Estimating Potential Non-Oil GDP in Azerbaijan[1]

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Abstract

This study assesses Azerbaijan's non-oil potential growth and its interplay with capacity utilization and inflation dynamics. Utilizing multiple estimation techniques, non-oil potential output growth is consistently estimated at around 5%. While short-term GDP growth exceeding the estimated level might suggest overheating, firm-level data suggest otherwise. Drawing on monthly survey data from enterprises across various industrial sectors covering the period of 2019–2024, we find that elevated growth does not always lead to inflationary pressures, especially when firms operate below full capacity. In such cases, capacity utilization can increase without a significant cost increase. The findings of this study emphasize the importance of incorporating capacity utilization metrics into inflation monitoring and highlight the need for policy responses in emerging economies with structural supply-side constraints.

Keywords: potential growth, non-oil GDP, steady state growth, capacity utilization

JEL Codes: O40, O47, D24

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[1] The views expressed in this working paper are those of the author(s) and do not necessarily represent the official views of the Central Bank of the Republic of Azerbaijan.I am grateful to Ramiz Rahmanov and Vugar Ahmadov for their valuable insights and suggestions.

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1. Introduction

Estimating potential output and identifying overheating risks are fundamental to the design of effective macroeconomic policies, particularly for emerging and resource-rich economies. Understanding both the long-term growth potential and the short-term cyclical dynamics of the Azerbaijan economy is crucial for formulating effective monetary and fiscal policies. This study provides estimates of the long-term growth potential of Azerbaijan's non-oil economy, which can be sustained without generating inflationary pressures, given the technological capabilities and resource constraints. While estimates of potential output illuminate the structural capacity of the economy, they do not fully capture short-term fluctuations that influence inflation dynamics.

Using multiple methodologies such as the Hodrick-Prescott filter, the Kalman filter, and the Cobb-Douglas production function, this study estimates Azerbaijan’s non-oil GDP growth potential. The estimations show that the non-oil GDP growth potential is around 5%. The analysis further explores the impact of the short-term output gap volatility, deviations from the potential level, on the inflation level. Findings reveal that when excess demand emerges, firms may increase capacity utilization without a proportional rise in marginal costs or labor expenses. This observation suggests that heightened demand does not necessarily translate into inflationary pressures, challenging the conventional interpretation of output gaps and capacity utilization rates as straightforward indicators of overheating. To investigate these complex interactions, the study analyzes the relationship between firm-level capacity utilization and labor market activity in non-oil industrial sectors. Granular survey data reveal sector-specific patterns and temporal fluctuations in capacity utilization, and their associations with labor adjustments and inflation signals.

The results have significant implications for macroeconomic policy in Azerbaijan. The Central Bank of Azerbaijan’s primary objective is to ensure price stability, which requires carefully distinguishing between structural capacity constraints and cyclical overheating. Our results suggest that industries operating below full capacity, even at their natural utilization rates associated with stable growth, may still accommodate excess demand without triggering inflation. While potential output remains a critical benchmark for assessing excess demand, the transmission of demand pressures into inflation is influenced by additional factors, especially pricing strategies and labor market responses.

In sum, this study contributes to the understanding of the interplay between capacity utilization, labor dynamics, and inflation in Azerbaijan’s non-oil sectors. By integrating firm-level data, econometric models, and theoretical frameworks, we provide evidence that can enhance the central bank’s ability to maintain price stability in a complex economic environment.

2. Literature review

The accurate estimation of potential GDP is crucial, especially in the context of analysing excess demand. Since deviation of actual output from its potential level is commonly referred to as the output gap, which serves as a key indicator of demand pressures in the economy. Therefore, validating estimates of excess demand or supply conditions, one way to validate potential output estimates is by examining their implication for inflation dynamics. Theoretically, the Phillips curve suggests a positive relationship between excess demand and inflation, as excess demand puts upward pressure on marginal cost.

In this regard, a widely used empirical specification is based on the "approximate proportionate relation between marginal cost and output" (Gali & Gertler, 1999, p. 201). When real GDP exceeds its potential level, signalling excess demand, businesses typically respond by expanding employment or extending working hours. This elevated demand for labor exerts upward pressures on wages, as firms compete to attract or retain workers. The resulting increase in labor costs raises unit labor costs, which in turn contributes to inflationary pressures. This relationship is typically formalized through a New Keynesian Phillips Curve:

$$mc_{it}^{r} = k(y_t - y_t^{*}) \tag{1}$$

where mc_{it}^{r} dnotes real marginal cost, k is the output elasticity of marginal cost, y_t is the log output and y_t^{*} is the potential (or natural) level of output. Surprisingly, Gali and Gertler's (1999) analysis using the Generalized Method of Moments (GMM) for the U.S. found a negative correlation between the output gap and inflation, which contradicts conventional theory. This anomaly has been explored in heterodox economic literature. For instance, Lavoie (2022) argues that firms generally operate below full capacity, allowing them to increase production without raising marginal costs when demand rises. As a result, inflation may not emerge when output exceeds historical norms, suggesting that the "true" potential output might differ from standard estimates.

In contrast, Neiss and Nelson (2005) revisited the output gap's role using a more theoretically consistent framework. Their findings indicated that when the output gap is measured consistently with economic theory rather than via determined output, it reveals a significant and positive relationship with inflation in the U.S., UK, and Australia. Similarly, Forbes, Gagnon, and Collins (2021) examined the role of slack—defined as the deviation from full capacity—and found similar inflationary dynamics in their analysis of 31 countries, reinforcing the centrality of the output gap in explaining inflation.

Today, many central banks employ advanced techniques such as the Kalman filter to estimate the output gap and its relationship with inflation (Capek, Hlédik, Kotlán, Polák, & Vávra, 2003). Economists at the

Czech National Bank argue that such models are explicitly designed to estimate a measure of potential output that effectively forecasts inflation. “For example, an observation that inflation is rising makes it more likely that there was excess demand at the time (or a bit earlier, given the lags in the system)” (Capek, Hlédik, Kotlán, Polák, & Vávra, 2003, p. 14).

While this approach aligns conceptually with the marginal cost method, it may lead to misestimation of potential output in the context of global business cycle synchronization. Specifically, when a country is sufficiently large to influence global commodity markets, domestic inflation may reflect external pressures rather than domestic excess demand. Natural resource production is subject to long supply lags, making global commodity prices highly sensitive to shifts in worldwide demand (Lavoie, 2022, p. 131). During periods of global business cycle synchronization, when rising global demand increase the demand for domestically produced goods in small open economies, empirical models frequently exhibit a strong correlation between demand and inflation (Benes, Hlédik, Vávra, & Vlãek, 2003). Adjustments are made for global commodity prices or imported inflation. In this context, when a small open economy operates below full capacity, inflation is not primarily driven by strong domestic demand but rather by rising global commodity prices resulting from heightened global demand (Yusifzada, 2024).

Potential output can also be estimated using a production function approach, which assumes that potential GDP is independent of short-run output fluctuations (Serrano, 2019). However, Serrano critiques this approach, arguing that labor is rarely a binding constraint and that capital accumulation is predominantly shaped by demand trends through the supermultiplier mechanism. This perspective suggests that both cyclical fluctuations and long-term growth are fundamentally driven by effective demand, thereby challenging the assumption that potential output is fully detached from actual demand dynamics.

Finally, potential output can be estimated using econometric model-based equilibrium approaches. These models aim to forecast an economy’s steady-state growth over the long run. However, like univariate filter and production methods, they rely exclusively on historical data; in other words, it is backwards-looking. As Serrano highlights, potential output is not fixed but may evolve in response to shifts in effective demand, particularly in environments where excess labor persists.

Given the respective strengths and limitations of each methodology, as well as the underlying theoretical critiques, there is no universally accepted approach for estimating an economy's potential output. Consequently, many empirical studies adopt multiple methods and compare the resulting estimates to enhance robustness. In line with these practices, we estimate the potential output of Azerbaijan’s non-oil GDP using four available approaches: i) the Hodrick-Prescott filter, ii) the Kalman filter, iii) the Cobb-Douglas production function, and iv) VAR-based growth forecasting model.

3. Data and Methodology

3.1. Data

This study employs a comprehensive dataset to estimate the potential growth rate of non-oil GDP. The data includes a range of macroeconomic indicators such as real GDP, capital stock, labor force, and total factor productivity (TFP), among others. Data were obtained from the State Statistical Committee of the Republic of Azerbaijan (SSCRA), the Central Bank, International Monetary Fund (IMF), covering the period from 2003 to 2023. All variables are expressed in real terms to account for the effects of inflation.

The non-oil real GDP is calculated by subtracting the value added from mining and taxes from the total real GDP. Capital stock data includes both private and public investments, offering a comprehensive perspective on the economy's productive capacity. Labor force data, including total employment, were obtained from SSCRA and have been seasonally adjusted to smooth short-term fluctuations. Total factor productivity, representing technological progress and efficiency gains, is derived as a residual from the production function by subtracting the contributions of labor and capital from real GDP.

3.2. Methodology

To estimate the potential growth rate of the non-oil GDP, this study employs a combination of well-established econometric models and filtering techniques. Given the inherent complexity of capturing long-term economic trends, multiple methods are integrated to ensure a comprehensive and robust assessment of potential output. Each method plays a distinct role in capturing both short-term dynamics and long-run trends.

Specifically, the Hodrick-Prescott (HP) filter and the Kalman filter are applied to smooth the non-oil GDP data and extract its underlying long-run growth path by isolating cyclical variants from the structural component. The Cobb-Douglas production function is employed to provide a structural estimate of the potential output model by exploring the relationships among capital, labor, and total factor productivity. Finally, three Vector Autoregressive (VAR) models are used to capture the short-term interactions among key macroeconomic indicators, with the resulting forecasts informing long-run growth of the non-oil GDP.

This study integrates a combination of univariate, multivariate, and structural models, each offering distinct advantages and encountering specific limitations. By adopting this multifaceted approach, we aim to capture both the short-term fluctuations and the long-run potential growth trajectory of non-oil GDP, thereby offering a robust and reliable estimate of the economy's productive capacity. In the following sections, each method is described in detail, with a focus on explaining its application and relevance to the overall study.

Table 3.1. Models utilized in this study

Model type	Model name	Description
Univariate models	Hodrick-Prescott (HP) Filter	A smoothing technique that separates the trend from cyclical fluctuations in GDP
Multivariate models	Kalman Filter	Estimates potential GDP by analyzing the relationship between excess demand and inflation using the New Keynesian Quarterly Projection Model
Structural models	Cobb-Douglas Production Function	Uses structural relationships between inputs like labor, capital, and productivity to estimate potential GDP.
	Structural VAR (SVAR)	A multivariate model that captures the interactions between macroeconomic variables (e.g., output, inflation, unemployment).

3.2.1. Hodrick-Prescott (HP) filter

To estimate potential output, this paper employs the Hodrick-Prescott (HP) filter, a widely used technique in macroeconomic analysis for decomposing time series data into trend and cyclical components. The HP filter is particularly effective in extracting the long-term trend, which, in this context, represents the potential output, while separating out short-term fluctuations that correspond to the business cycle. In alignment with (Hodrick & Prescott, 1981)

$$\boldsymbol{min}\left(\sum_{t=1}^{T}(y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1}[(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2\right) \tag{2}$$

where, $\boldsymbol{y_t}$ denotes the actual observed non-oil output at time $\boldsymbol{t}$, $\boldsymbol{y_t^*}$ represents the estimated potential (trend) output, and $\boldsymbol{\lambda}$ is the smoothing parameter that governs the trade-off between fidelity to the actual data and smoothness of the estimated trend. The first term in the objective function minimizes the deviation between actual and potential non-oil output, ensuring that the trend closely follows data. However, excessive responsiveness may lead to the trend capturing short-term swings associated with business cycles or temporary shocks, which are not reflective of long-term potential. The second term imposes a penalty on abrupt changes in the growth rate of the trend, ensuring smoothness and gradual evolution over time. Overemphasis on smoothness, however, can result in an overly rigid trend that fails to reflect genuine structural changes in the economy.

The smoothing parameter λ plays a critical role in balancing this trade-off. A lower λ yields a trend more responsive to short-term movements, while a higher λ emphasizes long-run stability, potentially overlooking significant shifts in output dynamics. Therefore, selecting an appropriate value of λ is essential for producing a credible estimate of potential non-oil output.

Despite its limitations, including the choice of λ, potential over-or under-smoothing, and endpoint bias that reduces reliability near the sample edges (Alichi, et al., 2017), the HP filter remains a widely used and useful tool for estimating potential output when applied carefully.

3.2.2. Kalman filter

As a more advanced filtering technique, this study employs the Kalman filter to estimate the potential output within the framework of the New Keynesian Quarterly Projection Model (QPM). As outlined in the literature review, the QPM links the IS curve with the Phillips curve to theoretically derive the output gap, which serves as a key determinant of inflationary dynamics (Yusifzada et al., 2024). The Kalman filter, a recursive algorithm, continuously updates estimates of unobserved variables such as potential GDP as new data becomes available (Meese & Rogoff, 1983). This dynamic adjustment capability enables the model to account for economic shocks and structural shifts, making it particularly effective for real-time macroeconomic analysis. By integrating historical relationships captured in the QPM model with incoming data, the filter produces updated estimates of potential output.

A key advantage of the Kalman filter lies in its capacity to refine estimates over time, providing a more responsive and accurate assessment of long-term economic trends. As new data becomes available, the filter continuously adjusts its estimates, ensuring that potential output reflects the most current economic conditions. This adaptability makes the Kalman filter well-suited for macroeconomic forecasting in economies characterized by frequent structural changes. However, despite its strengths, the Kalman file is not without limitations. It is notably sensitive to model specification errors, meaning that inaccurate assumptions regarding the relationships among variables can result in biased estimates (Rodríguez & Ruiz, 2012). Moreover, the method requires a substantial volume of high-quality data, and deficiencies in data may affect the accuracy of the output.

3.2.3. Cobb-Douglas function

Thirdly, we employed the Cobb-Douglas production function to estimate the potential output of the economy. The Cobb-Douglas function is a widely used structural model in macroeconomic analysis, capturing the relationship between output and key inputs, particularly capital and labor. The general form of the Cobb-Douglas production function (Cobb & Douglas, 1928) is given by:

$$Y = AK^{\alpha}L^{1-\alpha} \quad (3)$$

where Y denotes non-oil GDP, while K and L denote capital and labor inputs, respectively, and A represents total factor productivity (TFP), capturing the efficiency with which these inputs are utilized. The parameters α and $1-\alpha\ (or\ \beta)$ represent the output elasticities of capital and labor, with both parameters representing the contribution of each input to the production process.

The Cobb-Douglas function relies on several underlying assumptions. Most notably, it assumes constant returns to scale, implying that a proportional increase in both capital and labor leads to an equivalent proportional increase in output. increase in output. This condition is satisfied when the sum of the elasticities equals one, which is defined as $\alpha+\beta=1$. Furthermore, it assumes that the output elasticities and TFP remain constant over time, implying that the percentage change in output due to a percentage change in capital or labor remains fixed. In addition to the theoretical limitations outlined in the literature review, the Cobb-Douglas production function assumes constant output elasticities and exogenous total factor productivity, which may not hold across different economies or fully capture the impact of technological progress and productivity shocks. Nevertheless, due to its simplicity and solid theoretical foundation within growth theory, the Cobb-Douglas function continues to be a widely used and valuable tool in macroeconomic research.

3.2.4. Short-term non-oil GDP forecasting model

We used the VAR model results presented in the working paper by Ramazanova and Qahramanov (2024), which are up-to-date short-run output forecasting models developed for the Central Bank of Azerbaijan (CBAR). The authors analyzed three VAR models in a two-stage approach to forecast non-oil GDP. In the first stage, several VAR specifications were estimated using different combinations of variables, and their forecasts were retained. These models were subsequently ranked based on forecasting performance, with those yielding the lowest root mean square errors (RMSEs) selected for further analysis.

The generalized form of the VAR model employed in their study is as follows:

$$Y_t = \mathrm{c} + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t \qquad (4)$$

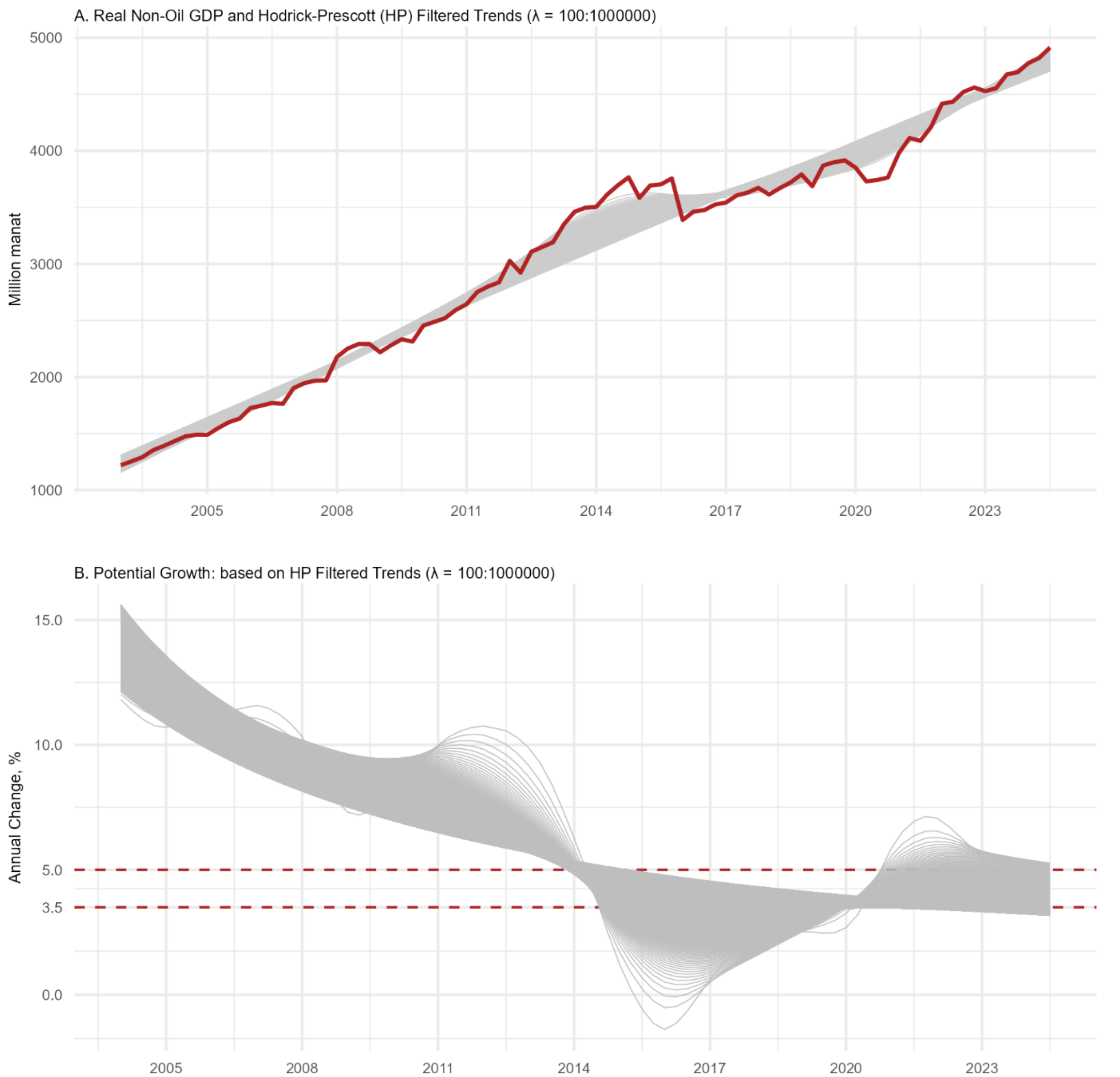
where Y_t is a vector of endogenous variables at time t, $A_1, A_2 \ldots, A_p$ are coefficient matrices to be estimated, p denotes the number of lags, and u_t is a vector of white noise error terms.

The authors examined three specific VAR models. Model 1 includes real net exports, real retail trade turnover, real budget expenditures, M2, and electricity production. Model 2 modifies this by excluding real net exports and including the number of employees. Model 3 incorporates real industrial production, real household consumption, and real budget expenditures. Despite its strengths, a key limitation of the VAR framework is its backward-looking nature, which may reduce the reliability of out-of-sample projections.

4. Results

4.1. HP Filter Results

Figure 4.1. HP Filter Results



Source: Author's calculation

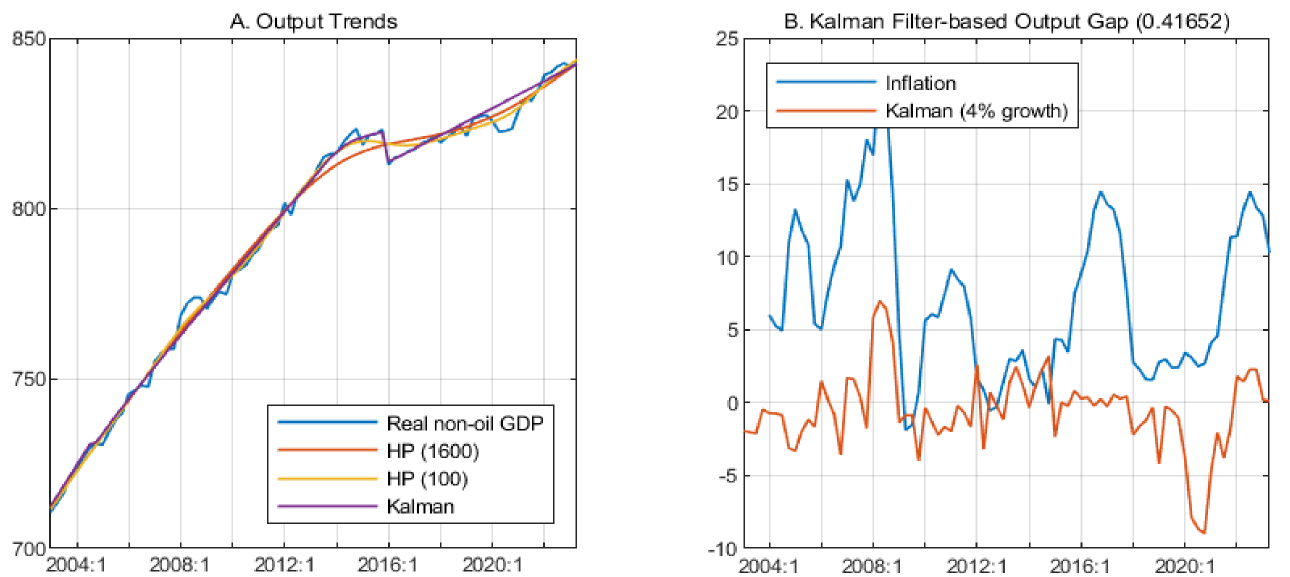
Note: The red line in Figure A highlights the original real non-oil GDP series, while the grey lines represent the trends obtained from the HP filter with lambda values ranging from 100 to 1,000,000.

The HP filter, which typically employs a smoothing parameter (lambda) of 1600 (Choudhary, Hanif, & Iqbal, 2014), is frequently used to estimate deviations of actual GDP from its potential levels. However, given Azerbaijan's distinct developmental context, the applicability of this standard lambda value for the country. Due to cross-country differences in development stages and economic structures, the use of a single, default lambda may not yield optimal estimates across all economies (Choudhary, Hanif, & Iqbal, 2014). Estimating a precise, country-specific lambda for Azerbaijan, however, lies beyond the scope of this study.

To account for potential sensitivity in the choice of the smoothing parameter we employ a range of lambda values from 100 to 1,000,000. For each lambda, we compute the trend of real non-oil GDP in levels (Figure 4.1.A). We then calculated the annual growth rate of each trend corresponding to the various lambda values. As illustrated in Figure 4.1.B, although different lambda values show varying potential growth rates in the past due to a structural break that occurred in 2016, they converge within a narrower range in recent years. This convergence, between 3.5 and 5% annual growth, can be interpreted as the potential growth rate range for the non-oil economy.

4.2. Kalman Filter Results

Figure 4.2. Kalman Filter Results With Structural Breaks

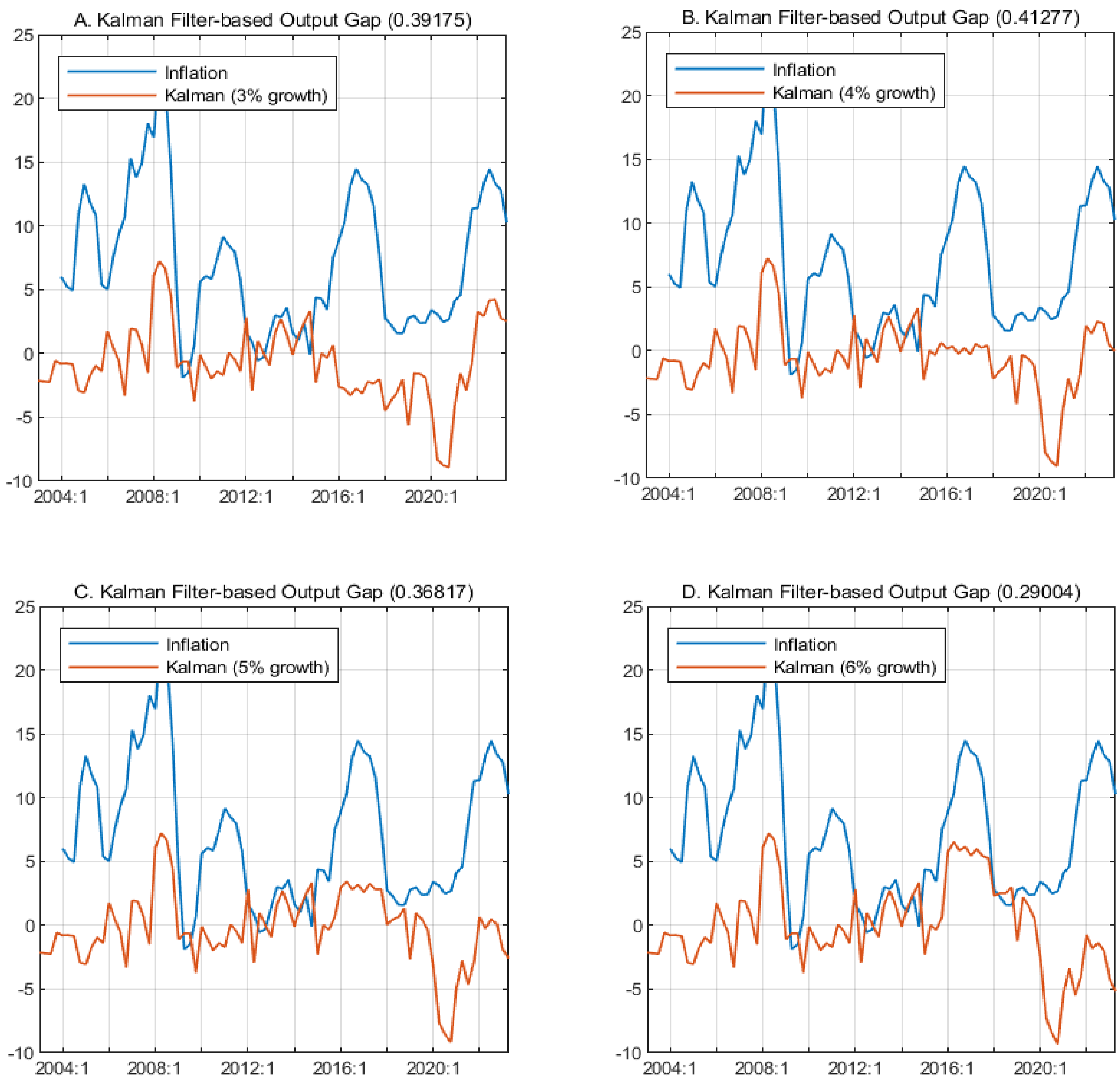


Source: Author's calculation

As outlined in the literature review, our estimation of potential GDP via the Kalman filter is based on the theoretical relationship between excess demand and inflation. Specially, we seek to determine the level of potential GDP at which actual output begins to exert upward pressures on prices. However, analysis of analysis of non-oil GDP dynamics (see Figure 4.1.A and Figure 4.2.A) reveals evidence of structural breaks, which precludes the use of a single steady-state growth rate across the full sample period. To account for this, we introduce two structural breaks: the first following the global financial crisis, and the second after a significant oil price shock leading to the weakening of nominal effective exchange rate.

Consistent with the framework discussed earlier, potential growth rates for each sub-period are calibrated to best capture the historical relationship between the output gap and inflation. Based on this approach, the estimated potential growth rate is appromixately 11% prior to the gobal financial crisis and 9% for the period between 2009 and 2015.

Figure 4.3. Kalman Filter Final Results

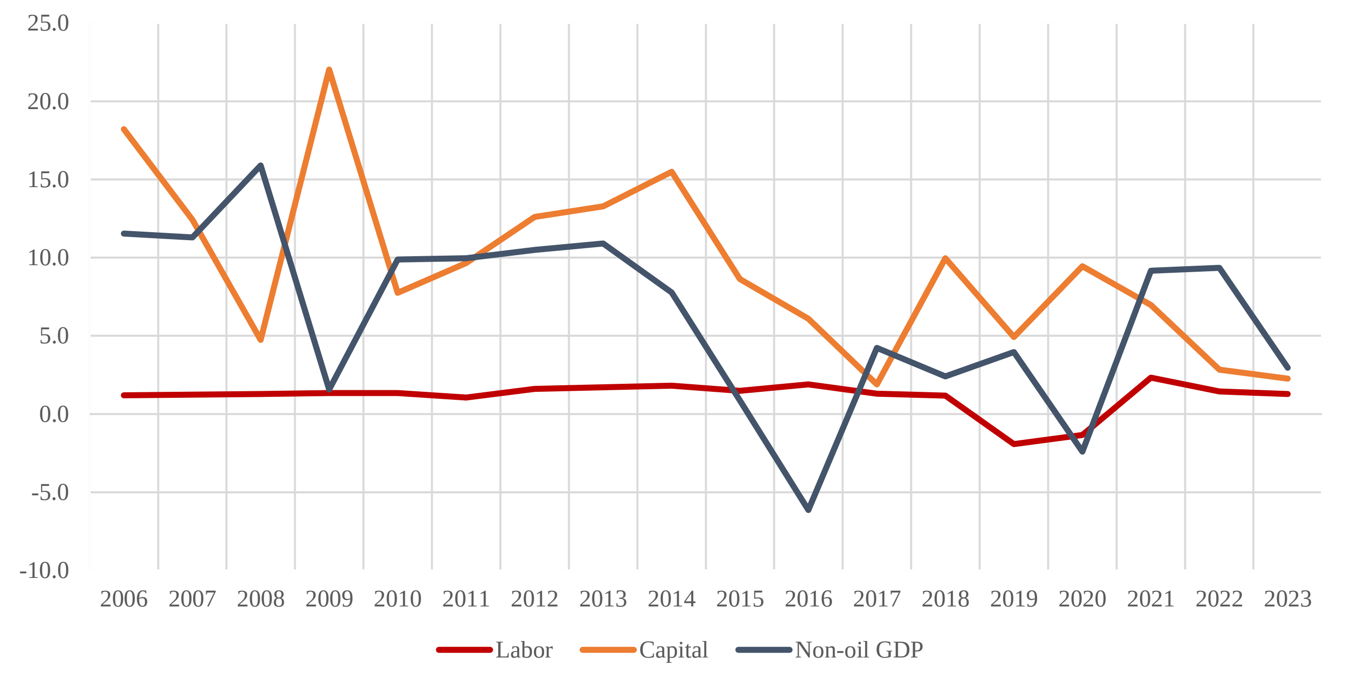


Source: Author's calculation

Following the identification of potential growth rates corresponding to structural breaks, our analysis turns to more recent economic developments. To estimate potential growth for the post-2016 period, we once again assess the relationship between inflation and the output gap. For this period, potential growth is assumed to lie within a range of 3% to 6%, based on recent estimates derived from the Hodrick-Prescott (HP) fileter (see Figure 4.1).

As illustrated in Figure 4.3, the correlation between inflation and the output gap reaches 0.39 when potential GDP growth is set at 3%. Inceasing the assumed potential growth by one percentage point results in corresponding correlation coefficients of 0.41, 0.37, and 0.29, respectively. The highest correlation peaking is at a 4% potential growth, suggesting that Kalman filter-based excess demand estimates and observed inflation dynamics, particularly during and after the COVID-19 pandemic. Cobb-Douglas Production Function Results

Figure 4.4. Growth rate of production function inputs



Source: Authors' calculation

Figure 4.4 illustrates the growth trajectories of labor, capital, and non-oil GDP in Azerbaijan from 2006 to 2023, highlighting the dynamics of the key inputs in the production function. Over this period, labor growth remained relatively stable, contributing only marginally to overall economic performance. In contrast, capital exhibited pronounced volatility, with significant investment surges, particularly around 2009, followed by a sharp decline after 2015. Non-oil GDP growth closely followed these fluctations in capital accumlation, underscoring the the sector's strong reliance on capital inflows. The concurrent decline in both capital and non-oil GDP growth rates post-2015 suggests that diminished capital accumulation has become a binding constraint. These descriptive trends indicate that capital has been the dominant driver of non-oil GDP expansion in Azerbaijan, while the role of labor has remained relatively lower.

We utilize Cobb-Douglas production function to estimate the long-run growth rate of the non-oil sector of GDP. Following the Mankiw et al. (1992) we transform equation (3) into log-linear form and use it in ordinary least squares regression model. The functional form is expressed as follows:

$$\text{Log}\,(Y) = \text{Log}(A) + \alpha\text{Log}(K) + (1 - \alpha)\text{Log}\,(L) \qquad (5)$$

This transformation facilitates the estimation of the output elasticities for capital (α) and labor (1-α), where Y denotes real non-oil GDP, K represents the capital stock, L is labor input, and A captures total factor productivity (TFP). The estimated coefficients will subsequently be applied within the (Solow, 1956) growth model framework to compute the potential output of the non-oil sector.

Table 4.1: Least squares results of the production function equation

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LOG(non-oil capital stock)	0.54	0.18	2.97	0.01
LOG(total employed)	0.46	1.45	0.32	0.75
C	2.75	0.42	6.55	0.00

According to the results of OLS regression presented in Table 4.1, the estimated coefficient for non-oil accumulated capital is 0.54. This implies that a 1% increase in non-oil capital stock is associated with a 0.54% increase in non-oil real GDP. The coefficient is statistically significant, confirming that capital is a key determinant of non-oil GDP. This finding is consistent with the analysis that reinforces the conclusion that non-oil capital stock has been the primary engine of non-oil sector. In contrast, the coefficient for labor is 0.46, indicating that a 1% increase in labor input is associated with 0.46% rise in non-oil GDP. However, this relationship is not statistically significant, as indicated by a p-value is 0.75, consistent with the descriptive statistics. The insignificance of labor's contribution may attributed to several structural factors, inclucing inefficiences in the labor market, suboptimal utilisation of human capital, or broader institutional weaknesses that constrain the direct influence of labor on non-oil sector output. The constant term, estimated at 2.75, and statistically significant, implies a robust baseline level of non-oil GDP even in the absence of variations in capital and labor. This intercept likely captures the effects of unobserved factors such as technological progress, institutional quality, or exogenous economic shocks that influence growth beyond measurable inputs.

To estimate the long-run potential of non-oil GDP, we employ the Solow growth model (Solow, 1956), which is a widely recognized neoclassical framework. This model attributes long-term economic growth to the contributions of labor, capital, and technological progress. In its steady state form, where the growth rates of capital per worker and output per worker are constant, economic growth is driven primarily by technological progress and population growth, rather than by continued capital accumulation. The steady-state growth equation, derived from the Cobb-Douglas production function, is expressed as:

$$\frac{\dot{Y}}{Y} = \frac{g_a}{1-\alpha} + n \quad (5)$$

, where $\frac{\dot{Y}}{Y}$ denotes the growth rate of GDP, g_a is the growth rate of total factor productivity (TFP), n represents the labor growth rate. Assuming an average annual population (labor force) growth rate of 0.5%, which is based on recent trends, and an estimated TFP growth of 2.75%, the long-run non oil GDP growth rate is calculated as follows:

$$\frac{\dot{Y}}{Y} = \frac{2.75}{1-0.54} + 0.5 = 6.48 \quad (6)$$

The final result implies a potential non-oil GDP growth rate of 6.48%, with the TFP accounting for 5.97 percentage points and labor growth contributing the remaining 0.5 percentage points. These findings emphasize the central role of technological progress in driving long-run growth, underscoring the importance of policy interventions that foster innovations, enhance knowledge diffusion, and promote the adoption of advanced production techniques.

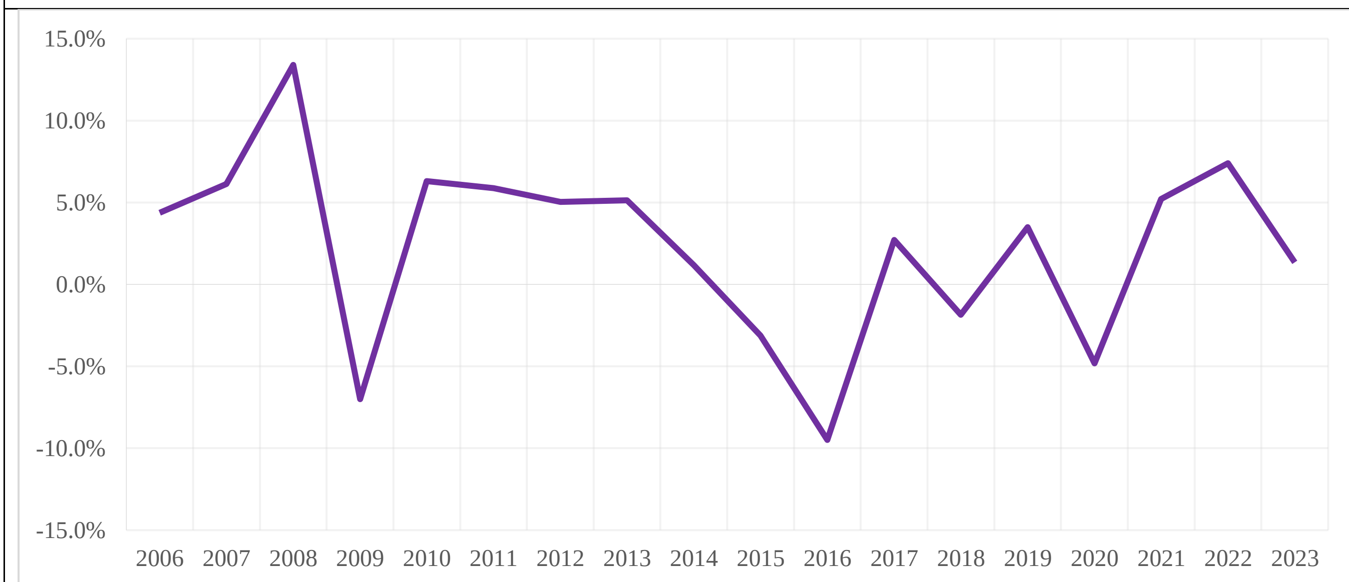
We alternatively estimated the potential non-oil GDP growth rate by referring to the literature, which suggests that the capital share typically ranges between 0.3 and 0.4, depending on a country's stage of development (Oduor, 2010). For the purposes of our analysis, we adopted a capital share of 0.35, which aligns with values commonly observed in both developing and developed economies. To ensure constant returns to scale in the steady-state analysis of the Cobb-Douglas production function, the labor share was set at 0.65. Prior to calculating the alternative potential growth of non-oil output, we computed total factor productivity using the following equation:

$$\Delta A = \Delta Y/Y - \alpha \Delta K/K - (1-\alpha)\Delta L/L \quad (7)$$

Where, $\Delta Y/Y$ is the real growth rate of non-oil GDP; $\Delta K/K$ is the growth rate of non-oil real capital stock (adjusted for depreciation); $\Delta L/L$ is a c the growth rate of labor; ΔA is the growth rate of TFP calculated as a residual, estimated at 2.3% over 2003 and 2023 years. Using historical data for non-oil GDP, real capital stock, and labor force, we calculated the relative growth rates over the sample period. Using equation (6) we derived a steady state growth rate of 4.0 per cent. This result represents the share of non-oil GDP growth that is not explained by changes in capital and labor inputs but stems from improvements in productivity and efficiency.

The figure 4.5 illustrates the evolution of the TFP from 2006 to 2023, revealing periods of notable expansion and contraction. A pronounced upward trend is observed between 2006 to 2008, potentially driven by surges in oil revenues and corresponding spillover effects. This is followed by a sharp decline in 2009, likely resulting from the global financial crisis and falling oil prices. After a brief recovery in 2010, the period between 2013 to 2016 shows a steady downturn, reflecting again high oil revenues and structural challenges. From 2017 to 2021, TFP exhibits volatility. A notable recovery is evident in 2021-2022, potentially linked to post-pandemic economic recovery, but is followed by a deceleration in 2023.

Figure 4.5: Total Factor Productivity dynamics over the sample period (can be changed)

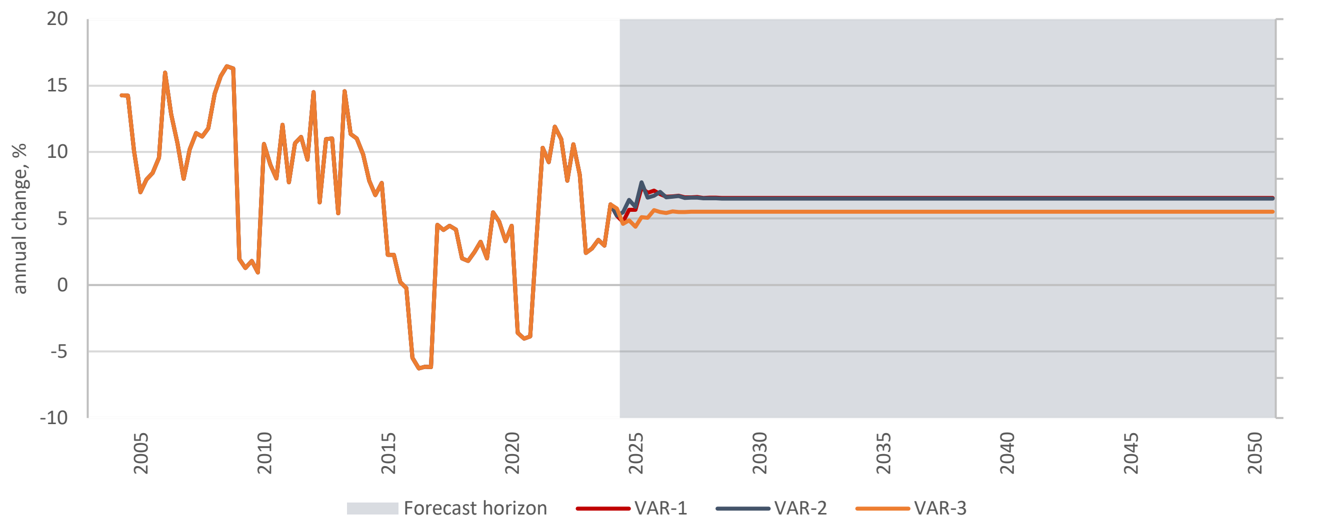


Source: Authors' calculation

4.3. VAR Model Results

To estimate potential non-oil GDP, we now utilize short-run GDP forecast models based on VAR In this approach, we estimate long-run non-oil GDP using each of the three up-to-date short-run CBAR models. The convergence points of these models are selected to be the steady-state growth rate of non-oil GDP, yielding potential growth rates of 6.54%, 6.49%, and 5.51% (Figure 4.6). As previously noted, these models are inherently backward-looking, meaning their projections are strongly influenced by historical growth dynamics. As a result, the models forecast a higher steady-state growth rates compared to other estimations.

Figure 4.6. Long-run growth forecast



Source: Author's calculation

5. Discussion and Policy Implications

In summary, Azerbaijan's non-oil growth potential is estimated 4.5% based on the HP filter, 4% from the Kalman filter, 4.35% from the Cobb-Douglas production function, and 6.54%, 6.49%, and 5.51% from VAR models. Despite methodological differences, the estimates show a relatively close alignment, suggesting that recent non-oil GDP growth has stabilized around 5%. Looking ahead, and assuming no significant structural changes in the economy, it is reasonable to expect the economy to maintain a steady growth trajectory of around 5%.

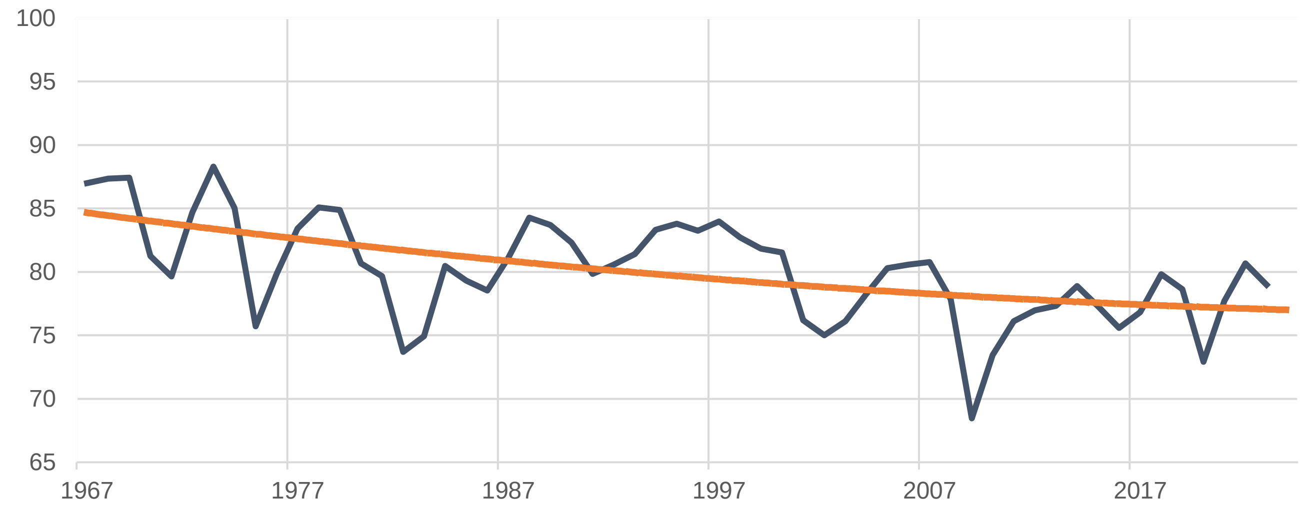
However, it is important not to differentiate between long-term potential growth and short-term capacity utilization. A growth rate that temporarily exceeds 5% does not automatically indicate overheating of economy or the emergence of inflationary pressures. As emphasized by Lavoie (2022), normal capacity utilization in equilibrium can fall below 100%, even in the presence of stable, long-run growth. This phenomenon is also observed in advanced economies. As shown in Figure 5.1, capacity utilization in the U.S. has declined by approximately 10 percentage points between 1960 and 2024, recently fluctuating around 77.5%.

Therefore, when excess[5] demand (defined as growth exceeding 5% in the case of Azerbaijan) occurs, firms may respond by increasing capacity utilization without incurring significant increases in marginal costs. Consequently, elevated demand may not necessarily lead to increased labor costs or inflation.

[5] We refer to excess demand as demand exceeding the levels normally observed.

To investigate this hypothesis in Azerbaijan, we examine the relationship between firm-level capacity utilization and labor dynamics using survey data. This monthly survey, conducted by CBAR between 2019 and 2024, encompasses 105 enterprises across 10 industrial sectors.

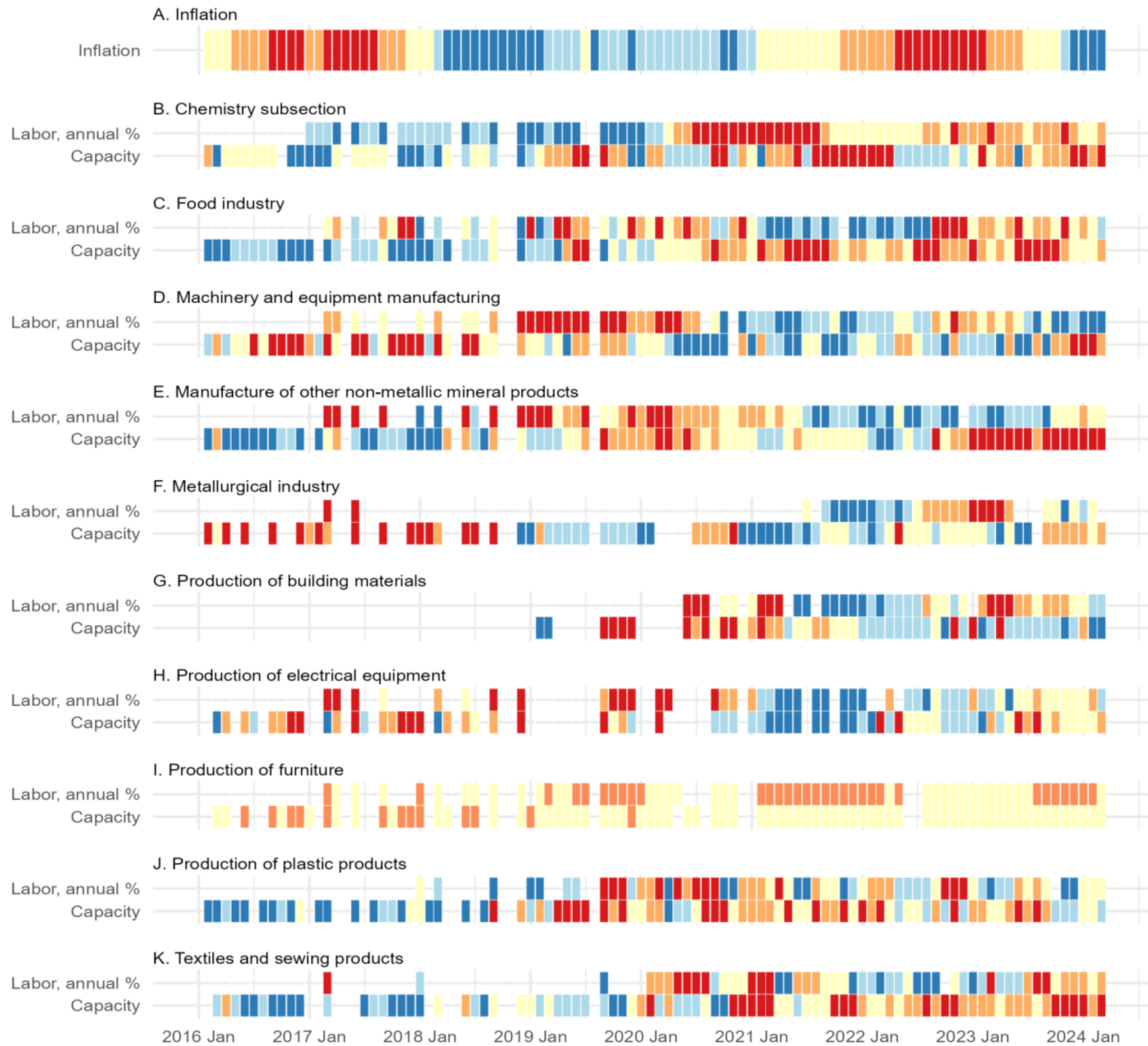
Figure 5.1. Capacity Utilization in the US



Source: Author's calculation

With these industry-specific capacity utilization data, we conduct a descriptive analysis to explore the potential relationship between capacity utilization, labor, and inflation dynamics. As shown in Figure 5.2, signs of overheating were evident across different periods and sectors. Notably, prior to the post-pandemic inflation surge, sectors like chemicals, furniture manufacturing, plastics, and textiles displayed elevated capacity utilization levels, potentially causing inflationary pressures. During the inflation surge, sectors such as food processing, machinery, metallurgy, and building materials exhibited signs of overheating. Following this period, capacity utilization continued to increase in sectors like mineral products and electrical equipment.

Figure 5.2. Capacity Utilization, Labor, and Inflation Dynamics



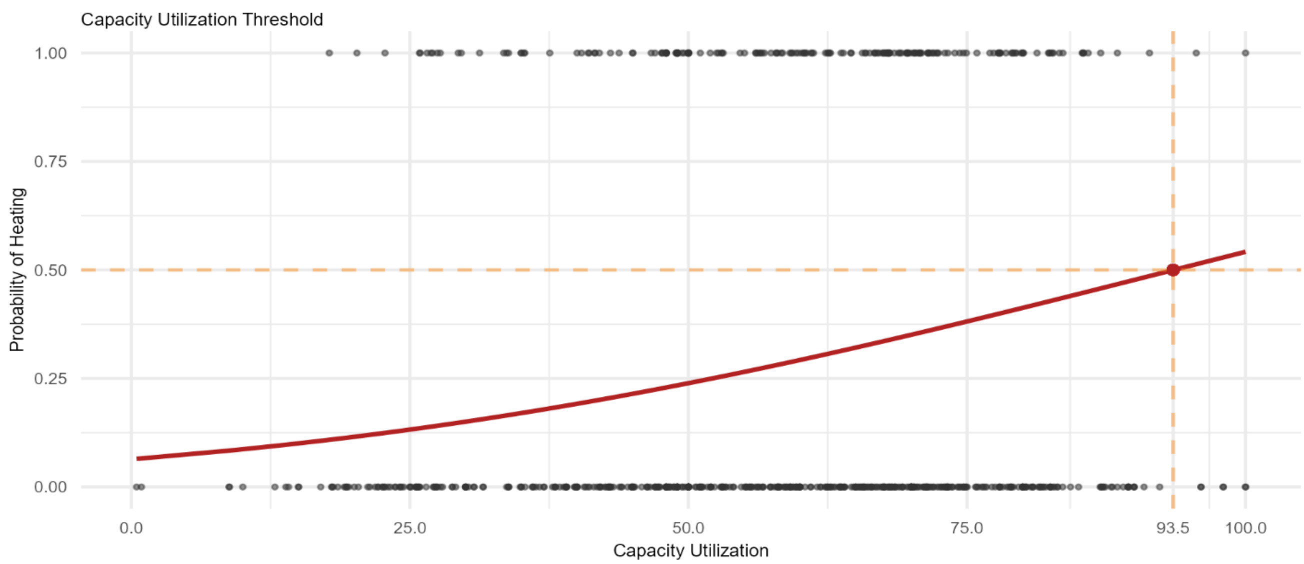
Source: Author's calculation

However, unlike the earlier industries such as chemistry, furniture, plastic products, and textiles, it is more difficult to attribute the recent increase in capacity utilization in certain sectors directly to demand pressures. This may reflect a heightened markup appetite in a high-inflation environment. Under such cases, elevated capacity utilization may not necessarily indicate stronger demand, but rather a strategic response by firms to raise prices and benefit from inflationary dynamics.

Consequently, it is challenging to determine whether the heating in capacity utilization is a driver of inflation or is a result of it, especially when relying solely on heatmap analysis. To address this ambiguity, we employ more advanced techniques to examine the relationship between capacity utilization and inflation. Building on theoretical foundations, we develop an economic heating indicator. This indicator takes the value of 1 if firms hire new workers in a high-inflation environment, defined as inflation exceeding 6%[6], and 0 otherwise.

With both the binary heating index and capacity utilization rates in place, we estimate the probability of economic overheated when capacity utilization exceeds its normal level. The normal capacity utilization rate is identified using a Random Effects Panel Probit model.[7] As illustrated in the Figure 5.3, the model indicates that the economy becomes overheated when capacity utilization exceeds 93.5%.

Figure 5.3. Capacity Utilization and Economic Heating



Source: Author’s calculation

However, unlike the earlier observed industries such as chemicals, furniture, plastic products, and textiles, the observed heating in these later sectors is more difficult to attribute directly to demand-side pressures. This ambiguity may stem from the firm’s stronger markup behavior in a high-inflation environment. In such cases, increased capacity utilization may not reflect heightened demand, but rather a strategic inclination by firms to raise prices and exploit inflationary conditions.

Accordingly, distinguishing whether the observed heating in capacity utilization is a cause or consequence of inflation becomes challenging when relying solely on descriptive tools such as heatmaps. This insight holds important implications for policymaking, especially in conditions when the primary objective of the central bank is to ensure price stability rather than to achieve. If industries are operating below their full

[6] The 6% rate is considered high as it represents the upper bound of CBAR’s inflation target corridor.

[7] Since the primary focus of this paper is on estimating potential output, we do not provide specific details about the panel probit model here, but they are included in the appendix. While the model is used to explore the relationship between capacity utilization, and inflation, it does not directly address the central research question of determining Azerbaijan's potential growth rate.

capacity, even at the natural capacity utilization rate associated with stable growth (approximately 5%), there may be room to accommodate excess demand without triggering inflationary pressures. While potential output remains a key metric for evaluating excess demand, the extent to which such demand translates into inflation depends on factors beyond the conventional output gap, as evidenced by capacity utilization dynamics. This relationship underscores the need for further investigation in future research.

6. Conclusion

This study provides an assessment of Azerbaijan’s non-oil potential growth and its relationship with capacity utilization and inflation dynamics. Despite methodological differences, various estimation techniques converge around a non-oil potential growth rate of approximately 5%, suggesting recent growth trends are broadly sustainable under current structural conditions.

However, interpreting growth above this level as an automatic signal of overheating can be misleading. Our assessment demonstrates that elevated growth does not necessarily translate into inflationary pressures, particularly when there is slack in capacity utilization. Firm-level survey data reveal that sectors often respond to excess demand by increasing utilization rates without proportionate increases in labor costs, especially when operating below their natural capacity.

Moreover, the study highlights the complexities introduced by firm behavior in high-inflation environments, where increased capacity utilization may reflect pricing strategies rather than genuine demand-side pressures. The development of an economic heating indicator and the application of a panel probit model further support the conclusion that overheating is more likely when capacity utilization exceeds 93.5%, rather than being strictly tied to output growth rates.

These findings underscore the importance of integrating capacity utilization measures into macroeconomic monitoring frameworks. For policymakers, particularly central banks focused on price stability, this approach is useful in assessing inflation risks and guiding countercyclical interventions. Future research should continue to explore sector-specific dynamics and incorporate real-time firm-level data to refine our understanding of capacity-driven inflationary processes in emerging markets.

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Appendix

A. Panel Probit Model

Given the diversity of industrial dynamics across the 10 sectors examined in our study, it is essential to account for individual-specific effects to avoid inefficiencies in estimations (Amini, Delgado, Henderson, & Parmeter, 2012). To address this, we employ a random effects model, which allows for variation in individual-specific intercepts while maintaining a common relationship between the variables of interest. However, if there is correlation between unobserved individual-specific effects and the regressors, using a random effects model without controlling for endogeneity will lead to biased and inconsistent results (Amini, Delgado, Henderson, & Parmeter, 2012).

To assess whether the random effects model is suitable for our data, we conduct a Hausman test, as shown in Table A.1. The test reveals no evidence to reject the exogeneity of unobserved individual effects, supporting the use of the random effects model for our analysis (Amini, Delgado, Henderson, & Parmeter, 2012).

Table A.1. Hausman test results for unobserved variable endogeneity

Chi-squared Statistic:	4.6587
p-value:	0.3241

Alternative hypothesis: one model is inconsistent

Since the null hypothesis cannot be rejected, the random effects model offers efficiency advantages (Amini, Delgado, Henderson, & Parmeter, 2012). Following Yusifzada (2024), we estimate a random effects panel probit model as follows:

$$P(y_{it} = 1 | X_{it}, X_{it-1}, \dots, X_{it-n}, \alpha_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \alpha_i) \qquad \text{(A.1)}$$

where y_{it} is the binary outcome variable for individual i at time t, taking the value of 1 if "heating" is observed, and 0 otherwise. The term X_{it-n} represents the vector of explanatory variables for industry i at lag n, with β_n being the corresponding coefficients. The term α_i captures the individual-specific effect, while Φ is the cumulative distribution function of the standard normal distribution, which transforms the linear combination into a probability between 0 and 1.

The random effects specification incirporates unobserved heterogeneity across industries, modeled as (Greene, 2004):

$$\alpha_i = \eta + \mu_i \qquad \text{(A.2)}$$

where η denotes the average effect across all industries, and μ_i represents unobservable individual-specific effects, assumed to be normally distributed with a mean of zero and constant variance σ_{μ}^2.

Incorporating these random effects into the panel probit model, we have:

$$P(y_{it} = 1 | X_{it}, X_{it-1}, \dots, X_{it-n}, \eta, \mu_i) = \Phi(X_{it}\beta_0 + X_{it-1}\beta_1 + \cdots + X_{it-n}\beta_n + \eta + \mu_i) \quad \text{(A.3)}$$

Regarding the model's lag structure, we exclude lagged dependent variables to avoid endogeneity concerns commonly associated with dynamic panel probit model (Guevara & Navarro, 2015). Lagging the dependent variable can result in correlations with current independent variables, potentially leading to biased estimates (Carro, 2007). Instead, we focus on lagging independent variables from 1 to 4 periods, selecting those that are theoretically relevant. This approach allows us to capture dynamic relationships while minimizing endogeneity concerns.