# WORKING PAPER

# ANALYSIS OF LABOUR MARKET EFFICIENCY AND WAGE DYNAMICS IN SERBIA, 2011–2025

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## Analysis of labour market efficiency and wage dynamics in Serbia

Konstantin Sorak and Nevena Stošić

**Abstract**: In this paper, we analyse the dynamics of Serbia's labour market over the period 2011–2025 and their implications for wage developments. Using administrative data from the National Employment Service and the Statistical Office of the Republic of Serbia, we constructed a Beveridge curve for Serbia. In the initial period, movements along the Beveridge curve were recorded, driven by cyclical labour market tightening. From 2022 onwards, however, a shift in the curve became apparent, reflecting substantially higher vacancy rates at comparable unemployment rates than the historical pattern would suggest. The observed shifts were quantified using two measures of the matching efficiency between labour supply and demand: the residual from the Beveridge curve equation and matching function efficiency. In the next stage of the analysis, the Beveridge curve residual is incorporated into the estimation of a wage equation. The estimated coefficients have the expected signs: labour market tightness has a positive effect on wage growth, while the coefficient on the Beveridge curve residual has the expected opposite sign, since negative residual values indicate an improvement in labour market matching efficiency. As an indicative measure of the strength of the effects of these factors on wage developments, we decomposed the contributions of deviations of these variables from their respective long-run averages to the deviation of wages from their long-run average. The contribution decomposition implies that the effect of labour market tightness dominates over most of the period. Its negative contribution in the first part of the period gradually weakens as vacancies rise and unemployment falls. From 2022 onwards, matching becomes less efficient and works in the opposite direction to tightness, consistently with the shift in the Beveridge curve, with the effect peaking at the end of 2024. As a result, record labour market tightness is transmitted to wages only partially. During 2025, matching efficiency gradually improves. The findings suggest that measures of matching efficiency can provide additional insight into wage pressures beyond that offered by standard labour market indicators.
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**Keywords**: unemployment rate, Beveridge curve, matching efficiency, wage Phillips curve.
**[JEL Code]:** C22, E24, J31, J63, J64

## Non-technical summary

Serbia's labour market has changed substantially over the past fifteen years. The number of unemployed persons has fallen markedly, employment has increased and wages have recorded strong growth, which continued even after inflationary pressures eased. This raises the question of whether such developments reflect the recovery in economic activity or structural changes in the functioning of the labour market.

To address this question, we use the Beveridge curve, which depicts the relationship between the number of unemployed persons and job vacancies. The relationship between these two variables is normally negative: stronger economic activity increases labour demand and hence the number of vacancies, while the number of unemployed persons declines. It is possible, however, for a large number of vacancies and a large number of jobseekers to coexist. Such a situation suggests a structural mismatch between employers' needs and jobseekers. Sources of such mismatches may include unemployed persons having qualifications that do not correspond to employers' needs or difficulties with labour mobility.

The analysis is based on data from the National Employment Service and the Statistical Office of the Republic of Serbia for the period 2011–2025. Over the period observed, there was stable movement along the Beveridge curve, reflecting a continuous decline in the unemployment rate and an increase in the vacancy rate. A departure from the previous pattern emerges from 2022 onwards, when, at unemployment levels similar to those recorded in earlier years, the vacancy rate rises above its historically usual level. In other words, employers find it more difficult to fill vacancies even though the number of jobseekers has not changed significantly. The results also show that the decline in unemployment over the period as a whole was attributable primarily to unemployed persons finding jobs more quickly, and to a lesser extent to a lower incidence of job loss.

These changes also had implications for wages. Wage growth is shown to be faster when demand for workers is high relative to the number of unemployed persons, owing to workers' stronger bargaining power. This effect, however, also depends on the success with which vacancies are filled. During most of the period, wage growth is supported by a rising vacancy rate accompanied by a declining unemployment rate. From 2022, the gradual increase in the vacancy rate above its usual level began to exert a negative effect on wage developments. This effect peaked in 2024, when, despite the larger number of vacancies relative to unemployed workers, the effect of workers' bargaining power was only partially transmitted to wages precisely because of the weaker compatibility between labour supply and demand. Matching efficiency gradually improved during 2025.

The main conclusion of the paper is that standard labour market indicators, such as the unemployment rate, do not provide a complete picture of labour market dynamics. Monitoring the relationship between unemployed persons and vacancies, together with the effectiveness with which they are matched, provides a more detailed view of labour market developments and a more comprehensive assessment of wage pressures.

# Contents

## 1 Introduction

The unemployment rate is one of the key macroeconomic indicators and one of the most frequently studied variables in economics. Among the best-known methodological frameworks for analysing unemployment dynamics is the Phillips curve, i.e. the relationship between unemployment and inflation. Another equally important relationship is represented by the Beveridge curve, i.e. the relationship between vacancy and unemployment rates. In this paper, we use both frameworks to provide a more detailed explanation of labour market dynamics in Serbia between 2011 and 2025.

The original Phillips curve depicts a negative relationship between the growth rate of nominal wages and the unemployment rate. More recent versions of the wage Phillips curve, however, have sought to broaden this framework because nominal wage developments are determined by numerous factors and the unemployment rate alone is not a sufficient determinant of their dynamics (Gali, 2011). The limited informational content of the unemployment rate has raised the question of which measures can supplement this framework; inflation expectations, labour productivity and indicators of labour market tightness have most commonly been used for this purpose.

A detailed analysis of unemployment dates back to Keynesian theory, in which unemployment was interpreted as a consequence of insufficient aggregate demand. One question nevertheless remained unresolved: why can a large number of unemployed persons and a large number of unfilled vacancies coexist? Search-and-matching models were developed precisely to address this issue (Diamond, 1982; Mortensen and Pissarides, 1994). These models place the relationship between vacancies and unemployment, described by the Beveridge curve, at the centre of the analysis. The curve depicts a negative relationship between the two variables, while movements along it reflect cyclical changes in aggregate demand that lie at the heart of the Keynesian interpretation. Shifts in the curve itself, by contrast, point to structural changes, primarily in the efficiency with which labour supply and demand are matched (Petrongolo and Pissarides, 2001). Consolo and Dias da Silva (2019) introduce measures derived from such shifts into a wage Phillips-curve equation, showing that matching efficiency may provide some additional explanatory power for nominal wage developments beyond standard indicators of labour market tightness.

Serbia's labour market has undergone a pronounced transformation over the past decade. According to the National Employment Service, the registered unemployment rate fell from 25.3% in 2011 to 10.8% in 2025,[1] with wages and total employment rising at the same time. The question addressed in this paper is what drove this transformation, i.e. to what extent it resulted from cyclical labour market tightening and to what extent from structural changes in the process of matching labour supply and demand.

This paper follows the approach of Consolo and Dias da Silva (2019), and the analysis is conducted in four steps. First, we construct a Beveridge curve using data for Serbia's labour

[1] According to data from the SORS Labour Force Survey, the unemployment rate fell from 24.9% in 2011 to 8.9% in 2025.

market. We then apply the decomposition of unemployment fluctuations proposed by Shimer (2012) to determine how much of the change in the unemployment rate depended on hiring dynamics and how much on the frequency of job separations. Next, we construct two measures quantifying the effectiveness of labour supply-demand matching – the residual from the Beveridge equation and matching function efficiency – and examine these results alongside movements in the Beveridge curve. Finally, we use the resulting Beveridge-equation residual to estimate a Phillips-curve wage equation and determine the extent to which labour market tightness and matching efficiency affect wage dynamics.

The results show that, in the initial period, the Beveridge curve was characterised by a high unemployment rate and a low vacancy rate, i.e. a slack labour market. In 2015–2019, movement along the Beveridge curve reflected cyclical labour market tightening, while the curve itself remained stable, as indicated by a residual fluctuating around zero; the matching efficiency measure points to a slight improvement in the matching process. During the pandemic, the unemployment rate remained almost unchanged while vacancies declined slightly, against the background of government job-retention measures. From 2022 onwards, the Beveridge curve shifted: at comparable unemployment rates, the vacancy rate was substantially higher than the historical relationship would imply, pointing to structural changes in labour supply-demand matching and a decline in efficiency. The decomposition of unemployment fluctuations implies that movements in unemployment over the entire period were primarily driven by hiring dynamics rather than by the frequency of job separations. Estimation of the wage equation shows that labour market tightness has a positive effect on wage growth, while the coefficient on the Beveridge curve residual is statistically significant and has the opposite sign because negative residual values indicate higher efficiency, which has a positive effect on wages. The decomposition of contributions to deviations of wage growth from its long-run average shows that the negative contribution of low labour market tightness dominated in the first part of the sample and gradually weakened as the labour market tightened. From 2022, matching efficiency gradually deteriorated, consistently with the shift in the Beveridge curve, and these adverse effects peaked in 2024. The decline in efficiency partly dampened the impact of high labour market tightness on wage growth, while the effect of the efficiency measure began to improve gradually from mid-2025.

## 2 Data and methodology

The analysis is based on quarterly administrative data from the National Employment Service (NES) on registered unemployment and reported labour demand. Since the NES register does not contain data on total employment, quarterly Labour Force Survey (LFS) data from the Statistical Office of the Republic of Serbia (SORS) are used as an indicator of the number of employed persons. The analysis covers 2011–2025. Before all measures are calculated, the underlying series are seasonally adjusted using the X-13 ARIMA-SEATS method.

Since all measures are constructed from administrative data, the results relate to the formal segment of the labour market, i.e. the part of labour supply and demand in which the NES acts as intermediary. There are therefore limitations on both the supply and demand sides. On the supply side, the register covers only registered unemployment and excludes work in the informal sector. A significant proportion of unemployed persons also use alternative job-search channels (such as online platforms and informal contact networks), making the NES register incomplete. On the demand side, employers also use other recruitment channels, so the number of vacancies recorded in the register is lower than the actual number. In recent years, there has also been a noticeable change in the composition of registered unemployed persons and reported vacancies, as those registering are predominantly lower-qualified persons and employers tend to report vacancies for lower-qualified workers. The constructed measures should therefore be regarded as an approximation of conditions in the formal segment of the labour market rather than in the labour market as a whole. These limitations do not invalidate conclusions regarding the direction and drivers of developments, but they do call for additional caution when interpreting the levels themselves. Changes in the composition of the register over time are not merely a limitation, but the subject of the analysis considered below.

The main variables in the empirical analysis are the number of registered unemployed persons in quarter t ($U_t$), the number of reported vacancies in quarter t ($V_t$), the number of employed persons in quarter t ($E_t$) from the SORS Labour Force Survey, the number of newly employed persons – i.e. persons from the unemployment register who found employment in quarter t ($h_t$) – and the number of newly registered unemployed persons in the quarter ($n_t$). The registered unemployment rate in quarter t ($u_t$) is calculated as the ratio of unemployed persons to the labour force $\left(\frac{U_t}{U_t+E_t}\right)$, which differs from the SORS Labour Force Survey unemployment rate as it is based on NES data. The vacancy rate in quarter t ($v_t$) is defined as the ratio of vacancies to total jobs, comprising vacancies and filled jobs represented by the number of employed persons $\left(\frac{V_t}{V_t+E_t}\right)$. Based on these variables and the standard labour market flow framework (Pissarides, 2000; Elsby, Michaels and Solon, 2009; Shimer, 2012), three key indicators are defined: the job finding rate, the job separation rate and labour market tightness. The job finding rate identifies the proportion of persons unemployed in period t-1 who become employed in period t.

$$F_t = \frac{h_t}{U_{t-1}}$$

The job separation rate measures the inflow into unemployment in the current quarter originating from persons employed in the previous period.

$$S_t = \frac{n_t}{E_{t-1}}$$

Labour market tightness is defined as the ratio of vacancies to unemployed persons. A higher value of θ indicates a tighter labour market, characterised by stronger labour demand relative to supply, whereas a lower θ indicates that a large number of unemployed persons face relatively few available opportunities.

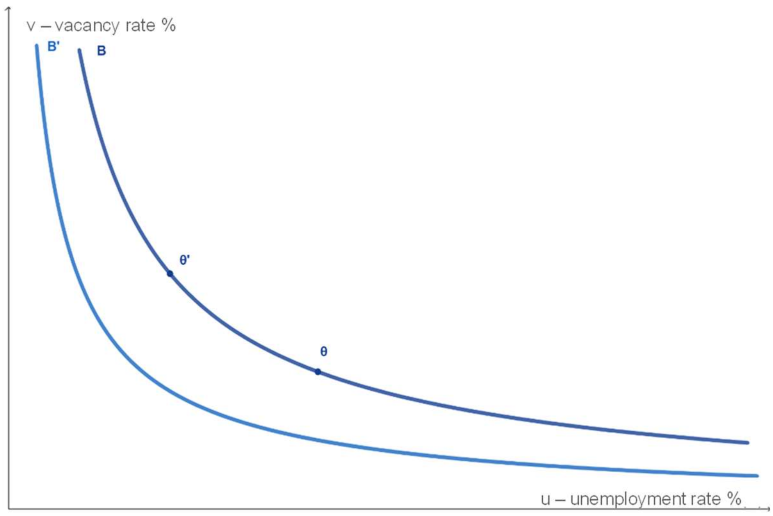
$$\theta_t = \frac{V_t}{U_t}$$

For estimation of the wage equation, we also use the average nominal net wage series and the Consumer Price Index (CPI), published by the SORS, together with a measure of labour productivity per person taken from the Eurostat database.

## 2.1 Beveridge curve

The Beveridge curve is an analytical framework for assessing labour market conditions and depicts a negative relationship between the unemployment rate ($u_t$) and the vacancy rate ($v_t$). This negative relationship is theoretically grounded in the search-and-matching model (Diamond, 1982; Mortensen and Pissarides, 1994), in which the curve represents a set of labour market equilibria. Two types of change are distinguished when interpreting labour market developments. Movements along the curve reflect cyclical aggregate demand shocks, i.e. changes in labour market tightness. If economic activity increases, labour demand rises and unemployment falls. Such developments raise our measure of labour market tightness θ, i.e. move it from θ to θ'. Shifts in the curve itself, by contrast, indicate structural changes, primarily in the efficiency of matching unemployed persons to vacancies, but also structural reforms and demographic changes (Petrongolo and Pissarides, 2001). A shift of the curve towards the origin, from B to B', indicates an improvement in matching efficiency because, for the same vacancy rate, the unemployment rate is lower, and vice versa. The observed shifts are formally quantified below using the Beveridge curve residual.

Chart 1 **Beveridge curve**




Source: Authors' illustration produced using GeoGebra.

## 2.2 Shimer decomposition

We apply the decomposition proposed by Shimer (2012) to identify the drivers of changes in the unemployment rate over the period observed. Under the Shimer decomposition, unemployment fluctuations can be described by the contributions of the job finding rate ($F_t$) and the job separation rate ($S_t$). Discrete quarterly probabilities are transformed into instantaneous (hazard) rates to correct for time-aggregation bias, since discrete measures do not capture changes of status within a quarter.

$$f_t = -\ln(1 - F_t), \quad s_t = -\ln(1 - S_t)$$

The starting point of the decomposition is the construction of the steady-state unemployment rate ($u_t$*) towards which the market converges under the influence of these two rates. The steady-state unemployment rate equals the share of the job-separation rate in the sum of the job separation and job finding rates $\left(u_t^* = \frac{s_t}{s_t+f_t}\right)$. Since convergence towards the steady state is rapid at quarterly frequency, the actual unemployment rate closely tracks the steady-state rate ( $u_t^* \approx u_t$), allowing fluctuations in the latter to be used as an approximation of fluctuations in the actual unemployment rate.[2]

The contribution of each channel is determined by comparing the steady-state unemployment rate with two counterfactual scenarios: one in which only the job finding rate varies while the job separation rate is fixed at its full-sample average:

$$u_t^{*,f} = \frac{\bar{s}}{\bar{s} + f_t}$$

and a scenario in which only the job separation rate varies, while the job finding rate is fixed at its full-sample average:

$$u_t^{*,s} = \frac{s_t}{s_t + \bar{f}}$$

The steady-state unemployment-rate series and both counterfactual series are log-transformed and decomposed into trend and cyclical components using the Hodrick-Prescott filter (Hodrick and Prescott, 1997), with smoothing parameter λ = 1600. Contributions are calculated from the cyclical component because the purpose of the decomposition is to explain fluctuations. In the subperiod decomposition, cyclical components are estimated over the full sample and then extracted for each subperiod, so the contributions for individual phases are expressed relative to a unique reference trend and average.

To calculate the relative contribution of each channel to total fluctuations in the steady-state unemployment rate, we use the ratio of the covariance between the relevant counterfactual and steady-state unemployment to the variance of steady-state unemployment,

$$\beta_f = \frac{Cov\left(u_t^{*,f}, u_t^*\right)}{Var(u_t^*)}, \ \beta_s = \frac{Cov(u_t^{*,s}, u_t^*)}{Var(u_t^*)}$$

where the condition is satisfied that $\beta_f + \beta_s \approx 1$ over the full sample. The paper also presents an analysis by subperiods, in which the sum of $\beta_f$ and $\beta_s$ need not satisfy this condition, since

[2] The correlation coefficient between the registered and steady-state unemployment rates is 0.95, indicating that the approximation is adequate.

the equilibrium unemployment rate is a non-linear function of two flow rates, whose average values are calculated over the entire sample.

## 2.3 Measures of labour market efficiency

Movements along the Beveridge curve and structural shifts in the curve can be approximately quantified using measures of labour supply-demand matching efficiency. The first is estimated as the deviation from the long-run relationship between the vacancy and unemployment rates, i.e. as the residual from the Beveridge-curve equation, while the second is estimated from the matching function described below.

### *2.3.1 Beveridge curve residual*

The efficiency measure based on the Beveridge curve residual ($\varepsilon BC$) is constructed in two steps. In the first step, a linear regression is estimated in which the vacancy rate ($v_t$) is the dependent variable and the unemployment rate ($u_t$) is the explanatory variable:

$$v_t = \beta_0 + \beta_1 \cdot u_t + \varepsilon BC_t \quad (1)$$

over the period Q1 2011 – Q4 2019. In the second step, the estimated coefficients $\widehat{\beta_0}$ and $\widehat{\beta_1}$ are applied to the full sample and the residual is calculated as

$$\widehat{\varepsilon BC_t} = v_t - \widehat{\beta_0} - \widehat{\beta_1} \cdot u_t \quad (2)$$

The estimation window ends in Q4 2019, thereby excluding both the temporary disruption during the pandemic and the persistent structural shift from 2022 onwards, described in Section 3.1. These two issues were tested separately. The Quandt-Andrews structural-break test (Andrews, 1993; Hansen, 1997) rejects the hypothesis of no persistent break and locates the break in Q3 2022 ($p < 0.0001$). The temporary deviation during the pandemic is confirmed by estimation over an extended 2011 – Q2 2022 window, in which a dummy variable for 2020–2021 is significant ($p < 0.001$).

The curve is estimated in linear form using rates. It is also tested in an alternative non-linear, log-log form implied by the steady state of the matching function. The estimated elasticity is -1.06 (standard error 0.27), and the tested value of -1 cannot be rejected, which is consistent with a hyperbolic curve. Since the curve is estimated over a relatively narrow range of unemployment rates, the linear and log-log forms yield similar estimates. This is also supported by the Ramsey RESET test, which does not indicate omitted curvature within the estimation window. The residuals from the two specifications are strongly correlated over the full sample (0.884), while their correlation within the estimation window is 0.974. Unit roots are tested using the augmented Dickey-Fuller test with a constant; the unit-root hypothesis cannot be rejected for either the unemployment rate or the vacancy rate, so both series behave as integrated of order one. The Engle-Granger test is used to test for a cointegrating relationship between the unemployment rate and the vacancy rate, with the latter as the dependent variable. It rejects the hypothesis of no cointegration ($\tau = -3.58$, $p = 0.044$) implying that the estimated residual series is stationary, a finding also confirmed by the Johansen trace test with one lagged difference. The hypothesis of no cointegrating relationship is also rejected for the log-log specification, although only at the 10% significance level ($\tau$ = -3.24, p = 0.087).

A positive residual ($\varepsilon BC$) indicates a deterioration in matching efficiency: at a given unemployment rate, there are more vacancies than the equilibrium relationship would suggest, implying that firms find it more difficult to recruit suitable workers. Negative residual values imply the opposite.

#### *2.3.2 Matching function efficiency (A)*

The second measure, matching function efficiency (A), is derived from a Cobb-Douglas matching function:

$$h_t = A_t \cdot U_{t-1}^{\alpha} V_t^{1-\alpha} \tag{3}$$

where $h_t$ is the number of new hires, $U_{t-1}^{\alpha}$ the total number of unemployed persons in the previous period, $V_t^{1-\alpha}$ the number of vacancies, $\alpha$[3] the matching elasticity and $A_t$ matching function efficiency. Dividing function (3) by the number of unemployed persons in the previous quarter transforms the left-hand side of the equation into the job finding rate from Section 2.2 $F_t = \frac{h_t}{U_{t-1}}$, which can be calculated as $F_t = A_t \cdot \left(\frac{V_t}{U_{t-1}}\right)^{1-\alpha}$, from which matching function efficiency can be calculated inversely

$$A_t = \frac{F_t}{\left(\frac{V_t}{U_{t-1}}\right)^{1-\alpha}} \tag{4}$$

as the rate of successful hiring for given stocks of vacancies and unemployed persons in the previous period. A higher value of the efficiency function (4) indicates that the market matches workers and employers more effectively, increasing the probability of finding a job and, analogously to the first measure, strengthening the bargaining position of unemployed persons.

### 2.4 Wage equation

In the next step of the analysis, following the approach adopted in the study published in the ECB proceedings (Consolo & Dias da Silva, 2019), we estimated a wage equation ($w_t$) using the ordinary least squares method, with annualised quarterly nominal growth in the average wage over the period Q1 2013 – Q4 2025 as the dependent variable, and the lagged logarithm of the labour market tightness measure ($\theta_{t-1}$) and the lagged Beveridge curve residual ($\varepsilon BC_{t-1}$) as a measure of the efficiency of the matching process in the labour market. Inflation expectations were approximated by the four-quarter moving average of the y-o-y inflation rate ($\bar{\pi}_t$), reflecting the predominantly adaptive formation of expectations among market participants in the wage-bargaining process. The equation also includes the y-o-y

[3] The matching elasticity with respect to unemployment, $\alpha$ = 0.5, was calibrated following Petrongolo and Pessaries (2001).

growth rate of real productivity per person ($prod_t$), measured as real GDP per employed person.

$$w_t = \beta_0 + \beta_1 \cdot \bar{\pi}_t + \beta_2 \cdot log\theta_{t-1} + \beta_3 \cdot \varepsilon BC_{t-1} + \beta_4 \cdot prod_t + u_t \qquad (5)$$

An increase in labour market tightness in the previous quarter translates into wage growth, as it implies greater bargaining power for workers, while a higher ratio of job vacancies to unemployment provides workers with a wider range of options and greater flexibility in finding employment. A positive Beveridge curve residual indicates structural skills mismatch: if job vacancies and unemployed persons remain unmatched, the labour market generates weaker wage pressures. Conversely, a negative residual indicates that matching is taking place successfully and that workers have genuine opportunities to change jobs.

## 3 Empirical analysis of labour market efficiency and wage dynamics

### 3.1 Beveridge curve in Serbia's labour market

The Beveridge curve for the Serbian labour market was constructed using the unemployment rate and the job vacancy rate defined in Section 2, for the period from 2011 to 2025. The period under review was divided into four subperiods: post-crisis stagnation (2011–2014), the period of recovery and fiscal consolidation (2015–2019), the pandemic crisis (2020–2021), and the post-pandemic period (2022–2025).

The first subperiod is characterised by simultaneously high unemployment (an average of 25.1%) and a low vacancy rate (0.18% on average). The Beveridge curve for this subperiod is located in the lower-right part of the coordinate system, with average labour market tightness of 0.005. This points to a very slack labour market in which a large number of unemployed persons compete for very few vacancies.

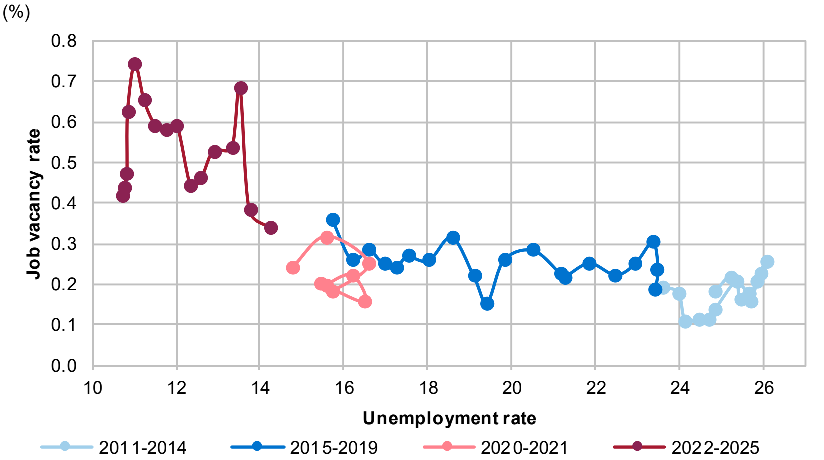
During the second subperiod, the labour market tightened markedly: the average unemployment rate fell to 19.8%, while the average vacancy rate increased to 0.25%. This can be characterised as movement along the Beveridge curve driven by cyclical labour market tightening, as explained in greater detail in Section 2.1. Aggregate demand increased during this period as economic activity recovered both in the broader euro-area environment and in the domestic economy. Together with fiscal consolidation and the introduction of a range of active labour market measures, these developments increased labour demand and reduced unemployment.

During the pandemic subperiod, the deviations that might have been expected given the nature of the shock were not recorded. The unemployment rate remained stable during the crisis at 15.8%, while the vacancy rate declined slightly to 0.22%. The absence of dramatic changes can largely be attributed to government job-retention measures characteristic of this period; consequently, the crisis was reflected primarily in employers' caution when hiring new workers.

The final subperiod displays the most pronounced differences relative to the rest of the sample. The unemployment rate continued to decline, to 12.1%, while the vacancy rate rose severalfold relative to its pre-crisis level, to 0.53%. Labour market tightness was consequently at its highest in this subperiod, at 0.04. The observations lie in the upper-left part of the coordinate system and clearly depart from the pattern seen in the rest of the sample, as the vacancy rate is substantially higher than the historical relationship would suggest. In other words, the Beveridge curve itself shifted, in contrast to the earlier movement along it.

The Beveridge curve for Serbia's labour market, shown in Chart 2, supports the descriptive analysis of these developments. The following sections introduce quantitative measures of the efficiency with which unemployed persons and vacancies are matched in order to explain these trajectories.

Chart 2 **Beveridge curve for Serbia**




Source: SORS, NES and authors' calculations.
Note: The unemployment rate is calculated as the ratio of the number of registered unemployed persons (NES) to the sum of registered unemployed persons (NES) and employed persons (Labour Force Survey, SORS). The job vacancy rate is calculated analogously, as the ratio of registered job vacancies (NES) to the sum of job vacancies (NES) and filled jobs, i.e. employed persons (Labour Force Survey, SORS).

## 3.2 Decomposition of unemployment fluctuations

The period observed as a whole is characterised by an almost uninterrupted decline in the unemployment rate. To identify the drivers of this movement, we apply the Shimer decomposition described in Section 2.2.

The average steady-state unemployment rate is 28.5%, substantially above the average registered unemployment rate of 18.6%. This is because it is calculated from flow rates (the job finding and job separation rates), which cover only two formal channels, inflows into the register and outflows through employment, while other forms of exit from the NES register are not included. The steady-state unemployment rate is therefore used solely to analyse fluctuations (dynamics). The correlation coefficient between the steady-state and registered unemployment rates is 0.95, indicating that the steady-state rate is an adequate approximation of the actual unemployment rate for this purpose.

Applying the Shimer decomposition to the period observed shows that the job finding rate explains 62% of fluctuations in the steady-state unemployment rate, while the remaining

38% is explained by the job separation rate. In other words, unemployment developments in Serbia are determined primarily by the speed at which unemployed persons find jobs rather than by the frequency with which existing jobs are lost. Sensitivity to the choice of smoothing parameter was tested by repeating the decomposition with λ = 400 and λ = 6400. The alternative parameter values changed the contribution of the job finding rate by less than 1 pp both for the full sample and across subperiods, indicating that the results are not dependent on the parameter choice.

Table 1: **Contributions to fluctuations in the steady-state unemployment rate**

| Period | $\beta_f$ | $\beta_s$ | Total | Observations |
|---|---|---|---|---|
| **2011–2025** | **0.62** | **0.38** | **1.00** | **59** |
| 2011–2014 | 0.80 | 0.31 | 1.11 | 15 |
| 2015–2019 | 0.89 | 0.10 | 0.99 | 20 |
| 2020–2021 | 0.04 | 0.92 | 0.96 | 8 |
| 2022–2025 | 0.60 | 0.32 | 0.92 | 16 |

Source: NES and authors' calculations.

Note: The sum of βf and βs in individual subperiods need not equal one because the steady-state unemployment rate is a non-linear function of the two flow rates, whose average values are calculated over the full sample.

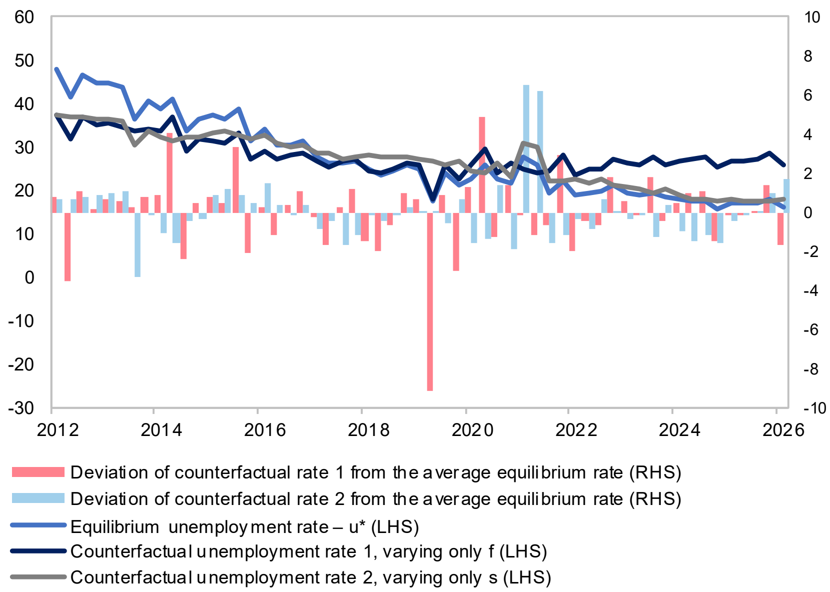
Table 1 shows that this relationship is relatively stable over time, with the exception of the pandemic shock. The job finding rate is the dominant channel in the first two subperiods and its contribution tends to increase, indicating that the pronounced decline in unemployment was almost entirely attributable to job finding, while the frequency of job separations played only a minor role. This finding is consistent with the movement of the Beveridge curve in the second subperiod, which was driven by stronger economic activity.

A reversal occurs during the pandemic, when the contribution of the job finding rate falls to only 4%, while the job separation rate explains 92% of fluctuations in steady-state unemployment. Caution in interpreting this subperiod is warranted for two reasons. It comprises only eight observations and was characterised by exceptionally strong government intervention through a broad range of measures. Nevertheless, the direction of the change is unambiguous. During this shock, labour-market measures helped preserve jobs by limiting dismissals. At the same time, employment relationships were terminated in segments not covered by these measures, such as the informal sector. In addition, the crisis brought a decline in new hiring, i.e. weaker labour demand.

In the final subperiod, the pre-pandemic pattern re-emerges and the job finding rate once again becomes the dominant contribution channel, albeit with reduced importance (60%). This finding points to a partial recovery of the labour market after the crisis, as unemployment dynamics are no longer driven exclusively by employment opportunities. The reduced importance of the job finding channel suggests possible difficulties in filling vacancies, consistent with the shift in the Beveridge curve observed in the same subperiod. The next section introduces measures of the efficiency with which jobseekers and employers are matched, in order to examine whether lower efficiency accounts for this change.

Chart 3 shows the movement of the steady-state unemployment rate. The series in which only the job finding rate varies, while the job separation rate is held fixed, tracks the steady-state unemployment curve almost completely. The exception is the Covid-19 crisis, when steady-state unemployment is better captured by the series based on variation in the job separation rate.

Chart 3 **Decomposition of fluctuations in the equilibrium unemployment rate**




Source: NES, NBS calculations using the Shimer (2012) decomposition.

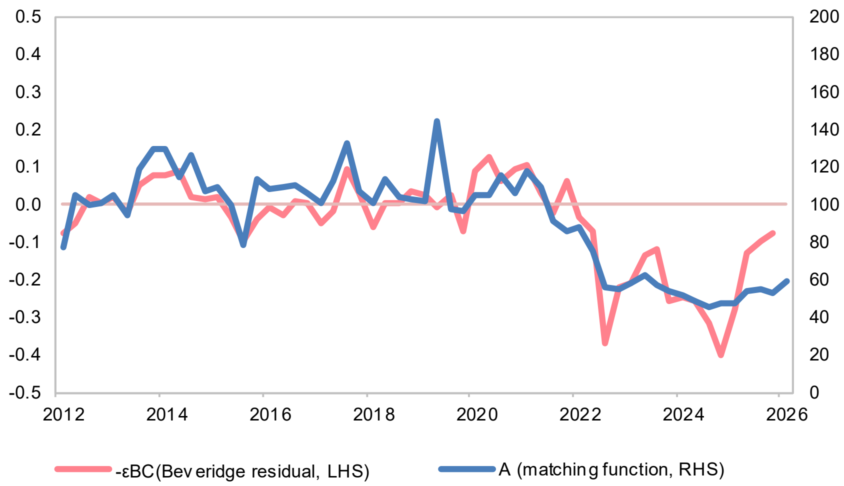
### 3.3 Developments in labour market matching efficiency measures

Consistent with movements in the Beveridge curve, up to 2019 the residual from Beveridge equation (2) fluctuated around zero, while matching efficiency (4) remained close to its historical average; the matching function measure points to a gradual improvement in job finding during this period. During the coronavirus pandemic the measures diverged: the residual indicates an improvement, reflecting weaker labour demand rather than a genuine increase in efficiency, while the second measure remains unchanged owing to job-retention measures. From 2022 onwards, both measures point to a deterioration in matching efficiency. In the case of the Beveridge curve residual, this can be linked to a substantially higher vacancy rate than would normally be associated with the prevailing unemployment rate, potentially indicating a shift in the curve and structural mismatch between employers and unemployed persons. The matching efficiency measure reaches a minimum value of 45 in Q3 2024, while the residual reaches its highest value (0.400) at the end of 2024. Both measures improve gradually during 2025, although efficiency has not yet returned to the historical curve.

The matching function efficiency measure A (4), however, is sensitive to changes in recruitment channels. The numerator of the job finding rate includes only hires achieved through the National Employment Service. When recruitment shifts to alternative channels such as online platforms, referrals or direct recruitment of students and graduates without formal entry in the register, the number of hires through the NES falls even if total hiring remains unchanged. The measure therefore records a decline in efficiency that does not necessarily reflect actual labour market conditions. The Beveridge residual does not depend on the recruitment channel because it uses stocks of unemployed persons and vacancies – the same rates shown in Chart 2 – which are formed independently of the way in which vacancies are ultimately filled. The residual therefore captures all factors affecting the position of the curve, including skills mismatch, demographic changes such as emigration and structural reforms, and thus provides a more informative approximation of overall market efficiency. For this reason, the wage-equation estimation presented below uses the Beveridge residual as the measure of efficiency.

The two efficiency measures are strongly negatively correlated (correlation coefficient -0.84 over the full sample). The sign is as expected, since a higher matching function efficiency value and a lower Beveridge curve residual both indicate more successful matching of labour supply and demand. The correlation is also negative within the stable 2011–2019 period (-0.64), indicating that the measures correspond even apart from the common structural shift.

Chart 4 **Measures of matching efficiency in the labour market**




Source: NES and NBS calculations.
Note: Beveridge residual is shown with the opposite sign, so that an increase in either measure indicates an improvement in matching efficiency in the labour market.

### 3.4 Effects on wage dynamics

In the next step of the analysis, following Consolo and Dias da Silva (2019), we estimated the wage equation (5) to examine whether the labour market measures constructed in the preceding sections contain information relevant to wage dynamics. The estimated coefficients are presented in Table 2. The results should be interpreted as indicative, given that the NES data do not cover the labour market in its entirety.

Table 2: **Estimated wage equation**

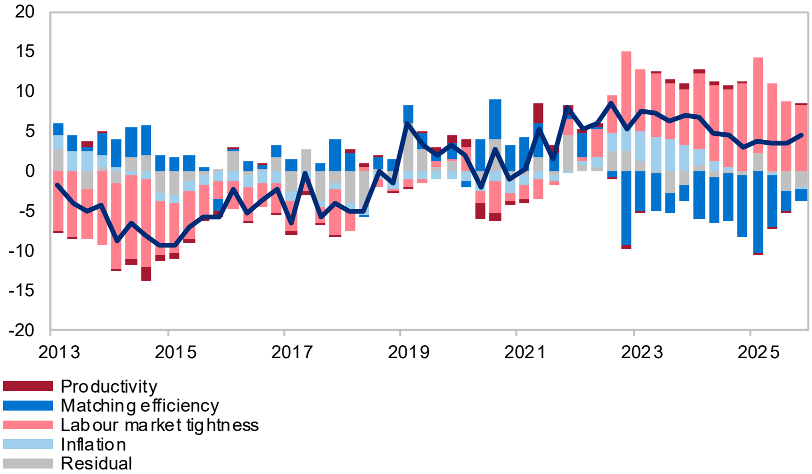
| **Dependent variable: annualised quarterly nominal wage growth** | | |
|---|---|---|
| **Estimation period:** | Q1 2013 – Q4 2025 (n=52) | |
| **Explanatory variable** | **Coefficient** | **Standard error** |
| Constant | $41.39^{***}$ | (3.83) |
| Four-quarter moving average of y-o-y inflation– $\bar{\pi}$ | $0.41^{***}$ | (0.09) |
| Labour market tightness – $\log\theta(-1)$ | $8.01^{***}$ | (0.81) |
| Beveridge curve residual– $\varepsilon BC(-1)$ | $-28.79^{***}$ | (5.12) |
| Y-o-y productivity growth– $\mathrm{prod}$ | $0.25^{**}$ | (0.12) |
| | $R^2$=0.82 | Adj. $R^2$=0.81 |
| | Standard error of regression = 2.30 | DW=1.69 |

Source: Authors' calculations in EViews.
*** Denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
The Breusch-Godfrey test does not reject the absence of serial correlation up to four lags (p = 0.135), while the Jarque-Bera test does not reject normality of the residuals (p = 0.76).

The estimated coefficients have the expected signs. Adaptive inflation expectations, labour market tightness (measured by the vacancy-to-unemployment ratio) and productivity contribute positively to wage growth, while the coefficient on the Beveridge curve residual is negative because positive residual values represent labour market matching inefficiency. A one-standard-deviation change in the residual corresponds to a change in wage growth of around 4 pp, while the comparable magnitude for labour market tightness is around 6 pp.

In the next step, we assess the strength of the effects of these explanatory variables on wage dynamics using historical data. This is done by calculating the contribution of each variable's deviation from its own long-run average to the deviation of annualised quarterly nominal wage growth from its long-run average. Since contributions are expressed relative to the 2013–2025 sample average, a positive contribution from efficiency in the earlier period does not necessarily indicate an improvement in matching at that particular time; rather, it reflects relatively more favourable residual values compared with the end of the sample. The decomposition of contributions to the deviation of wage growth from its long-run average (Chart 5) points to the dominant influence of labour market tightness. Although the decomposition depends on the estimated coefficients and therefore inherits the limitations already noted, it illustrates the relative strength of labour market tightness and matching efficiency across subperiods. In 2013–2014, the negative effect of low labour market tightness on wages dominates, during a period in which the number of unemployed persons was relatively high compared with vacancies, implying weaker worker bargaining power. Thereafter, the negative contribution of low tightness gradually weakens as the labour market tightens, from -7.7 pp in 2013 to -0.2 pp in 2019, accounting for almost the entire change over that period. The contribution of matching efficiency (measured by the Beveridge curve residual) remains approximately constant and positive over the same period. This reflects residual values below the sample average – an average heavily influenced by the marked deterioration in matching after 2022 – rather than necessarily an improvement in matching at the time, since the measure itself fluctuates around zero without a systematic deviation. In 2022–2023, both increasing labour market tightness and inflationary pressures contribute to above-average wage growth, while the adverse effect of the Beveridge curve residual already partly dampens the impact of tightness. In 2024, labour market tightness contributes an average of 10.0 pp above the long-run average, of which matching inefficiency absorbs around two thirds, leaving a substantially smaller net effect on wages than tightness alone would imply. In 2025, the share absorbed by matching inefficiency falls from around 85% in Q1 to around 17% in Q4, allowing tightness to exert increasingly strong pressure on wage growth. This interpretation should be viewed as a complement to, rather than a substitute for, standard labour market indicators, consistently with Consolo and Dias da Silva (2019), who conclude that matching efficiency adds a qualitative dimension to the analysis but that its quantitative implications for wages do not differ substantially from the standard approach.

Chart 5 **Contributions to the deviation of wage growth from its long-term average**
(contributions to annualised quarterly growth, pp)




Source: SORS, NES and authors' calculations.
Note: Contributions are calculated as the product of the estimated coefficient and the deviation of the corresponding variable from its average over the estimation sample. The residual captures the entire unexplained component.

## 3.5 Alternative specification of the wage equation

Table 3: **Wage-equation estimates using alternative efficiency measures**

| | Linear residual | Log–log residual |
|---|---|---|
| Sample | 2013Q1–2025Q4 | 2013Q1–2025Q4 |
| Constant | 41.39 (3.83)*** | 31.79 (2.97)*** |
| Four-quarter moving average of y-o-y inflation ($\bar{\pi}$) | 0.41 (0.09)*** | 0.31 (0.10)*** |
| Labour market tightness $log\theta(-1)$ | 8.01 (0.81)*** | 6.05 (0.63)*** |
| Beveridge curve residual $\varepsilon BC(-1)$ | −28.79 (5.12)*** | −7.42 (1.61)*** |
| Y-o-y productivity growth $\mathrm{prod}$ | 0.25 (0.12)** | 0.41 (0.13)*** |
| $R^2$ | 0.82 | 0.80 |
| Standard error of regression | 2.30 | 2.47 |
| DW | 1.69 | 1.23 |
| BG(4), F form | 0.135 | 0.006 |
| BG(4), $\chi^2$ form | 0.104 | 0.006 |
| VIF: ln θ / residual | 3.99 / 4.08 | 2.09 / 1.92 |
| Effect of 1 s.d. of residual | −3.66 pp | −2.21 pp |
| Effect of 1 s.d. of tightness | +6.36 pp | +4.81 pp |
| Ratio of 1 s.d. residual effect to 1 s.d. tightness effect | 0.58 | 0.46 |

Source: Authors' calculations in EViews.
*** Denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
The one-standard-deviation effect is calculated as the product of the estimated coefficient and the standard deviation of the relevant variable over the estimation sample of the equation concerned. Since the two variables are correlated, this is a descriptive comparison of relative importance rather than a decomposition of contributions.

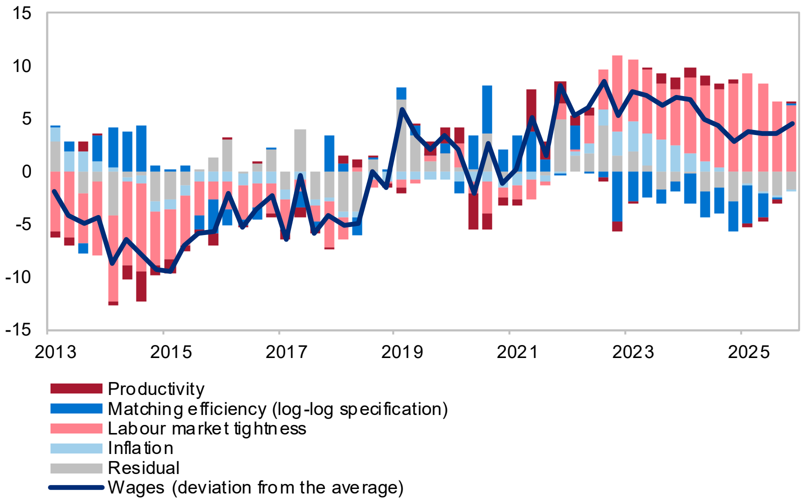
Section 2.3.1 describes two functional forms of the Beveridge curve. All results presented thus far have been obtained using the linear form, whereas in this section we consider the measure of matching efficiency based on the Beveridge curve residual derived from the log-log specification. Table 3 presents the same equation as in Section 3.4, but using the residual from the log-log form of the Beveridge curve. The equation is estimated over the same sample using the ordinary least squares method. In both specifications, all coefficients retain the expected sign and statistical significance. The coefficients on the Beveridge curve residual are not directly comparable, since the measures are expressed in different units. The coefficients on the labour market tightness measure are 8.01 in the linear specification and 6.05 in the log-log specification. The difference arises because both residual measures are correlated with the labour market tightness measure, although the correlation coefficient is lower in the log-log specification (0.67) than in the linear specification (0.84). This means that, in the linear specification, part of the shared variance is distributed between the two variables in a way that increases both coefficients. This is also supported by the centred variance inflation factor for the labour market tightness measure and the Beveridge curve residual, which indicates the extent to which the variance of an estimated coefficient is increased owing to the correlation of the respective variable with the other variables in the equation. Its values are approximately half the size in the log-log specification. Nevertheless, all values remain below the conventional threshold of 5 across in both specifications.

The linear equation is adopted as the baseline specification owing to its more favourable diagnostic properties, with the Durbin-Watson statistic standing at 1.69 in the linear specification and 1.23 in the log-log specification. The linear specification passes the test for serial correlation, as the Breusch-Godfrey test with four lags yields $p = 0.135$, whereas this is not the case for the non-linear specification ($p = 0.006$). In addition, the equation using the residual from the linear Beveridge curve exhibits a somewhat better fit, as reflected in a slightly higher coefficient of determination and a lower standard error of the regression.

Given that the coefficients are not comparable, their relative importance is assessed by comparing the effects of a one-standard-deviation change. A one-standard-deviation increase in the residual from the linear Beveridge curve results in annualised wage growth that is 3.66 pp lower, while the corresponding effect of an increase in the residual from the log-log curve is 2.21 pp. Similarly, a one-standard-deviation increase in labour market tightness raises annualised wage growth by 6.36 pp in the former case and by 4.81 pp in the latter. The ratio of these two effects is 0.58 in the linear specification and 0.46 in the log-log specification. Both channels operate in the same direction, although the alternative specification attributes a somewhat smaller role to matching efficiency.

Chart 6 shows the contribution decomposition obtained using the coefficients from the equation with the log-log residual, constructed in the same manner as Chart 5. The direction and timing of the changes are consistent with the baseline version: the contribution of tightness is negative until 2019, becomes positive in 2022 and continues to rise thereafter, while over the same period the contribution of matching efficiency changes sign, peaks in 2024 and recedes during 2025. Differences are apparent in the magnitude of the contributions, particularly that of matching efficiency, with the result that in the post-pandemic period the effects of labour market tightness are less strongly dampened by the adverse effects of

Chart 6 **Contributions to the deviation of wage growth from its long-term average (alternative specification)**
(contributions to annualised quarterly growth, pp)




Source: SORS, NES and authors' calculations.
Note: Contributions are calculated as the product of the estimated coefficient and the deviation of the corresponding variable from its average over the estimation sample. The residual captures the entire unexplained component.

matching inefficiency. It is important to note that the alternative specification contains a larger unexplained contribution, reflecting serial correlation in this equation.

## 4 Conclusion

The Serbian labour market over the period 2011–2025 was characterised by an almost continuous decline in unemployment accompanied by rising wages. In this paper, we sought to examine the extent to which these developments were attributable to cyclical labour market tightening and the extent to which they reflected structural changes in the matching of labour supply and demand. Following Consolo and Dias da Silva (2019), the analysis combines the Beveridge curve, the Shimer decomposition of unemployment fluctuations, two measures of matching efficiency and an augmented wage equation.

The measures employed provide a relatively consistent picture of labour market dynamics over the past fifteen years. The decline in unemployment was driven primarily by faster job finding, which accounts for 62% of fluctuations in the equilibrium unemployment rate. The analysis of movements in the Beveridge curve points to a gradual movement along the curve over the period 2015–2022, driven by cyclical labour market tightening, while matching efficiency remained stable. From 2022 onwards, the Beveridge curve itself shifted, with the job vacancy rate at a given unemployment rate becoming considerably higher than suggested by the historical relationship, indicating reduced matching efficiency between employers and jobseekers, especially towards the end of 2024 before gradually subsiding during 2025. The results obtained from the measures of matching efficiency are broadly consistent with these dynamics, although matching function efficiency is less reliable owing to its methodological properties and greater sensitivity to changes in recruitment channels. For this reason, in estimating the wage equation we used the Beveridge curve residual as a rough measure of matching efficiency in the labour market. The coefficients obtained from the estimated wage equation were in line with expectations: labour market tightness exerts upward pressure on wages, while the coefficient on the Beveridge curve residual has the opposite sign, as negative residual values imply an improvement in matching efficiency, with a favourable effect on wages. An examination of the contributions of the explanatory variables to the deviation of wage growth from its long-term average shows that the negative contribution of low labour market tightness gradually diminished over the period 2015–2019, accounting for almost the entire change during this part of the sample. From 2022 onwards, matching becomes less efficient and acts counter to labour market tightness, with the most pronounced negative effect occurring towards the end of 2024. As a result, record-high labour market tightness was only partially transmitted to wages, after which matching gradually improved during 2025.

Nevertheless, the conclusions should be interpreted in light of the data limitations and regarded only as an approximation of labour market dynamics, particularly since measures of matching efficiency are themselves inherently only rough approximations. The measures are constructed using NES administrative records and relate to the formal segment of the labour market. Unlike Consolo and Dias da Silva (2019), who use harmonised survey data, our analysis combines two data sources (NES and the Labour Force Survey). Furthermore, the measures constructed do not allow individual causes of changes in matching efficiency – such as skills mismatch, emigration or structural changes in recruitment channels – to be disentangled. Consequently, conclusions regarding the direction and drivers of developments are more robust than those concerning the levels themselves. With these caveats in mind, the findings suggest that measures of matching efficiency can provide additional insight into wage pressures beyond that offered by standard labour market indicators.

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