What happens to natives when immigrants get jobs?

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Abstract

This paper studies the impact of immigrants at the workplace on native worker employment. We use a rich matched worker-firm dataset to precisely measure the workplace level hiring of immigrants and this allows us to study worker reallocations at a detailed level. Estimation of a single risk duration model for native worker job spells shows that job separation rates increase if more immigrants are hired, and these effects are particularly pronounced for immigrants from Eastern Europe and least developed countries. Adjustment costs for natives are likely if immigrants lead to unemployment and in a competing risks duration model we find that immigrants from least developed countries increase the unemployment risk for natives while immigrants from Eastern Europe increase the native job change probability. Distinguishing between different types of natives we also find that the results only apply for low skilled workers, whereas workers with further education are unaffected by immigrants at the workplace.

Keywords: Immigration, native job separations, duration model.

JEL Classification: F22, J61, C41

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1 Introduction

The recent enlargements of the European Union with a number of Eastern European countries have sparked concerns among workers in the old and relatively rich EU-countries that workers from the new and poorer EU-countries will move to the richer EU-countries and undermine their labour markets. But what do in fact happen to natives if firms hire immigrants? There have been several attempts to answer this question, and it can be approached in a number of different ways. In this paper we seek to answer the question by studying the firm level employment situation of natives, when firms hire immigrants. Do natives leave the firms and if so, where do they go? Do they become unemployed or do they get a job in another firm?

There are numerous studies in the literature on how immigrants affect wages and/or net employment of natives in local areas. Examples of such analyses are Borjas, Freeman and Katz (1997) and Card (2001) both using U.S. data, Dustmann, Fabbri and Preston (2005) using U.K. data, Pischke and Velling (1997) using German data, and Angrist and Kugler (2003) using EU data. There is substantial variation in the results from this type of analysis, but the general conclusion seems to be that immigration has small negative net employment and/or wage implications for natives, see e.g., Longhi, Nijkamp and Poot (2006). However, Borjas (2003) criticizes this "local area"-approach and suggests that the analysis instead should be based on national data for different skill-groups. Using this approach, Borjas (2003) finds that immigration has a more pronounced negative impact on the wages of natives.

In contrast, we argue that much can be learned by analysing the relationship between immigration and native employment at the most disaggregate level, i.e., the workplace. For example, to focus on the net employment implications of immigration into local areas or skill groups may understate the costs of immigration for the native workers because even reallocations that do not lead to a net decline in employment may be associated with adjustment costs, see, e.g., Klein et al. (2003). Therefore, in this paper we seek to obtain information about the gross adjustments taking place at the firm level when firms hire
immigrants. More specifically, we estimate the impact of immigrants at the workplace on the individual job separation probability, and to the best of our knowledge this is a novel approach in the analysis of employment effects of immigration.

We use a very detailed linked employer-employee data set for the Danish labour market for the period 1993-2004. This is a period with a large inflow of immigrants into Denmark – in our data the immigrant share among employed workers increased from 3.0 percent in 1993 to 5.2 percent in 2004, which constitutes one of the most pronounced relative increases in immigration among developed countries in recent years.

The literature on job turnover at the individual level suggests that it is important to control for socio-economic characteristics such as gender and education, see, e.g., Royalty (1998). Also it is well known that job separation rates decline with time on the job because of, e.g., firm specific human capital, see Farber (1999) for an overview. Thus it is important to control for duration dependence. We use a duration model that controls for unobserved heterogeneity, and of particular importance is the fact that the workplace immigration share may be endogenous if, for example, unstable workers tend to self-select into workplaces with many immigrants. We attempt to account for potential endogeneity bias by simultaneously estimating a selection equation for workplace immigrant shares.

We find that immigrants at the workplace have important effects on native employment. Immigrants and natives are substitutes in the sense that native job separation rates increase if more immigrants are hired, and these effects are particularly pronounced for immigrants from Eastern Europe and least developed countries. Adjustment costs for natives are particularly likely if the hiring of immigrants lead to unemployment, and in a competing risks duration model we find that immigrants from least developed countries increase the unemployment risk for natives while immigrants from Eastern Europe increase the native job change probability. Distinguishing between different types of natives, we also find that the results only apply for low skilled workers, whereas workers with further education are unaffected by immigrants at the workplace.

The rest of the paper is organized as follows In section 2, we present the hypotheses considered in the paper. Section 3 presents our data, and in section 4 we present
the econometric model. Section 5 contains the results of the paper. Finally, section 6 concludes.

2 Immigration and native worker employment

The aim of this paper is to study a number of questions about the relationship between immigrants at the workplace and native worker employment. The first question we consider is: Do employment of immigrants substitute or complement employment of natives? To answer this question, we assess whether hiring of immigrants increase or decrease the probability that natives stay in a firm. Natives and immigrants are substitutes if the separation probability rises, and vice versa if the probability falls. There may be several explanations behind any observed complementarity or substitutability. One possible explanation is the technology in the firms. Another is the goods markets conditions of the firms. If immigrants are mainly employed in expanding firms, this tends to create an observed complementarity between the employment of natives and immigrants. A third possible source is the labour market conditions of firms. If immigrants are mainly employed in firms where natives no longer "want" to work, we will tend to find that natives and immigrants are substitutes. We attempt to determine whether the two types of labour are substitutes or complements, but we will not be able to distinguish directly between the different reasons for observed substitutability or complementarity between the employment of natives and immigrants.

Second, does the hiring of immigrants lead to adjustment costs for natives? Layoffs reflect that employment of immigrants imply adjustment costs for native workers. This is not the case – at least not to the same extent – if the native worker voluntarily quits the job. In our data, we can observe if native workers leave a firm and the firm simultaneously hires immigrants. However, we cannot observe whether the native worker quits the job or she is fired. Instead, we observe the destination state for workers ending their job spells, i.e., the data allows us to distinguish between job-to-job and job-to-unemployment transitions. A particularly strong indication of adjustment costs is if native workers
become unemployed when firms hire immigrants.

Third, are native workers affected differently by immigrants at the workplace across skill groups? If immigrants predominantly are of a certain skill type then natives in that skill group are more likely to be substitutes to immigrants, while other natives perhaps are more likely to be complements. To study this question, we operate with three different groups of natives: workers with basic education, vocational education and further education. We are also in a position to distinguish between immigrants from different countries which obviously may also be of relevance.

3 Data and the Danish labour market

An important characteristic of the Danish labour market is that it is heavily unionised and although a process of decentralisation of wage formation has been ongoing since the late 1980’s the wage structure is still relatively compressed even for European standards. Compared to other continental European labour markets, the Danish labour market is often described as being very flexible as employment protection is relatively weak, while at the same time replacement rates of UI benefits are high. A third distinguishing characteristic of the Danish labour market is that large sums are spent on active labour market policies (ALMP) – see Nickell et al. (2005) for a recent cross-country comparison of labour market measures on, e.g., union density and coverage, employment protection, UI benefit replacement ratios and ALMP expenditure. Together these ingredients form what by some has been dubbed the ‘flexicurity’ model. The idea behind this model is that Danish firms relatively easy may adjust employment according to demand. As compensation for high job turnover, workers receive relatively generous UI benefits when unemployed, but incentives to search for jobs during unemployment are reinforced by a strict ‘activation’ regulation. This labour market model has led to turnover rates and an average tenure which are in line with those of the Anglo-Saxon countries. In 1995 the average tenure in the Danish labour market was the lowest in continental Europe with 7.9 years just exceeding the number for UK (7.8 years), cf. OECD (1997).
To investigate the causes behind job separations of employed workers in Denmark, a very rich data set, which is drawn from administrative registers, is employed. The data set covers the full Danish population for the years 1993-2004 but to save on estimation time, only a 10 percent random sample is used in the analysis. In each year, detailed information about the labor market states of all individuals along with information on socioeconomic characteristics is available. These socioeconomic variables are extracted from the integrated database for labor market research (IDA) and the income registers in Statistics Denmark. Of particular importance is the fact that a workplace identity is associated with each worker at the end of each year. A firm can have more than one workplace so if a worker changes between two workplaces within the same firm, this is counted as a job change in the present analysis. Job spells are then straightforwardly constructed from successive years at the same workplace.

Here we are interested in the duration of job spells and transitions into new jobs and unemployment, and for the present purposes, job spells are flow sampled such that only spells starting in 1994 and later are included in the analysis.\(^1\) The destination state for all spells that end before 2004 is known, and if job spells end with transitions into other states than a new job or unemployment (e.g. out of the labor force), or if spells are not completed by the end of 2004, they are treated as independently right censored observations. In the following, we restrict attention to job spells of natives in private sector workplaces with at least 10 employees. In addition, all students with (student) jobs have been excluded from the sample. Some descriptive statistics for the job spells in the sample are given in Table 1. It is seen that more than 60 percent of the spells end in a job-to-job change while 5 percent end in unemployment.

Immigration is measured at the workplace as the share of immigrants among workers at the workplace or as the change in the number of immigrants relative to the initial

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\(^1\)We also use covariates measuring changes between two years, so spells starting in 1993 are not included in the analysis.
number of workers. Since we have access to data on the full population, we can construct exact measures for these variables. Immigrants are defined as individuals born outside Denmark with non-Danish parents. If there is no information about the parents and the individual is born outside Denmark he/she is also classified as an immigrant.

It may be important to distinguish between different types of immigrants as some immigrants (refugees) may have social problems while others may have come to Denmark for job reasons. Employment related immigration may in particular be the case for immigrants from the old EU-countries and other Nordic countries. Therefore we operate with the following four different types of immigrants: 1) EU-15 countries, Norway and Iceland, 2) The 10 new EU countries as of May 1, 2004, 3) All remaining developed countries according to the UN definition, and 4) all remaining countries, i.e., countries from least developed regions according to the UN definition. Figure 1 shows that since 1994 – the beginning of our sample window – the share of immigrants in the population of employed workers in Denmark has increased markedly. The increase corresponds to a relative increase of almost 75 percent over the period 1994-2004. It is also evident that the immigrant type with the steepest increase is type 4, i.e., immigrants from least developed countries. Of course, this substantial increase in the stock of immigrants is very useful in identifying effects from immigration.

It should be mentioned that we also tried to measure immigration at the local labour market level, but these variables never had any significant effects on job separations in the analysis below so they are omitted. This finding is consistent with the numerous studies with limited or no local labour market impacts of immigration cited in the introduction.

Finally, Table 2 displays summary statistics for all individual and workplace control

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\[\text{See http://esa.un.org/unpp/definition.html}\\]

\[\text{The local labor markets are so-called commuting areas, which are defined such that the internal migration rate is 50 percent higher than the external migration rate. This definition results in 51 commuting areas.}\\]
variables included in the analysis. Self-explanatory dummies for age, gender, the presence of children, marriage, and education are included. Also three geographic dummies are included to distinguish between the capital Copenhagen, 5 large cities, and all other localities (small city). Information on years of labour market experience is also included. Roughly one third of the observations (one observation is a person-year) are from workplaces without immigrants, while two thirds have immigrant co-workers. It is seen that natives in workplaces with immigrants are more likely to be older, live in Copenhagen and have further education, whereas workers with vocational education are more likely to have no immigrant co-workers.

4 Econometric model

To investigate the impact of workplace immigration on job separations, this section sets up an empirical model for job duration and selection into workplaces with different immigrant variables. In studies of individual job separations, it is important to control for duration dependence since the job separation rate typically declines with time on the job due to the accumulation of match specific human capital, see, e.g., Farber (1999) for an overview. Therefore, we use a duration model, which accommodates for right censored job spells and allows for duration dependency in the transition process out of the current job. Further, to distinguish between transitions from employment to unemployment and a new job, a competing risks duration model is specified (Sueyoshi 1992).

Even if there is access to a comprehensive data set, there might still be some unobserved heterogeneity left, as no measures for, e.g., ability or motivation are available. We capture unobserved worker characteristics by specifying a mixed proportional hazard model for the labor market transitions:

\[ \theta_i(t|x_t, z_t, v_i) = \lambda_i(t) \exp(\beta_i'x_t + \gamma_i z_t + v_i), \] (1)
where \( i = e, u \) indicates the different destination states for the transition (i.e., employment and unemployment), \( \lambda_i(t) \) is the baseline hazard capturing the time dependence for transitions into destination \( i \), and \( \exp(x_i\beta_i + \gamma_i z_t + v_i) \) is the systematic part giving the proportional effects of workplace immigration variables, \( z_t \), other observed and time-varying characteristics, \( x_t \), and unobserved characteristics, \( v_i \). The vector of workplace immigration variables may both include the workplace immigration shares of different types of workers and changes in workplace immigration as described in the previous section. All job spells that end with a transition to another state than one of the two described above (e.g. out of the labor force) are treated as independently right censored observations.

The annual nature of the data imply that the duration variable \( T \) is grouped into \( K + 1 \) intervals \( \{[0, t_1), [t_1, t_2), \ldots, [t_K, \infty)\} \), which must be accounted for in the econometric specification. Thus, following Kiefer (1990), the interval specific survival rate is defined as

\[
\alpha_k = P(T \geq t_k \mid T \geq t_{k-1}, x_t, z_t, v)
\]

\[
= \exp \left[ - \sum_{i=e,u} \int_{t_{k-1}}^{t_k} \theta_i(t \mid x_k, z_k, v) \, dt \right]
\]

\[
= \exp \left[ - \sum_{i=e,u} \exp(\beta_i' x_k + \gamma_i z_k + v_i) \Lambda_{i,k} \right]
\]

\[
= \prod_{i=e,u} \alpha_{i,k}
\]

where \( \Lambda_{i,k} = \int_{t_{k-1}}^{t_k} \lambda_i(t) \, dt \) and \( \alpha_{i,k} = \exp \left[ - \exp(\beta_i' x_k + \gamma_i z_k + v_i) \Lambda_{i,k} \right] \).

To find the contribution to the likelihood function from a job spell, it is noted that the probability that a spell ends in interval \( k \) is given by the conditional probability of failure in that interval times the probability that the spell survives until interval \( k \), or \((1 - \alpha_k) \prod_{j=1}^{k-1} \alpha_j\). Right censored spells contribute to the likelihood with the survivor function, \( \prod_{j=1}^{K} \alpha_j \), and so the contribution to the likelihood function from a job spell can
be written as:

\[ L_c(t|x_t, z_t, v_e, v_u) = (1 - \alpha_{e,k})^{d_e} (1 - \alpha_{u,k})^{d_u} \alpha_{k}^{1-d_e-d_u} \prod_{j=1}^{k-1} \alpha_j, \]

where \( d_e \) and \( d_u \) are destination state indicators. If the job spell is right censored then \( d_e = d_u = 0 \). Instead of imposing a functional form on the baseline hazard, we allow for a flexible specification by simply estimating the interval specific baseline parameters \( \Lambda_{i,k} \).

To account for possible endogeneity of the workplace immigrant variables, \( z_t \), we simultaneously model the workplace immigrant variable and the transition rate out of the job spell. The workplace immigrant share in year \( t \), \( m_t \), depends on explanatory variables, \( x_t \) and \( y_t \), and an unobserved component, \( v_m \), and since this variable takes the value zero in many workplaces, this equation must be specified as a tobit model\(^4\)

\[ m_t^* = \beta_m x_t + \gamma_m y_t + \varepsilon_t, \]

\[ m_t = 0 \text{ if } m_t^* \leq 0, \]

\[ m_t = m_t^* \text{ if } m_t^* > 0, \]

where \( x_t \) are the same explanatory variables that are included in the duration model, and \( y_t \) are variables that are included in the tobit model, but not in the duration model. For a given individual, the error term is composed of two components, an independently normally distributed idiosyncratic component and a random individual-specific effect,

\[ \varepsilon_t = u_t + v_m. \]

The likelihood contribution from a sequence of immigrant shares over a job spell is

\(^4\)When the immigration variable is measured as a change between two years it takes values between -1 and 1, and here the selection equations is estimated by OLS with an individual random effect.
thus

\[ \mathcal{L}_m(m_1, \ldots, m_t | x_1, \ldots, x_t, y_1, \ldots, y_t, v_m) = \prod_{t=1}^{t} \frac{1}{\sigma_u} \varphi \left( \frac{m_t - \beta_m x_t - \gamma_m y_t - v_m}{\sigma_u} \right)^{d_m} \times \left( 1 - \Phi \left( \frac{\beta_m x_t + \gamma_m y_t + v_m}{\sigma_u} \right) \right)^{1-d_m}, \quad (6) \]

where \(\sigma_u\) is the standard deviation of the idiosyncratic component, \(\varphi(\cdot)\) is the standard normal probability density function, \(\Phi(\cdot)\) is the standard normal cumulative distribution function, and \(d_m\) is an indicator variable taking the value 1 if \(m_t > 0\) and zero otherwise.

We assume that all sources of correlation between the two processes can be represented by the individual-specific heterogeneity terms. These terms are assumed to be time-invariant and hence constant across repeated spells for the same individual.

The unobserved heterogeneity is specified by the stochastic variables \(v_e, v_u, v_m\), so the complete contribution to the likelihood function for each individual is

\[ \mathcal{L} = \int_{v_e} \int_{v_u} \int_{v_m} \mathcal{L}_e(t | x_r, z_t, v_e, v_u) \cdot \mathcal{L}_m(m_1, \ldots, m_t | x_1, \ldots, x_t, y_1, \ldots, y_t, v_m) dF(v_e, v_u, v_m), \quad (7) \]

where \(F\) is the joint CDF for the unobserved heterogeneity. We use a flexible and widely applied specification of the distribution of the unobservables; it is assumed that \(v_e, v_u,\) and \(v_m\) each can take two values, where one of the support points in each destination specific hazard is normalized to zero (i.e., \(v_e = 0\), and \(v_u = 0\)), because the baseline hazard acts as a constant term in the hazard rates. Thus, there are 8 possible combinations of this unobserved heterogeneity distribution, each with an associated probability. For more details on this class of mixture distributions in duration models, see, e.g., van den Berg (2001).
4.1 Identification

To identify the causal relation between the workplace immigration variable and the outcomes of interest, two identification strategies may be pursued. The first identification strategy relies on multiple occurrences of job spells and workplace immigration for the individuals. This implies that we observe some individuals in several job spells with different values of the immigration variable. Moreover, during a given job spell, some persons work in workplaces with changing immigrant shares which further adds to the identification of the model parameters. This identification approach has recently been used in applied duration models by, e.g., Munch et al. (2006) and Munch et al. (2007).

The identification strategy requires that we – for at least a subset of individuals – observe job spells with different values of the workplace immigration variable. The intuition behind the identification strategy is provided by the following simple example (building on Panis (2004)): Suppose we only observe one worker in two job spells where the workplace immigration variable changes value. In this sample, there is no heterogeneity and no correlation across equations and so the equations are independent. The effect of the workplace immigration variable on exit rates from employment is identified because of repeated observations on job spells and variation in the immigration variable. More generally, conditional on heterogeneity, the equations are independent, and identification rests on repeated outcomes with variation in the workplace immigration variable. In our sample, almost 18 percent of the workers are observed with multiple job spells (see Table 1), which is comparable to other studies using the same identification strategy (Munch et al. 2006 and 2007).

The second identification strategy uses exclusion restrictions, that is, the existence of a set of variables that affect the workplace immigrant share but have no direct impact on job separations is postulated. While we use the first identification strategy as our baseline scenario, we check robustness of the results by estimating the model using both identification strategies. In the literature on immigration and local labour markets this strategy has been employed by, e.g., Card (2001) and Cortes (2006).
5 Results

This section presents results of estimating different versions of the duration model outlined above. We start out with a simplified model, where we do not distinguish between different causes behind job separations, \(i.e.,\) a single risk model. Next we distinguish between job-to-job and job-to-unemployment transitions in a competing risks model, and this is followed by a model with differential impacts on natives with different educational attainments. Finally, we consider robustness of our results by studying the importance of controlling for possible endogeneity of the immigration variables.

We measure immigrants at the workplace in different ways as mentioned in the data section. One aim is to find the effect of hiring more immigrants on native job separation rates, and this calls for variables that capture the change in immigrants at the workplace. It may be important to distinguish between a changing number of immigrants in the current period and the previous period, as for example any displacement effects are likely to be manifested with a time lag. Thus, we both include the change in the number of immigrants at the workplace in the current period measured relative to the initial number of workers at the workplace and the change in the number of immigrants in the previous period measured relative to the initial number of workers at the workplace.\(^5\) In addition, we also include the share of immigrants in the current period measured as the number of immigrants relative to the total workplace labour force. This variable is likely to capture more structural or long term effects of immigration and it may be thought of as measuring accumulated changes in immigrants at the workplace. Finally, it should be recalled that we distinguish between four different types of immigrants, so this leaves us with 12 different immigration variables.

Table 3 presents estimation results from different specifications of the single risk duration model. Before we proceed to the impacts of immigration variables, we note that all model specifications include as control variables the variables listed in Table 2. The effects of these variables are not shown in the table, but there are no surprising results. For

\(^5\)Job separations happen in the current period, \(i.e.,\) between time \(t\) and \(t + 1\).
example, young workers, male workers and workers at relatively large workplaces are least likely to separate from their jobs. In the first column, only the four immigration variables for the relative change in immigrants in the previous period are included. All four coefficients are positive, but there is a relatively strong positive impact on the job separation hazard rate from hiring type 2 immigrants (that is, workers from the Eastern European EU countries). Thus there is evidence that immigrants, and especially immigrants from Eastern Europe, substitute the employment of native workers. The quantitative importance of the estimated coefficient of 1.0654 to type 2 immigrants can be assessed by calculating the relative (percentage) change in the separation rate in response to a 1 percentage point increase in the immigration measure as \( \exp(1.0654 \times 0.01) - 1 = 0.0107 \). That is, the separation rate rises 1.07 percent if the immigration variable rises one percentage point.

The second column shows immigration effects where only the four change variables in the current period are included. All four variables have significantly negative effects with type 1 (immigrants from EU-15) and type 3 (immigrants from other developed countries) immigrants having the strongest negative impacts. This probably reflects that if firms hire immigrants they tend to do so when they grow – firms hire immigrants as well as natives – and so the job separation rate for natives is low.

The third column includes the four share variables and here all four variables are positive, again with the impact of type 2 immigrants being the strongest. These results are consistent with the view that previous period hiring of immigrants (column 1) and the share variables (column 3) tend to capture the same aspect of immigration which we are looking for, namely the extent to which immigrants are substitutes or complements to native labour. The results are unequivocal in suggesting that immigrants are substitutes to native workers although to a varying extent across the four types of immigrants.

In the final column, we enter all 12 immigration variables, and it is seen that it is now only type 2 immigrants that displace native workers in the short run, while it is only type
4 immigrants (immigrants from least developed countries) that have long run positive impacts on native job separation rates as reflected in the positive coefficient to the type 4 share variable.

Having established that immigrants appear to substitute native workers, we turn to the next question we set out to answer in section 2 – does the hiring of immigrants lead to adjustment costs for natives? We analyse this question by distinguishing between transitions into new jobs or unemployment. Clearly, if immigration leads to unemployment, there may in particular be important costs associated with immigration. Job-to-job changes on the other hand are more likely to reflect voluntary quits, but it should be noted that many job-to-job changes are observed following layoffs. According to Browning et al. (2006) more than half of the displaced workers in the Danish labour market have no unemployment at all in the displacement year. This is possible in flexible labour markets as the Danish, and it is therefore also likely that immigration affects the job change probability. If the worker takes a wage cut after a job change such transitions may also involve adjustment costs, but this issue will not be explored further in this paper.

Table 5 displays results of estimating the competing risks model, and it is seen that the positive impact of a change in type 2 immigrants in the previous period found in the single risk model may entirely be ascribed to a higher job-to-job transition rate, while there is no impact on the unemployment hazard. Thus, immigrating workers from Eastern Europe are substitutes for natives but these immigrants tend to be hired when natives voluntarily leave their jobs or involuntarily are pushed into new jobs. On the other hand the, positive impact of the type 4 immigrant share variable is seen to primarily lead to transitions into unemployment although there is also a positive effect on the job-to-job hazard rate. To sum up, immigrants from Eastern Europe have a positive impact on the native job separation rate but it is not clear that it is associated with adjustment costs for natives, while immigrants from least developed countries tend to increase the unemployment risk of natives.

Insert Table 4 about here
The third question we look at is whether different groups of natives are affected differently by immigrants at the workplace. To study this issue, we interact the immigration variables with three education indicators for the native workers: workers with basic education, vocational education and further education. Several interesting results are found. First, it is seen from Table 5 that type 1 immigrants (immigrants from EU-15 countries) have a positive effect on the job change hazard but only for workers with vocational or further education. This probably reflects the fact that type 1 immigrants are relatively well educated and therefore are more likely to act as substitutes for native workers. Second, the variable measuring changes in type 2 immigrants in the previous period does not affect workers with further education, while less educated workers see their job-to-job change hazard increase. This suggests that Eastern Europeans are only substitutes for natives with basic or vocational education. Third, much the same picture emerges with respect to the share of type 4 immigrants; further educated workers are not affected while especially workers with just basic schooling have higher job-to-job and job-to-unemployment transition rates if they have co-workers from least developed countries.

6 Conclusion

This paper has analysed the impact of immigration on native worker employment. As a novel feature, our data allows us to look at this relationship at a very detailed level – immigrants at the workplace and employment outcomes for the individual native worker. In contrast to much of the existing literature that typically study the issue at the local labour market level, we find clear evidence of employment effects on natives.

Our data set is linked employer-employee data set for the Danish labour market for the period 1993-2004. This is a period with a very large inflow of immigrants into Denmark as the immigrant share among employed workers increased from 3.0 percent in 1993 to 5.2 percent in 2004. This increase is clearly very helpful in identifying immigration effects.
Estimation of a duration model for native worker job spells shows that natives and immigrants tend to be substitutes in the sense that native job separation rates increase if more immigrants are hired. These effects are particularly pronounced for immigrants from Eastern Europe and least developed countries. Adjustment costs for natives are likely if immigrants lead to unemployment, and in a competing risks duration model we find that immigrants from least developed countries increase the unemployment risk for natives while immigrants from Eastern Europe increase the native job change probability. Distinguishing between different types of natives, we also find that the results only apply for low skilled workers, whereas workers with further education are unaffected by immigrants at the workplace.

References


### A Appendix: Tables

#### Table 1. Job spell statistics

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<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Number of persons</td>
<td>103,517</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of spells</td>
<td>177,947</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Persons with more than one spell (share)</td>
<td>0.1798</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean duration of spells (years)</td>
<td>3.0887</td>
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<td></td>
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<tr>
<td>Proportion of spells:</td>
<td></td>
<td></td>
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<tr>
<td>- right-censored spells</td>
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<td>- end with job change</td>
<td>0.6047</td>
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<td></td>
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<tr>
<td>- end with unemployment</td>
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<tr>
<td>- end in other destinations</td>
<td>0.0471</td>
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#### Table 2. Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>All observations</th>
<th>Workplaces without immigrants</th>
<th>Workplaces with immigrants</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Stdv.</td>
<td>Mean</td>
</tr>
<tr>
<td>Age 18-24</td>
<td>0.1203</td>
<td>0.3253</td>
<td>0.1619</td>
</tr>
<tr>
<td>Age 25-29</td>
<td>0.1619</td>
<td>0.3684</td>
<td>0.1718</td>
</tr>
<tr>
<td>Age 30-39</td>
<td>0.3465</td>
<td>0.4758</td>
<td>0.3158</td>
</tr>
<tr>
<td>Age 40-49</td>
<td>0.2192</td>
<td>0.4137</td>
<td>0.2066</td>
</tr>
<tr>
<td>Age 50+</td>
<td>0.1473</td>
<td>0.3544</td>
<td>0.1397</td>
</tr>
<tr>
<td>Female</td>
<td>0.3284</td>
<td>0.4696</td>
<td>0.3085</td>
</tr>
<tr>
<td>Children 0-17 years</td>
<td>0.2537</td>
<td>0.4352</td>
<td>0.2489</td>
</tr>
<tr>
<td>Married</td>
<td>0.4894</td>
<td>0.4999</td>
<td>0.4753</td>
</tr>
<tr>
<td>Copenhagen</td>
<td>0.2253</td>
<td>0.4178</td>
<td>0.1435</td>
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<tr>
<td>Large city</td>
<td>0.1330</td>
<td>0.3396</td>
<td>0.1412</td>
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<tr>
<td>Small city</td>
<td>0.6416</td>
<td>0.4795</td>
<td>0.7153</td>
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<tr>
<td>Experience (years)</td>
<td>0.1474</td>
<td>0.0924</td>
<td>0.1440</td>
</tr>
<tr>
<td>Basic education</td>
<td>0.3454</td>
<td>0.4755</td>
<td>0.3397</td>
</tr>
<tr>
<td>Vocational education</td>
<td>0.4754</td>
<td>0.4994</td>
<td>0.5389</td>
</tr>
<tr>
<td>Further education</td>
<td>0.1793</td>
<td>0.3836</td>
<td>0.1214</td>
</tr>
<tr>
<td>Workplace characteristics:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10-50 employees</td>
<td>0.4023</td>
<td>0.4904</td>
<td>0.7962</td>
</tr>
<tr>
<td>51-200 employees</td>
<td>0.3036</td>
<td>0.4598</td>
<td>0.1937</td>
</tr>
<tr>
<td>&gt; 200 employees</td>
<td>0.2941</td>
<td>0.4556</td>
<td>0.0101</td>
</tr>
<tr>
<td>Share with basic education</td>
<td>0.3522</td>
<td>0.1778</td>
<td>0.3378</td>
</tr>
<tr>
<td>Share with further education</td>
<td>0.1760</td>
<td>0.1989</td>
<td>0.1190</td>
</tr>
<tr>
<td>Share female</td>
<td>0.3283</td>
<td>0.2343</td>
<td>0.3146</td>
</tr>
<tr>
<td>Share age above 40</td>
<td>0.4185</td>
<td>0.1758</td>
<td>0.4006</td>
</tr>
<tr>
<td>Imm. share type 1</td>
<td>0.0138</td>
<td>0.0251</td>
<td>0.0104</td>
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<tr>
<td>Imm. share type 2</td>
<td>0.0021</td>
<td>0.0083</td>
<td>0.0032</td>
</tr>
<tr>
<td>Imm. share type 3</td>
<td>0.0076</td>
<td>0.0236</td>
<td>0.0116</td>
</tr>
<tr>
<td>Imm. share type 4</td>
<td>0.0162</td>
<td>0.0444</td>
<td>0.0247</td>
</tr>
<tr>
<td>Person-years</td>
<td>466,906</td>
<td>160,414</td>
<td>306,492</td>
</tr>
</tbody>
</table>

20
Table 3. Estimation results: Single risk model

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ_{t-1,t} imm. share type 1</td>
<td>0.0191 0.0181</td>
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<td></td>
<td>0.0233 0.0190</td>
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<tr>
<td>Δ_{t-1,t} imm. share type 2</td>
<td></td>
<td>1.0654 0.1271</td>
<td></td>
<td>1.2632 0.1118</td>
</tr>
<tr>
<td>Δ_{t-1,t} imm. share type 3</td>
<td></td>
<td>0.0307 0.0430</td>
<td></td>
<td>0.0595 0.0412</td>
</tr>
<tr>
<td>Δ_{t-1,t} imm. share type 4</td>
<td></td>
<td>0.0668 0.0234</td>
<td></td>
<td>-0.0083 0.0224</td>
</tr>
<tr>
<td>Δ_{t,t+1} imm. share type 1</td>
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<td>-2.7880 0.0967</td>
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<td>-2.5444 0.1003</td>
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<td>-1.2509 0.3034</td>
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<tr>
<td>Δ_{t,t+1} imm. share type 3</td>
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<td>-3.0328 0.1328</td>
<td></td>
<td>-2.3091 0.1371</td>
</tr>
<tr>
<td>Δ_{t,t+1} imm. share type 4</td>
<td></td>
<td>-1.1582 0.0601</td>
<td></td>
<td>-1.3892 0.0596</td>
</tr>
<tr>
<td>Initial imm. share type 1</td>
<td></td>
<td></td>
<td>0.2370 0.0992</td>
<td>-0.0567 0.1015</td>
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<tr>
<td>Initial imm. share type 2</td>
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<tr>
<td>Initial imm. share type 3</td>
<td></td>
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<td>0.4355 0.1071</td>
<td>0.0787 0.1138</td>
</tr>
<tr>
<td>Initial imm. share type 4</td>
<td></td>
<td></td>
<td>0.5297 0.0554</td>
<td>0.6554 0.0538</td>
</tr>
</tbody>
</table>

Note: Bold numbers indicate a significant parameter estimate (5% level). All models have been estimated with the individual control variables listed in Table 2. Unobserved heterogeneity is controlled for using a two-point discrete distribution. Parameter estimates of individual covariates, the unobservables distribution and duration dependence are available from the authors upon request.
<table>
<thead>
<tr>
<th></th>
<th>Job change hazard</th>
<th>Unemployment hazard</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>Std. err.</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 1</td>
<td>0.0179</td>
<td>0.0207</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 2</td>
<td><strong>1.0730</strong></td>
<td>0.1392</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 3</td>
<td><strong>0.1143</strong></td>
<td>0.0406</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 4</td>
<td>0.0308</td>
<td>0.0204</td>
</tr>
<tr>
<td>$\Delta_{t,t+1}$ imm. share type 1</td>
<td><strong>-2.0782</strong></td>
<td>0.1301</td>
</tr>
<tr>
<td>$\Delta_{t,t+1}$ imm. share type 2</td>
<td>-0.2921</td>
<td>0.3723</td>
</tr>
<tr>
<td>$\Delta_{t,t+1}$ imm. share type 3</td>
<td><strong>-1.8641</strong></td>
<td>0.1533</td>
</tr>
<tr>
<td>$\Delta_{t,t+1}$ imm. share type 4</td>
<td><strong>-2.0963</strong></td>
<td>0.0701</td>
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<tr>
<td>Initial imm. share type 1</td>
<td>0.0532</td>
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<tr>
<td>Initial imm. share type 2</td>
<td>-0.0216</td>
<td>0.3658</td>
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<tr>
<td>Initial imm. share type 3</td>
<td><strong>-0.6085</strong></td>
<td>0.1444</td>
</tr>
<tr>
<td>Initial imm. share type 4</td>
<td><strong>0.2681</strong></td>
<td>0.0665</td>
</tr>
</tbody>
</table>

Note: Bold numbers indicate a significant parameter estimate (5% level).
All models have been estimated with the individual control variables listed in Table 2.
Unobserved heterogeneity is controlled for using a four-point discrete distribution.
Parameter estimates of individual covariates, the unobservables distribution and duration dependence are available from the authors upon request.
Table 5. Estimation results: Interaction effects

<table>
<thead>
<tr>
<th></th>
<th>Job change hazard Coeff.</th>
<th>Std. err.</th>
<th>Unemployment hazard Coeff.</th>
<th>Std. err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 1 $\times$ basic edu.</td>
<td>-0.0508</td>
<td>0.0276</td>
<td>-0.0929</td>
<td>0.0918</td>
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<tr>
<td>$\Delta_{t-1,t}$ imm. share type 1 $\times$ vocational edu.</td>
<td>0.1751</td>
<td>0.0332</td>
<td>0.0560</td>
<td>0.2368</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 1 $\times$ further edu.</td>
<td>0.1531</td>
<td>0.0519</td>
<td>0.0391</td>
<td>0.3332</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 2 $\times$ basic edu.</td>
<td>0.9132</td>
<td>0.2508</td>
<td>0.9133</td>
<td>0.7569</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 2 $\times$ vocational edu.</td>
<td>1.0946</td>
<td>0.2445</td>
<td>1.0013</td>
<td>0.8549</td>
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<tr>
<td>$\Delta_{t-1,t}$ imm. share type 2 $\times$ further edu.</td>
<td>0.1039</td>
<td>0.2461</td>
<td>0.0422</td>
<td>2.3866</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 3 $\times$ basic edu.</td>
<td>0.0156</td>
<td>0.0769</td>
<td>-0.0645</td>
<td>0.2999</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 3 $\times$ further edu.</td>
<td>0.0351</td>
<td>0.0743</td>
<td>0.0350</td>
<td>0.3848</td>
</tr>
<tr>
<td>$\Delta_{t-1,t}$ imm. share type 4 $\times$ basic edu.</td>
<td>0.0704</td>
<td>0.0326</td>
<td>0.0689</td>
<td>0.1197</td>
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<tr>
<td>$\Delta_{t-1,t}$ imm. share type 4 $\times$ vocational edu.</td>
<td>-0.0396</td>
<td>0.0490</td>
<td>-0.0909</td>
<td>0.1847</td>
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<tr>
<td>$\Delta_{t-1,t}$ imm. share type 4 $\times$ further edu.</td>
<td>-0.0310</td>
<td>0.1032</td>
<td>-0.0736</td>
<td>0.5355</td>
</tr>
</tbody>
</table>

Note: Bold numbers indicate a significant parameter estimate (5% level).

All models have been estimated with the individual control variables listed in Table 2.

Unobserved heterogeneity is controlled for using a four-point discrete distribution.

Parameter estimates of individual covariates, the unobservables distribution and duration dependence are available from the authors upon request.
Figure 1: Share of immigrants among employed workers

- Immigrants from EU-15
- Immigrants from the new EU countries
- Immigrants from other developed regions
- Immigrants from least developed regions