CPI_{yoy}]$. The reason for placing the ER variable before labor costs and prices is that, in doing so, all domestic shocks are

eliminated, reducing correlations between currency volatility and the others. In this configuration, a structural shock to ULC represents a pure domestic labor-market disturbance orthogonal to immediate exchange-rate fluctuations.

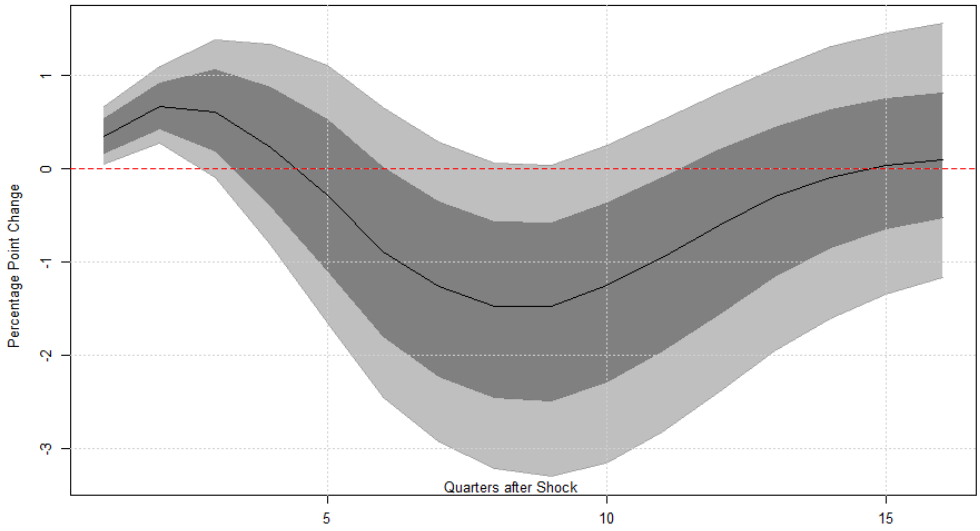


Figure 20. Cholesky decomposition based impulse response function of unit labor costs to a shock to core inflation in the model that includes exchange rate variable (variables are ordered as GDP-ER-ULC-CPI)

The results generated by this specification with four variables, presented in Figure 20, offer evidence confirming the findings of the thesis. Although the exchange rate has been added to the model as a control variable, the underlying structural connection between the cost of labor and inflation still holds.

The median response of Core Inflation to a ULC shock is positive and robust. Its starting point is 0.34 percentage points at Quarter 0 and peaks at 0.66 p.p. in Quarter 2. These figures align well with the baseline estimates, indicating that domestic wage dynamics have a transmission mechanism through which they affect prices, separate from the depreciation of the national currency. The reversal

pattern typical in the medium term is clearly visible. The median response goes below zero at Quarter 5 (-0.29 p.p.) and bottoms out at Quarter 9 (-1.48 p.p.). Credible intervals confirm the statistical significance of the first impulse in the inflation response function for the first year, namely, Quarters 0-3. This suggests that even in a currency-sensitive economy like Ukraine, labor market imbalances are a reliable indicator of price movements.

The historical decomposition assigns the observed volatility of the variable to the shocks to the structure of the system. The baseline model (Figure 13) implied the significant return of labor cost pressures for the period 2024–2025. Nevertheless, the results obtained using the extended 4-variable model (Figure 21) imply a more complicated picture.

In the baseline model, the large inflationary outbreak in 2015 was assigned mostly to the CPI Shock (26.07 p.p.) and partly to the ULC Shock (7.22 p.p.). The role of the ER shock becomes essential in the extended model. From 2013 to 2014, the share of inflation explained by the ER shocks was up to 6.91 p.p. This means that the 2015 shock was predominantly the result of the currency crisis. Therefore, the role of the pure CPI shock became less important, implying that most of the previous "price idiosyncratic shock" was actually due to the depreciation of the national currency.

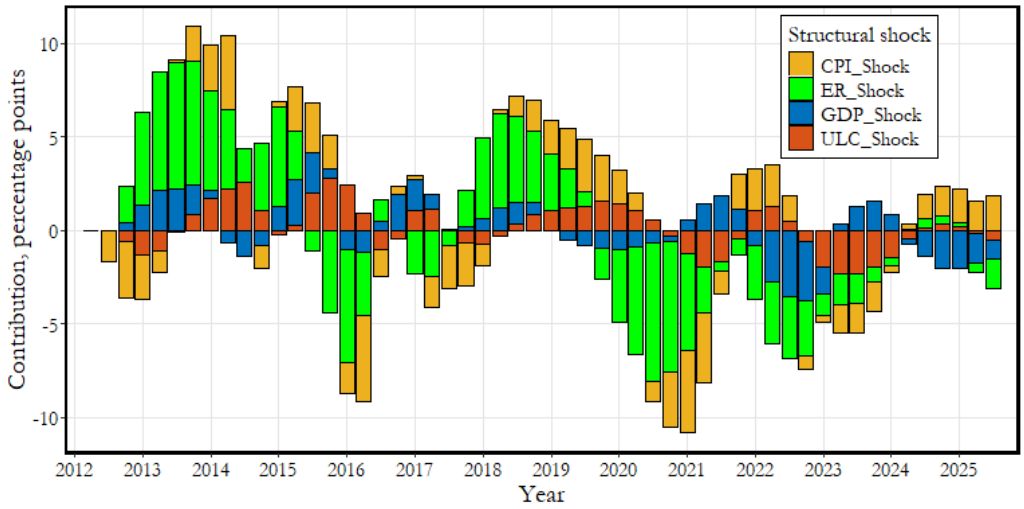


Figure 21. Historical decomposition of the core CPI in extended 4-variable model (variables are ordered as GDP-ER-ULC-CPI)

According to both models, domestic shocks played an instrumental role in bringing down inflation rates during the first phase of the war. For instance, according to the 4-variable model, the contribution of the ULC shock to the inflation rate amounted to -2.04 p.p. in Q2 2023. Despite the volatility of the exchange rate, the drastic decline in the labor demand and real wages functioned as a structural barrier that hindered a further increase in inflation. In addition, a currency shock turned into a disinflationary one later in 2022. The reasons behind this could be attributed to the freeze of the exchange rate together with substantial foreign aid.

However, the key distinction between the two models is seen in the 2025 observations. The baseline model (3-Var) estimated that labor costs increased inflation by +2.60 percentage points in the second quarter of 2025. In contrast, the extended model (4-Var) indicates that the contribution of the ULC shock to inflation in this period was –0.29 percentage points. From an objective standpoint, it can be concluded that incorporating the exchange rate into the model greatly reduces the contribution of labor costs in recent observations. Whereas the IRF

analysis indicated that a shock in wages can lead to higher prices, the decomposition of historical data revealed that the inflation in 2025 was mainly due to the exchange rate and other price shocks.

In summary, it can be concluded that the extended model (4-Var) proves the significance of exchange rate and supply shocks as determinants of inflation in Ukraine. While the structural analysis confirmed the independent impact of labor costs on prices, historical decomposition shows that labor market pressures were much less significant than exchange rate fluctuations and lower aggregate demand in recent years.