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JOB ACQUISITION PROCESSES AND JOB SEARCHES IN THE HUNGARIAN LABOUR MARKET

Examining regional and county differences

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ABSTRACT

This article focuses on estimating the matching function that models job-matching processes in the Hungarian labour market. This matching function, which characterises the costly process of matching labour market demand and supply, is estimated using both aggregated data and regional and county-level data sources. Based on the estimated parameters of the function, we draw conclusions about how sensitive the finding rate is to changes in labour market tightness. Furthermore, we assess how changes in the number of job vacancies and unemployed individuals affect the outcome of successful matches in the Hungarian labour market. The results indicate that labour market tightness has a positive effect on the finding rate. On the aggregated labour market, labour supply plays a more significant role in determining successful job matches than labour demand.

Due to the geographical immobility of the Hungarian labour force – characterised by a low willingness to relocate or commute – the domestic labour market is divided into regional and county-level sub-markets, each represented by matching functions with different parameters. Using regional and county-level data, we highlight the differences in job-matching processes across territorial units, as well as the potential factors and causes underlying these disparities. Initially, we hypothesise that the variation arises from differences in the technological parameter of the matching function. Subsequently, separate matching functions are estimated for each region and county. These estimations are based on datasets from Eurostat, the Hungarian Central Statistical Office (KSH), and the National Employment Service (NFSZ), covering time series data from the second quarter of 2010 to the third quarter of 2023.

JEL codes: J21, J23, J61, J64

Keywords: labour market, matching function, job acquisition, regions, counties

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1 INTRODUCTION

The labour market represents an important component of a country's economy. In most macroeconomic models, labour is a resource, a production factor that is essential for the productive operation of companies. For example, for a company to be able to produce goods or provide services, it requires labour. Reducing the vacancy rate and the unemployment rate is a priority, as when a company fills a vacant position, it can carry out its activities more efficiently. Workers, by securing a job and receiving regular income, can build a higher standard of living and continuously create domestic demand in the national economy. For a job position to become productive and for an employee to receive regular income, there needs to be a meeting point between supply and demand, which is the result of a successful job acquisition process.

Matching supply and demand in the labour market is the successful outcome of a costly search process. Jobseekers gather information about available opportunities and fill the offered job positions, thus becoming employed and reducing the overall number of unemployed individuals, as well as the unemployment rate. Successful job acquisition requires both available labour capacity and vacant positions. In other words, successful labour market matches are determined by the unemployed, representing the supply, and the vacant positions, representing the demand. This costly job acquisition process for both parties can be characterised in an economy by a matching function.

In order to understand the labour market processes in the Hungarian economy, it is important to study the job acquisition process in detail, by estimating the matching function characteristic for Hungary.

The matching function can be estimated based on aggregated-level databases for the unemployed and job vacancies, as well as labour market flows or computed finding rate that quantify successful labour market matches. When making statements about the labour market of the Hungarian economy, we assume that there are no constraints in the job acquisition process, although this is not the case in reality. The immobility of the Hungarian workforce, as well as its low willingness to commute or relocate, justifies treating Hungary not as a single labour market, but rather as an aggregation of local sub-markets. However, in this way, we emphasise that both demand and supply-side actors take into account only the locally available alternatives. The job acquisition processes of local sub-markets, defined by regional and county boundaries, may differ in the roles of demand and supply, or even in the efficiency of the job acquisition process itself, that is, in the parameters of the matching function.

This article deals with the estimation of the aggregated, as well as regional and county-specific, matching functions characteristic of the Hungarian labour market. We shall seek to answer the following questions: In the Hungarian economy, are successful labour market matches – in line with the theoretical framework – truly determined by the combined development of labour demand and labour supply, and if so, are these effects of equal magnitude? How sensitively does the finding rate respond to changes in labour market tightness in the Hungarian labour market, or in other words, how do successful labour market matches relate to the changes in the number of unemployed individuals and vacant positions? Does the job acquisition process show differences between the regions and counties? If so, in which parameters of the function do these differences manifest, what explains them, and what consequences might they have?

This article looks at the domestic labour market in geographical terms. The job acquisition process in the labour market is modelled using a matching function. We estimate local matching functions, first at the aggregated level characterising the entire Hungarian economy, and then broken down into sub-markets according to geographical units. We also analyse the differences between regions and counties. With the results in hand, we examine the extent to which changes in demand and supply play a role in the search processes and successful labour market matches in the Hungarian labour market, as well as in the individual regions and counties. We also analyse the differences in job acquisition efficiency characterising the different geographical areas.

The structure of the article is as follows: *Chapter 1* provides a summary of the literature related to labour market search processes, as well as unemployment resulting from structural, particularly geographical, differences. *Chapter 2* presents the demand and supply sides of the applied labour market model framework, introducing the key players, with the assumptions described here being applied throughout the article. *Chapter 3* deals with the theoretical summary of the matching function describing the labour market job acquisition process, outlining its characteristics and specifications. The function characterising the Hungarian labour market provides the opportunity to describe Hungarian labour market processes and to compare the effective job acquisition practices in different regions and counties. *Chapter 4* summarises our own estimation results, covering the estimation of the aggregated labour market matching function in Hungary, followed by the estimation using panel data sources. This is followed by an analysis of the region-specific matching functions. *Chapter 5* presents the conclusions drawn from the results and outlines potential directions for further research.

2 REVIEW OF THE LITERATURE

This article presents the estimation of the matching function characteristic of the Hungarian economy. The matching function is suitable for modelling the job acquisition processes in the labour market, specifically the meeting point of demand and supply. In each period, there are companies advertising new job openings and workers searching for employment. The matching function describes the process, which can also be interpreted as a technology, in which workers gather information about vacant positions through advertisements, newspapers, employment agencies, personal connections, and other networks, apply for these positions, and if the process is successful, a new employment relationship is established (Petrongolo–Pissarides, 2001). Lindeboom et al., (1994), in studying the job acquisition process, specifically examine the effectiveness of the previously mentioned job search channels (advertisements, intermediaries, and informal networks). In our estimations, we do not distinguish between the different job acquisition channels and do not address their varying levels of effectiveness.

In his 2000 paper, Pissarides highlights that the job acquisition processes between jobseekers and companies advertising job openings in the labour market are costly for both demand and supply. Consequently, the success of the search process – whether an unemployed individual manages to secure a job or a company manages to fill its advertised positions – is not immediate. The reason for this lies in the heterogeneity of demand and supply, as well as the information gap.

Based on Blanchard and Diamond's (1989) study, we assume that the matching function characteristic of the Hungarian economy is of the Cobb–Douglas type. We also estimate the function using aggregated data that characterises the entire Hungarian economy. We then divide the Hungarian labour market into regional and county-level sub-markets and estimate the function using panel data with the goal of revealing territorial differences. These differences may manifest as variations in the technological or efficiency parameters of the function, as well as differing weights of the roles of demand and supply.

There are several studies related to the examination of the labour market matching function. Blanchard and Diamond (1989) focus on estimating the matching function for the US labour market, while Sahin et al. (2014) define an index to quantify the missed labour market matches due to geographical separation, which is also based on the matching function characteristic of the US labour market. Petrongolo and Pissarides (2001) provide a meta-analysis summarizing research on the estimation of the labour market matching function, including various approaches, potential extensions, and their findings.

The endogeneity of the variables used in estimating the matching function, and thus the handling of the potential bias in the estimated coefficients, is also a subject of research. Endogeneity arises because the search efficiency influences the number of vacant positions advertised by profit-maximising firms. In other words, a shock affecting efficiency directly impacts the resulting matches and also indirectly influences them (Borowczyk–Martins et al., 2013). Borowczyk–Martins et al. (2013) compare this endogeneity to how productivity shocks directly affect aggregate production and also influence the demand for production factors. Similarly, in the labour market, shocks affecting job acquisition efficiency also impact the intensity and willingness of firms to advertise job openings. In their research, to address this issue in the estimation of the matching function, they treat the time-series data as an ARMA process. We do not address the detailed treatment of this bias in our estimations.

The estimation of the matching function is carried out in various specifications with different explanatory variables for both aggregated and region-specific databases. For this, the calculation of unemployment probabilities from unemployment data is also necessary. The method for calculating probabilities is derived from Shimer's (2005) study. In the calculations, we distinguish between employed and unemployed status. However, Kónya (2016) points out that when calculating the probability, the decision of an inactive person to enter the labour market is also relevant. Consequently, the model framework should be extended to include flows from inactivity to the labour market. Lindeboom et al. (1994), focusing on labour market flows from employment to employment, analyse whether search efficiency shows significant differences between individuals who move into a new position from unemployment or from employment. They conclude that the job acquisition rate is higher for those with an initial employment status. In our analysis, we focus solely on job acquisition from unemployment, that is from registered jobseeker status.

Blanchard and Diamond (1989) focus on estimating the matching function for the entire US economy as well as for the manufacturing sector. Lisauskaite (2022) estimates industry-specific matching functions using the example of the United Kingdom. In her study, she accounts for worker heterogeneity, thereby relaxing the assumption that all workers have an equal probability of finding work; this probability is instead made dependent on individual characteristics.

In their study, Jackman and Roper (1987) divide the labour market not only by qualifications and sector, but also by geographical units, as we do in this article. The units of the local labour sub-markets in Hungary are the regions and counties, between which there is no mobility. This is because the mobility of the Hungarian workforce is constrained by low willingness to relocate and a tendency to commute only short distances within counties, meaning that labour demand and supply primarily consider locally available alternatives during the job search process (Csizmady et al., 2020). The regional breakdown used in our study is justified by the lack of spatial mobility among the Hungarian population. Spatial mobility can include changes of residence, relocation, or commuting (Kulcsár, 2006).

Jackman and Savouri (1992) emphasise that the ownership structure of real estate is a key factor in determining labour mobility. The geographical mobility of the Hungarian population and their willingness to relocate is low. One significant reason for this is the system of property ownership: Hungarian people tend to prefer owning their homes (Csizmady et al., 2020). Commuting is the temporary relocation for employment purposes. This option is primarily determined by transportation conditions. In these processes, crossing county borders is rare, and the maximum acceptable commuting time is around 50 minutes, which reinforces the assumption of workers remaining within the county (Csizmady et al., 2020). This study does not address flows between regions and counties. The estimation of local matching functions is done for counties and regions.

Coles and Smith (1996) reinforce Jackman and Roper's (1987) assertion that labour market processes should be studied based on regional units, from a geographical perspective. They analyse the UK labour market using a geographical approach. In our research, we divide the Hungarian labour market into regional and county-specific sub-markets. Coles and Smith (1996) conduct estimations for the UK labour market, dividing it into sub-markets and using cross-sectional, urban data. Their study also explores which demographic and area-specific variables, such as population density, may influence search efficiency. Furthermore, they also examine the relationship between wages specific to each area and their impact.

Bennett and Pinto (1994), in their research, estimate the matching function separately for 104 distinct territorial units in the UK, thus highlighting that the matching function is not only suitable for describing processes in the aggregated labour market of a country, but can also be separately estimated for the local sub-markets within the country. The number of successful labour market matches is also determined by the changes in the number of unemployed individuals and vacant job positions in the local labour markets. Burda and Profit (1995), in their study of the Czech Republic's labour market matching function, conclude that, alongside administrative region or county borders, the distance between the place of residence and work can also have an impact on labour market flows. Marinescu and Rathelot (2016), using the example of the USA, highlight the importance of correctly defining local sub-markets when geographically analysing the labour market to gain an accurate understanding of job acquisition processes. In our article, we divide the domestic labour market into regional and county-specific sub-markets, examining the differences in the matching function between territorial units.

3 THE LABOUR MARKET MODEL: JOBSEEKERS AND EMPLOYED INDIVIDUALS

In the estimation of the matching function, we disregard the labour market flows from inactivity to employment (Kónya, 2016). The labour market model and its participants, based on Blanchard and Diamond (1989), are outlined below.

An active individual in the model can either be employed (denoted as E) or unemployed (denoted as U). The employed and unemployed population together form the labour force (denoted as L). The following equality (1) holds for the supply side of the labour market:

$$L = E + U. \tag{1}$$

On the demand side of the labour market, we can examine job positions, which may be filled (denoted as F) or advertised but unfilled (denoted as V for vacancy); there are also those that, using the terminology of Diamond and Blanchard (1989), are improductive (denoted as I), meaning they are neither advertised nor filled. They are called improductive because it is not profitable for the company to hire someone for the given position; the position has become redundant, possibly due to mechanised technology making it improductive. For all (A, denoting all) job positions, we can write the following equality (2):

$$A = V + F + I, \tag{2}$$

Among these, productive positions are denoted as P (productive), and the relevant job positions for analysis are:

$$P = V + F. \tag{3}$$

We can assume that the number of filled positions in the given period equals the number of employed individuals: E = F, meaning that each employed person holds exactly one job. In this study, for simplicity, we ignore labour market flows where an employed individual (already holding a job) searches for another job (on-the-job search), for example, due to dissatisfaction with their current position, as well as flows from inactivity to employment.

4 THE LABOUR MARKET MATCHING FUNCTION

The workforce dynamics shaping the demand and supply sides of the labour market are constantly changing. The search and matching process is stochastic and time-dependent. The process where the unemployed individuals (supply side) and the vacant job positions (demand side) meet can be described by the matching function (Blanchard–Diamond, 1989).

Data sources that can be used for estimating the matching function include aggregated-level data, which characterises the economy of a country, or data that can be estimated for individual sectors, sub-markets, local labour markets, or micro-level data (Petrongolo–Pissarides, 2001). Initially, we estimate the function using aggregated data, and then, after controlling for regional differences and assuming geographical constraints, we also conduct estimations based on regional and county-level panel data.

In case of the matching function, the stock of unemployed individuals and active jobseekers, as well as the number of unfilled vacancies, determines the number of new hires, meaning the transition into employment status. The matching function can be expressed in the following form:

$$H = m\,(U, V) \tag{4}$$

where:

H: the number of new hires, when an active individual transitions into employment (in our narrowed case, the flow from unemployment or active job searching to employment);

U: the number of unemployed individuals;

V: the number of unfilled, advertised vacancies.

Using the above function, using the data for H, U, and V, it is possible to determine the number of hires per unemployed individual, the finding rate, as the ratio of $\frac{H}{U}$ and the probability that a position will be filled by an employee: $\frac{H}{V}$.

The function is assumed to be concave and monotonically increasing in both arguments, homogenous of degree one, and is typically assumed to exhibit constant returns to scale in most studies (Petrongolo–Pissarides, 2001). We assume a Cobb–Douglas type matching function based on Blanchard and Diamond (1989). The model is also extended with a time dimension. Consequently, when estimating the function, we may encounter the problem of handling time. The problem arises because the search and matching model is continuous in time, while the data required for estimation is available only at discrete time points. The method of handling time series may differ during the empirical estimation of the matching function. In the equations estimated by Blanchard and Diamond (1989), they assume that the match occurring in period t – 1 is empirically observed as a new hire in the subsequent period t. Sahin et al. (2014) and Lisauskaite (2022), when estimating the aggregate function, do not apply any lag. We also adopt the lag-free functional form they use:

$$H_t = \eta_t \cdot V_t^{\alpha_1} \cdot U_t^{\alpha_2} \tag{5}$$

If we apply a lag following Blanchard and Diamond (1989), the time index on the right-hand side of equation (5) is t – 1. When estimating the matching function based on the aggregated database, we also estimate an equation with a lag. Assuming that the matching function exhibits constant returns to scale, the parameters of the function and the estimation equation can be expressed as follows:

$$\alpha_2 = 1 - \alpha_2 \tag{6}$$

By dividing equation (5) by U_t, the equation to be estimated based on the data is as follows:

$$\log\left(\frac{H_t}{U_t}\right) = \log(\eta) + \alpha \cdot \log\left(\frac{V_t}{U_t}\right) + \varepsilon_t \tag{7}$$

The equation can be extended with trends, seasonal, and sector-specific variables depending on the frequency of the data used for estimation and the characteristics of the respective labour market. In equation (7) estimated in this way, the left-hand side represents the logarithm of the finding rate $\left(\frac{H_t}{U_t}\right)$, while the right-hand side features the logarithm of the $\left(\frac{V_t}{U_t}\right)$ ratio, indicating labour market tightness.

The estimated parameter α is the elasticity indicator, showing how sensitively the finding rate $\left(\frac{H_t}{U_t}\right)$ reacts to changes in the labour market tightness $\left(\frac{V_t}{U_t}\right)$. If we start from the form of the matching function in equation (5), the parameter indicates how changes in the number of vacancies (V_t) affect the number of successful job matches, while $1 - \alpha$ reflects the role of the unemployed, thus the supply side. If the estimated α coefficient is 0.5, it means that the number of successful job matches is equally influenced by demand and supply. If the parameter is less than 0.5, we can infer that the impact of changes in supply is more significant; otherwise, demand is more decisive in determining successful labour market matches. The parameter η, appearing as a multiplier in the matching function (5), represents the technological aspect describing search efficiency in the given economy.

In the case of the aggregate estimation of the matching function, our goal is to analyse the job acquisition process in the Hungarian labour market through the interpretation of the estimated parameters of the function. By controlling for regional and county differences, we also highlight the differences between geographical units and, furthermore, estimate separate matching functions for local sub-markets (Bennett–Pinto, 1994).

As the dependent variable in the matching function, we can use the logarithm of the finding rate characterising the labour market, as Kónya (2016) did in their estimation of the Hungarian matching function. If we assume that the matching function is of the Cobb-Douglas type with constant returns to scale, the left side of estimation equation (7) includes the logarithm of the number of hires per unemployed person, which represents the finding rate (f_t) (job-finding probability). Thus, the matching function can also be interpreted as how the labour market tightness $\left(\frac{V_t}{U_t}\right)$, determined by the jobseekers and the number of vacancies results in a certain job acquisition probability (f_t) (finding rate):

$$\log(f_t) = \log(\eta) + \alpha \cdot \log\left(\frac{V_t}{U_t}\right) + \varepsilon_t \tag{8}$$

We use the method developed by Shimer (2005) to determine the job acquisition rate on the left-hand side of the matching function estimation equation. The core idea of the method is to distinguish between short-term and long-term unemployment. Short-term unemployed individuals are identified with an s (short-time) index. Suppose that in period t, a long-term unemployed individual finds a job with probability (f_t). Then, in period t + 1, the number of unemployed individuals is:

$$U_{t+1} = U_t \cdot (1 - f_t) + U_{t+1}^s \tag{9}$$

The finding rate (job acquisition probability) can be expressed as follows:

$$f_t = 1 - \frac{U_{t+1} - U_{t+1}^s}{U_t} \tag{10}$$

This model takes into account only the labour market flows between unemployment and employment. Kónya (2016) emphasises that important processes occur in the transition from inactivity to labour market participation, and neglecting these processes may lead to distortions in the calculations characterising labour market processes. In Chapter 4, we will focus on estimating the equations (7) and (8), which will be estimated using aggregated databases, as well as regional and county-level data.

5 ESTIMATION OF THE MATCHING FUNCTION

Our goal is to estimate the parameters of the matching function that characterises the Hungarian economy, and from this, to infer how sensitively the finding rate responds to changes in labour market tightness, and the role that demand and supply play in determining successful labour market processes.

If the estimated value of the parameter α in the Cobb–Douglas type, constant returns to scale matching function in equation (5) is 0.5, it means that in determining labour market matches, the roles of demand and supply are symmetric. In other words, changes in the number of vacant positions and unemployed individuals affect the changes in successful labour market matches to the same degree. The question is whether this value characterises the Hungarian economy or whether there is any shift in demand or supply. Therefore, we investigate whether the elasticity parameters of the matching function in the Hungarian labour market are symmetric, that is, whether demand and supply influence the job acquisition process equally, and whether there can be a shift on either the supply or demand side.

In addition to estimating the aggregated function, our aim is to explore regional and county-level differences in the job-finding process. These differences may manifest in the efficiency of the matching technology or in the differing roles of demand and supply. To examine the differences in matching efficiencies, we assume that the α parameter is the same in all geographical units. Bennett and Pinto (1994) demonstrated that the matching function is suitable not only for describing labour market processes in the entire country but also for modelling local, and – in case of Hungary – regional, and county-level labour markets. For the domestic regions and counties, we define separate matching functions, allowing for differences in the α_i parameter between geographical units, thus examining the role of demand and supply in local job acquisition processes.

5.1 Estimation of the aggregated matching function

The estimation of the matching function characteristic of the Hungarian labour market is carried out using two types of data sources. First, we work with aggregated-level data, and then, by breaking down the Hungarian labour market into regions and counties, we estimate the function using panel data.

5.1.1 Based on aggregated data

When estimating the matching function, which is assumed to be of the Cobb-Douglas type with constant returns to scale, we use quarterly time series data that characterises the entire Hungarian labour market from an aggregated database. In the A.1 specification – where the "A" denotes the aggregated data source – we apply the following estimation equation:

$$\log\left(\frac{H_t}{U_t}\right) = \log(\eta) + \alpha \cdot \log\left(\frac{V_t}{U_t}\right) + \varepsilon_t \qquad \text{A.1}$$

where H_t represents the number of new hires in period t, U_t represents the number of unemployed individuals in period t, and V_t represents the number of unfilled positions.

In the A.2 specification, we use a simultaneous lag, assuming that a successful match between demand and supply that occurs in period t – 1 will empirically appear as a new hire in period t, meaning the next period (Blanchard–Diamond, 1989):

$$\log\left(\frac{H_t}{U_{t-1}}\right) = \log(\eta) + \alpha \cdot \log\left(\frac{V_{t-1}}{U_{t-1}}\right) + \varepsilon_t \qquad \text{A.2}$$

In the following specification, we estimate equation (8), where the left-hand side variable, as used in Kónya (2016), represents the job-finding probability (finding rate) calculated from short-term unemployment using equation (10). This estimation result is presented in *Table 1*, as equation A.3.

5.1.2 Panel data at regional and county level

The matching function is also determined using panel data. Our goal is to achieve a more accurate estimation of the α parameter and to map the differences in the labour market search efficiencies (η_{region}, η_{county}) across different geographical units. The Hungarian labour market is divided into regional and county sub-markets (i = index of the given geographical unit).

We assume that the unemployment and job statistics for a given geographical unit only affect the job acquisition process of that specific sub-market. This means that a jobseeker registered in region or county "*i*" only appears as labour supply within their own region or county, implying that there is no migration between geographical units. This assumption is justified by the immobility of the Hungarian labour force. Moreover, vacant job positions represent demand only within local sub-markets. Compared to the aggregated data sources, we also control for regional and county-specific differences here. Our hypothesis is that there may be differences in the efficiency of processes defined by the matching function characteristic of the labour market in different geographical units, as various specific factors could have influenced the job search process. For estimating the aggregated function, we also assume a Cobb-Douglas type matching function with constant returns to scale in the panel regression. The logarithms of the relevant variables are included in the estimation equation.

$$\log\left(\frac{H_{i,t}}{U_{i,t}}\right) = \text{dummy}_i + \alpha * \log\left(\frac{V_{i,t}}{U_{i,t}}\right) \qquad \text{P.1}$$

$$\log\left(\frac{EX_{i,t}}{U_{i,t}}\right) = \text{dummy}_i + \alpha * \log\left(\frac{V_{i,t}}{U_{i,t}}\right) \qquad \text{P.2}$$

$$\log\left(f_{i,t}\right) = \text{dummy}_i + \alpha * \log\left(\frac{V_{i,t}}{U_{i,t}}\right) \qquad \text{P.3}$$

Note: the "P" notation refers to the panel-level data source.

In the P.1, P.2, and P.3 equations, H_{it} refers to the number of people employed from the unemployment benefits in the given period, U_{it} represents the number of registered jobseekers, V_{it} denotes the number of unfilled job positions, EX_{it} is the number of individuals exiting the register, f_{it} stands for the job finding probability, and subscript „*i*" indicates the respective region or county. In the case of the three estimation equations (P.1, P.2, P.3), we used different dependent variables, which will be described in the next subsection about the data.

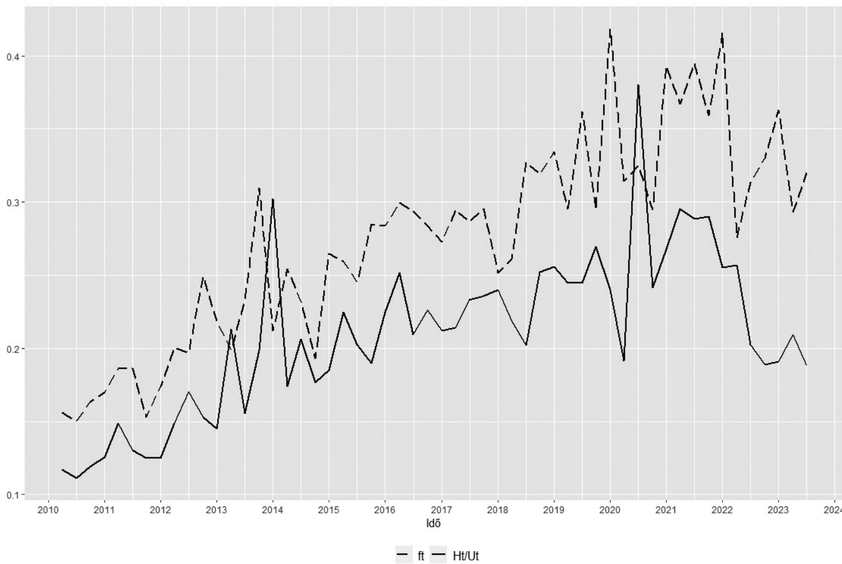
5.1.3 Aggregated data source

In order to estimate the aggregated matching function based on the A.1 and A.2 types of equations, we need a variable describing new hires. In this case, this variable represents the labour market flows from unemployment to employment.

Eurostat provides quarterly data on labour market flows for EU countries, including Hungary. The flow data is available from the second quarter of 2010 to the fourth quarter of 2023. However, Eurostat did not publish flow data for the first quarter of 2021. The missing values in the time series are filled using linear interpolation, as applied by Kónya (2023). The statistics for vacant job positions are available on a quarterly basis, starting from the first quarter of 2006.

The third variable needed is the total number of unemployed individuals in the labour market, for which Eurostat also provides quarterly data. Moreover, for calculating the finding rate defined in equation (10), we treat the stock of short-term unemployed individuals as a separate variable. In the study, short-term unemployment is defined, deviating from Shimer's (2005) one-month definition, as unemployment lasting no more than three months, or one quarter, as applied by Kónya (2016). The downloaded time series are adjusted for quarterly seasonality using the X-13-ARIMA-SEATS program. Due to the short length of the time series, the trend of the series was not specifically addressed.

Figure 1
The development of the finding rate (f_t) and the number of hires per unemployed individual $\left(\frac{H_t}{U_t}\right)$ in Hungary



Note: dashed line: finding rate (f_t); solid line: number of hires per unemployed individual $\left(\frac{H_t}{U_t}\right)$ (Q2 2010 – Q3 2023).
Source: Eurostat, my own calculations

Figure 1 shows the time series of those variables, the logarithmic values of which are the dependent variables in the aggregate-level estimation equations. The finding rate (f_t) is the dependent variable in equation A.3, and $\left(\frac{H_t}{U_t}\right)$ is the dependent variable in equations A.1 and A.2. Both variables show an increasing trend, supporting the decrease in the unemployment rate in the most recent period. The calculated finding rate (f_t) is above the $\left(\frac{H_t}{U_t}\right)$ ratio during the examined period, but the direction of the variables' trends is similar. The time series data are available from Q2 2010 for the first estimation equation. The Covid pandemic may have had an impact on labour market processes, and its effect is filtered out using a dummy variable for the Covid period.

5.1.4 Regional, county-level data source

We use the National Employment Service (NFSZ) database to estimate the matching function for Hungary using panel data. The NFSZ publishes monthly data on the number of registered jobseekers by region and county. In the estimation equations, the registered jobseekers represent the stock of unemployed individuals. Monthly data is also available for the number of unfilled job vacancies, broken down by region and county. We use quarterly frequency time series by utilizing data from the last month of each quarter.

The primary issue with the available data is that we do not have a completely reliable data source that clearly represents labour market matches for new hires at the county or regional level. To address this issue in the estimation equations (P.1, P.2, P.3), we use three different dependent variables. As an illustration, we compare the three explanatory variables for the Western Transdanubian region in *Figure 2*. In the first estimation equation (P.1), we use the number of individuals who found employment from unemployment benefits in the given territorial unit as a proxy for matches, as this data is available in the NFSZ registry.

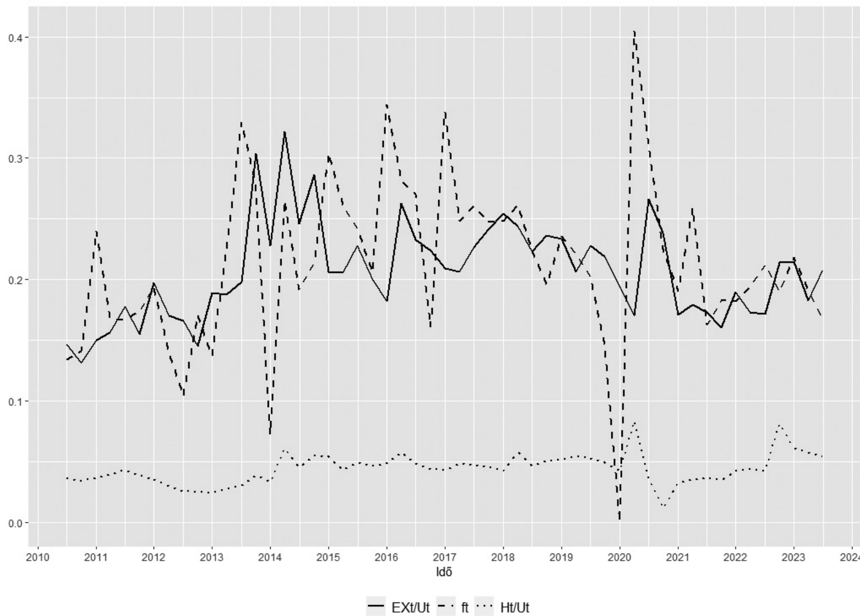
A registered jobseeker receives unemployment benefits for 90 days, so in this case, we are examining the employment of short-term unemployed individuals. However, these flow data underestimate the total number of matches occurring in the given period.

In the second type of estimation equation (P.2), the number of individuals exiting the jobseeker register represents successful labour market matches. However, there are two possible outcomes in this case: the individual exiting the database of registered jobseekers will either become employed or inactive, thus there is still a potential source of error. In the third estimation, we use the finding rate as the dependent variable, which is calculated based on equation (10), supplemented with the subscript ‚*i*' indicating the specific region, as per the following formula:

$$f_{i,t} = 1 - \frac{U_{i,t+1} - U^{s}_{i,t+1}}{U_{i,t}} \tag{11}$$

In the (11) equation, short-term unemployment is defined by the number of individuals newly entering the registered jobseeker database. Upon examining the time series of the three defined dependent variables, a typical quarterly seasonality can be observed for each region and county, which is filtered using the X-13-ARIMA-SEATS program. However, the trend for the variables is not significant.

Figure 2
The finding rate: ($f_{i,t}$), the development of the number of individuals exiting the register per unemployed person $\left(\frac{EX_{i,t}}{U_{i,t}}\right)$, and the number of individuals finding employment through unemployment benefits per unemployed person $\left(\frac{H_{i,t}}{U_{i,t}}\right)$ in the Western Transdanubia region (Q2 2010 – Q3 2023)



Note: Solid line: number of people exiting the register per unemployed person $\left(\frac{EX_{i,t}}{U_{i,t}}\right)$, dashed line: finding rate: ($f_{i,t}$), dotted line: number of individuals finding employment through unemployment benefits per unemployed person $\left(\frac{H_{i,t}}{U_{i,t}}\right)$ in Western Transdanubia
Source: NFSZ, my own calculations

Based on *Figure 2*, the variable $\left(\frac{H_{i,t}}{U_{i,t}}\right)$ determined from the number of individuals finding employment through unemployment benefits indeed underestimates the finding rate $\left(\frac{EX_{i,t}}{U_{i,t}}\right)$, ($f_{i,t}$) calculated from the other two variables, although the time series for these variables exhibit similar directional changes. The time series applied in the case of the Western Transdanubian region are shown in the figure, however, for the other regions and counties, the three types of explanatory variables exhibit similar relationships.

We performed the aggregate-level estimates using data series available from the second quarter of 2010, so this was the starting point for the data used in the panel data source as well. The impact of the COVID-19 pandemic was also filtered using period-specific category variables during the use of panel data.

5.1.5 Estimation results: the matching function characteristic of the Hungarian economy

The estimation results for parameter α, derived from both aggregated and panel data, are summarised in *Table 1*. The highest α value was obtained in the case of the finding rate calculated from short-term unemployment stock, both for aggregated data and regional and county-level panel data. The analysis of the differences in efficiencies between regional and county levels is discussed in *Chapter 4.1.5*.

Table 1
Summary of the aggregated matching function estimation results (α)

	A.1	P.1 (region)	P.1 (county)
α	0.2434*** (0.0292)	0.2526*** (0.0333)	0.2215*** (0.0189)
	A.2	**P.2 (region)**	**P.2 (county)**
α	0.2128*** (0.0304)	0.2250*** (0.0158)	0.2274*** (0.0102)
	A.3	**P.3 (region)**	**P.3 (county)**
α	0.2630*** (0.0235)	0.3103*** (0.0282)	0.2735*** (0.0175)

Note: *** $p < 0.001$, ** < 0.01, * < 0.04, the standard errors are shown in parentheses.
Source: Eurostat, NFSZ, own estimation results

The impact of COVID-19 was not significant in any type of estimation equation; we observed deviations on the order of hundredths for the coefficients when controlling for the Covid period. These results are contained in *Appendix 1*. The coefficients determined using both the aggregated data source and the panel data provided similar results, approximately of the same magnitude.

The significance of the estimated coefficients demonstrates that labour market tightness indeed impacts the development of the job acquisition process. The positive sign suggests that if the labour market is tight, meaning that there are few unemployed individuals per vacant job, employees are more likely to find a job, hence the finding rate increases. If we base the analysis on the preliminary forms of the matching function (5), (7), we can conclude that both demand and supply play a crucial role. For each data source, the A.3 and P.3 equations, estimated alongside the finding rate we calculated, produced the highest values. However, the largest value obtained for the α parameter (0.3103) was lower than the value assumed for the USA by Sahin et al. (2014) at 0.5 and the value estimated for the UK by Lisauskaite (2022) at 0.337.

One possible explanation for the difference is that in Hungary, the stock of unemployed individuals has a greater impact on labour market flows than the number of vacant jobs representing labour demand. This suggests that the elasticity parameter of the Hungarian matching function is asymmetric and characterised by a positive shift on the supply side.

Another possible explanation for the difference is that the data sources used in the estimations were limited. We made efforts to estimate the finding rate as accurately as possible using various methods, but the actual probabilities determined by the real matches are likely to differ from the values obtained, implying that measurement errors must be taken into account. Petrongolo and Pissarides (2001) also draw attention to the fact that data on vacancies often underestimates the real figures and are not always reliable. Köllő and Varga (2016) highlight the measurement difficulties of unemployment stock data. The estimation of the matching function would require stock data that includes those economically active individuals who are actually looking for a job. For instance, we must account for the participants in the public employment programmes, who are temporarily excluded from databases during the period of public employment. Job seekers often find themselves moving back and forth between public works employment and unemployment. As a result, the unemployment stock data may be skewed in both the aggregate and panel data.

5.1.6 Estimation results: differences in search efficiency between local sub-markets

From the estimation of the matching function characteristic of the Hungarian aggregate economy, we can infer not only the weight of the roles of demand and supply, but also uncover differences in the efficiency and technological parameters of the function (η_{region}, $\eta_{country}$) representing the job acquisition process. This is because in the P.1, P.2, and P.3 estimation equations, assuming a constant α based on panel data, we hypothesised that the geography-specific effect impacts the efficiency of the search process. Significant differences in search efficiencies were found at both regional and county levels in the P.2 equation. The regional differences are presented in *Table 2*.

Table 2
Region-specific efficiencies

Region	Region-specific impacts	η_{region}
Southern Great Plain	−1.3813*** (0.0345)	0.2513
Southern Transdanubia	−0.0795* (0.0324)	0.2321
Northern Great Plain	−0.1050** (0.0322)	0.2262
Northern Hungary	−0.1634*** (0.0324)	0.2134
Central Transdanubia	0.0786* (0.0321)	0.2718
Central Hungary	−0.0893** (0.0322)	0.2298
Western Transdanubia	0.0883** (0.0323)	0.2744

Notes: 1. In the case of the Southern Great Plain, the estimated equations include a constant parameter, while for the other regions, the region-specific effects are considered, where the exponential of these effects represents the efficiency parameter (η_{region}).
2. The efficiency parameters come from the P.2 regional estimation results.
Source: NFSZ, own estimation results

In the row for the Southern Great Plain in the first column of *Table 2*, the constant value of the P.2 regression estimate is presented, while for the other regions, the effects of regional differences are shown. Based on the results, we can conclude that Northern Hungary, lagging behind other areas, is characterised by the lowest job acquisition efficiency, and the deviation is also negative for Central Hungary, Northern Great Plain, and Southern Transdanubia. This observation is important because these regions are the ones with the highest unemployment rates and stock data in Hungary. The result indicates that the job acquisition process is not efficient enough to enable a higher proportion of unemployed individuals in these areas to become employed compared to other parts of the country. Consequently, this limits the number of successful job matches and fails to reduce the employment lag in these regions.

The new hires provided by the matching function are determined not only by the stock data but also by the search efficiency (η_{region}), which indicates how much effort employees and employers put into the job search process. In other words, it shows how intensively a jobseeker searches for a job, and how urgently a company wants to fill the vacant, productive position (Pissarides, 2000). According to Bennett and Pinto (1994), the extent to which an employee strives to increase the efficiency of their job search is influenced by the information available about alternatives and the transaction costs of obtaining that information. A tighter labour market and higher available income can provide an incentive for jobseekers. Comparing the average wages published by the Hungarian Central Statistical Office (KSH)[2] across different regions, the regions with the lowest job search efficiency – Northern Great Plain, Northern Hungary, and Southern Transdanubia – are characterised by the lowest average wages. The tightness in these regions – for example, compared to Western Transdanubia characterised by higher search efficiency – is lower, which also provides less incentive to increase search intensity on the supply side (Pissarides, 2000).

Companies can also influence search efficiency. For employers, lower wages and labour productivity can provide an incentive to increase efficiency. In these regions, the lack of the latter factor could be the main indicator of lower efficiency. Lőcsei (2010), in his analysis of spatial imbalances after the crisis, points out that Hungary can be divided into two areas with different productivity levels since the regime change. The less favourable areas include the highlighted regions, namely Eastern and Southern Hungary, that is Northern Great Plain, Southern Great Plain, Northern Hungary, and Southern Transdanubia. The Central Transdanubian regions and the Western Transdanubian region show positive deviations, and hence higher efficiency, which can be explained by higher labour productivity, tighter labour markets, and as a result, the role of employers in increasing efficiency.

So far, we have assumed a regional breakdown. Since Hungarian labour is immobile, with low willingness to migrate or commute (Csizmady et al., 2020), a county-level breakdown is justified. *Table 3* shows the county-level differences.

2 KSH: 20.2.2.9. The gross average earnings of full-time employees, based on the location of the employer's registered seat, by county and region, cumulated quarterly.

Table 3
County-specific efficiencies

Region	County	County-specific impact	$\eta_{country}$
Southern Great Plain	Bács-Kiskun	−1.3857*** (0.0324)	0.2501
Southern Great Plain	Békés	−0.0303 (0.0374)	0.2427
Southern Great Plain	Csongrád-Csanád	0.0932* (0.0374)	0.2746
Southern Transdanubia	Baranya	−0.1279*** (0.0373)	0.2201
Southern Transdanubia	Somogy	−0.0307 (0.0374)	0.2426
Southern Transdanubia	Tolna	−0.0311 (0.0373)	0.2425
Northern Great Plain	Hajdú-Bihar	−0.0908* (0.0374)	0.2284
Northern Great Plain	Jász-Nagykun-Szolnok	−0.0295 (0.0373)	0.2429
Northern Great Plain	Szabolcs-Szatmár-Bereg	−0.1229** (0.0373)	0.2212
Northern Hungary	Borsod-Abaúj-Zemplén	−0.1577*** (0.0373)	0.2137
Northern Hungary	Heves	−0.0724 (0.0374)	0.2327
Northern Hungary	Nógrád	−0.2471*** (0.0374)	0.1954
Central Transdanubia	Fejér	0.0784* (0.0373)	0.2705
Central Transdanubia	Komárom-Esztergom	0.1087** (0.0377)	0.2789
Central Transdanubia	Veszprém	0.1195** (0.0373)	0.2819
Central Hungary	Budapest	−0.1194** (0.0375)	0.2220
Central Hungary	Pest	0.0038 (0.0377)	0.2511
Western Transdanubia	Győr-Moson-Sopron	0.3257*** (0.0383)	0.3465
Western Transdanubia	Vas	0.0323 (0.0376)	0.2584
Western Transdanubia	Zala	−0.0090 (0.0373)	0.2477

1. *Note:* In the case of Bács-Kiskun County, the constant parameter of the estimated equations is presented, while for the other counties, the county-specific effects, the exponential of which is the efficiency parameter ($\eta_{country}$)
2. *Note:* the efficiency parameters come from the results of the P.2 county-level estimates
Source: NFSZ, own estimation results

Lower search efficiency characterises the counties of the Northern Great Plain and Northern Hungary. Within the Northern Great Plain, Szabolcs-Szatmár-Bereg County, which is marked by the highest unemployment rates, exhibits the lowest job acquisition efficiency. In Northern Hungary, the lowest value is found in Nógrád, primarily due to the relatively few unfilled positions compared to the substantial number of unemployed individuals. In Central Hungary, lower search efficiency can be observed around Budapest. In Southern Transdanubia and Southern Great Plain, the counties with the largest unemployment stocks also have the lowest search efficiency. The counties of Central and Western Transdanubia generally exhibit higher efficiency, with the exception of Zala County, which is characterised by a positive shift on the supply side. Particularly high values are characteristic of Győr-Moson-Sopron, Veszprém, and Komárom-Esztergom counties.

The county-level results also corroborate that the productivity of the available workforce and the development of the concerned region enhance the employers' role in improving efficiency. In counties within a given region, higher efficiency tends to correlate with greater development and a more productive workforce, as compared to GDP per capita data provided by the Hungarian Central Statistical Office[3]. Based on the results, we conclude that companies, as demand-side actors facing labour shortages, can influence the efficiency parameter more significantly in a positive direction than jobseekers. In the counties of Western and Central Transdanubia, where a higher proportion of unfilled job positions are concentrated, job acquisition efficiency is higher. The positive impact of companies advertising job positions on the efficiency parameter is also demonstrated by the differences observed at the county level, as in Csongrád-Csanád County, which is characterised by the lowest share of jobseekers in the Southern Great Plain region and where the surplus of unfilled positions is typical. In areas characterised by higher labour supply, job acquisition efficiency is typically lower.

The fact that job acquisition processes are less efficient in the highlighted regions can also be explained by the imperfect flow of information (Pissarides, 2000). The lower labour market matches in these regions can also be attributed to further educational and industry-specific knowledge heterogeneity within the region, although this will not be addressed in this article.

In regions where the job acquisition process is less efficient, a smaller proportion of vacant positions become productive, and unemployed individuals are less likely to gain employment. Examining regional data, we estimated lower job search efficiency in those regions, particularly counties, that are characterised by the

3 KSH: 21.1.2.2. Gross domestic product per capita by county and region

highest levels of unemployment. A similar statement can be made for the county-level data. The implication of this result is that in areas characterised by higher levels of unemployment, a significant reduction in the unemployment rate and a decrease in regional and county-level differences is unlikely. Comparing regional and county-level search efficiencies, we demonstrated that although regional differences exist, it is also important to examine the differences between counties within the same region. Furthermore, the search efficiencies characteristic of the various regions do not exhibit differences in direction or scale that would contribute to reducing disparities between geographical areas.

5.2 Estimation of the matching function for local sub-markets

The matching function characterises the labour market of a country's economy. In *Subsection 5.1*, we focused on determining the matching function representing the entire Hungarian labour market. We defined the matching function characterising Hungarian job acquisition processes using log-linear estimation equations, assuming that the finding rate (f_t) responds equally sensitively to changes in labour market tightness $\left(\frac{V_t}{U_t}\right)$ and that the roles of supply and demand in determining the number of successful matches are the same across all regional units. In other words, the matching function's parameter, denoted as α is a constant representing the entire country, consistent in every region and county of Hungary. Differences between geographical units are reflected in the job acquisition efficiency. Bennett and Pinto (1994) demonstrate in their study that the matching function can serve not only as an analysis tool for a whole economy but also for local sub-markets. Therefore, in the following, we estimate separate matching functions for each region and county, where we allow the α_i parameters to vary between geographical units:

$$\log\left(f_{i,t}\right) = \text{konstans\_i} + \alpha_i * \log\left(\frac{V_{i,t}}{U_{i,t}}\right) \qquad \text{P.4}$$

The estimation results summarised in *Table 4* provide an overview of whether the role of demand and supply in determining successful labour market matches differs across regions.

Table 4
The results of estimating regional matching functions for the α parameter

Region	α_{Region}
Southern Great Plain	0.2947*** (0.0527)
Southern Transdanubia	0.3295*** (0.0690)
Northern Great Plain	0.3295*** (0.0690)
Northern Hungary	0.3862*** (0.0847)
Central Transdanubia	0.3256*** (0.0917)
Central Hungary	0.2028** (0.0589)
Western Transdanubia	0.2266* (0.0963)

Note: ***p<0.001, **<0.01, *<0.04, the standard errors are shown in parentheses
Source: NFSZ, own estimation results

The estimated values for each region confirm that, similarly to the aggregated matching function, the labour market tightness has a significantly positive impact on the evolution of the finding rate. Furthermore, the results show a greater role for the supply side in determining successful labour market matches. In the Central Hungary and Western Transdanubia regions, the elasticity parameter specific to the area is lower than the value characterising the aggregated labour market. Thus, in these two regions, the role of labour supply is even more significant in the job acquisition process. In the other regions, the estimated α_i is higher than the values obtained at the aggregated level. Based on the results, we conclude that in the Southern Great Plain, Southern Transdanubia, Northern Hungary, Northern Great Plain, and in the Central Transdanubia region, as distinct submarkets, the role of demand is more prominent in determining successful job acquisition processes. In these regions, the job vacancies advertised by employers primarily serve as local alternatives for jobseekers. Hence, in these local labour markets, an increase in the number of advertised vacancies increases the number of new, successful local hires to a greater extent, and companies can contribute more significantly to enhancing successful labour market matches by advertising more vacancies, compared to the aggregated economy or other regions. According to the alternative interpretation, an increase in labour market tightness most significantly enhances the finding rate in these areas.

There are also differences between counties belonging to the same region. In the case of county-level matching functions, the estimated parameters in the *Appendix 2* are often close to the aggregated value, which strengthens the dominant role of the supply side in those counties. The smallest parameters were estimated for Vas County in Western Transdanubia, Komárom-Esztergom County in Central Transdanubia, and Pest County in Central Hungary, where the obtained values remained well below value α characterising the aggregate labour market. The differences between the counties within the given region are evidenced by the fact that in Central Hungary, Budapest, as well as the other two counties in Western Transdanubia, had estimated values close to the average, while in Central Transdanubia, the values were above the average. In the counties where the characteristic α_i exceeded the previously estimated value, the demand side's greater role can be identified. Notable counties in this regard include Csongrád-Csanád, Szabolcs-Szatmár-Bereg, and Nógrád. In these areas, the elasticity parameters of both the supply and demand sides approach the 0.5 value, suggesting a more balanced role for supply and demand. The parameter for these counties is also considered an outlier in relation to other counties in the region.

5 SUMMARY

In this article, we focused on estimating the matching function characterising the job acquisition processes in Hungary's labour market at the aggregate, regional, and county levels. These estimations help in understanding the processes characteristic of the Hungarian labour market and provide potential explanations for which factors facilitate or hinder successful labour market matches in different regions and counties.

We saw that a matching function characterising an economy can be estimated based on aggregated and panel-type databases, using various variables, and the conclusions drawn from the estimated parameters are consistent across all cases. The conclusion of the estimation for the Hungarian aggregated labour market's matching function is that the increase in market tightness has a positive effect on the finding rate in Hungary's economy. That is, a tightening labour market increases the likelihood of jobseekers successfully finding employment. Furthermore, we observed that changes in both the number of job vacancies and the size of the unemployment pool influence successful labour market matches, with the latter having a greater effect. In other words, the supply side contributes more significantly to successful job acquisition than demand. That is, if there are many unfilled job vacancies in the country, this does not necessarily increase the number of successful labour market matches; unused capacity is also needed. We further observed that the efficiency of the job acquisition process varies across different areas of the country.

In regions and counties where there is a higher concentration of unemployed individuals, the efficiency of job acquisition tends to be lower. Based on the results, we can conclude that the regional and county-level disparities in the Hungarian labour market do not help to reduce the differences in development and living standards. One potential source of this issue is the convergence of unemployment rates, their reduction in any sub-market. However, in areas characterised by more unfilled job vacancies, greater development, and higher productivity, the estimates for search efficiency were higher. Search efficiency is also influenced by region-specific factors such as available wages, workforce productivity, level of regional development, or the tightness of the respective sub-market.

At a geographical level, it can be said that the Hungarian labour force is immobile. Thus, the unemployed represent a relevant labour supply only within their own regions, and even more so in their own counties. Based on this fact, these geographical areas can be characterised by their own job matching functions. Our regional and county-specific estimation results showed that the role of supply is more significant in determining job acquisition processes. However, the degree of this shift also differs between counties within a given region. There are regions and counties where the estimated parameters proved that demand plays a more significant role in local job acquisition processes, meaning that employers can contribute more to successful job acquisition by advertising new vacancies in local sub-markets.

In our research, we examined the Hungarian labour market exclusively from a geographical perspective, assuming that within a given region and county, the labour supply and demand are homogeneous, and that the matches are influenced only by stock data beyond the territorial-specific technology and efficiency. To enrich our understanding of the job acquisition processes in local labour markets, we must also account for further heterogeneity within the supply and demand-side actors of a given territorial unit. For instance, the available workforce in different regions and counties varies in terms of qualifications, experience, and industry-specific knowledge. Employers cannot apply a randomly chosen jobseeker to the advertised positions, which further limits the possibility of successful matches.

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APPENDICES

Appendix 1
The analysis of the impact of the COVID-19 pandemic

	A.1	P.1 (region)	P.1 (county)
α	0.2365*** 0.0292	0.2469*** 0.0334	0.2279*** 0.0188
	A.2	**P.2 (region)**	**P.2 (county)**
α	0.2054*** 0.0307	0.2263*** 0.0159	0.2285*** 0.0103
	A.3	**P.3 (region)**	**P.3 (county)**
α	0.2574*** 0.0234	0.3351*** 0.0269	0.2895*** 0.0170

Note: (***p<0.001, **<0.01, *<0.04), the standard errors are shown in parentheses
Source: Eurostat, NFSZ, own estimation results

Appendix 2
County-specific matching functions

Region	County	α_{county}
Southern Great Plain	Bács-Kiskun	0.2278*** (0.0555)
	Békés	0.2479*** (0.0546)
	Csongrád-Csanád	0.4093*** (0.0658)
Southern Transdanubia	Baranya	0.2470*** (0.0619)
	Somogy	0.2665* (0.1057)
	Tolna	0.2463** (0.0751)

Region	County	α_{County}
Northern Great Plain	Hajdú-Bihar	0.3612*** (0.0693)
	Jász-Nagykun-Szolnok	0.2635*** (0.0709)
	Szabolcs-Szatmár-Bereg	0.4166** (0.1426)
Northern Hungary	Borsod-Abaúj-Zemplén	0.2246** (0.0703)
	Heves	0.3599*** (0.0846)
	Nógrád	0.4162*** (0.0100)
Central Transdanubia	Fejér	0.3167*** (0.0709)
	Komárom-Esztergom	0.1494 (0.0855)
	Veszprém	0.3165*** (0.0675)
Central Hungary	Budapest	0.2343*** (0.0505)
	Pest	0.1460* (0.0626)
Western Transdanubia	Győr-Moson-Sopron	0.2291** (0.0677)
	Vas	0.0621 (0.0988)
	Zala	0.2934*** (0.0792)

Note: *** p < 0.001, ** < 0.01, * < 0.04), the standard errors are shown in parentheses
Source: NFSZ, own estimation results