Refugee immigrants, occupational sorting and wage gaps

Authors: Christopher F. Baum, Hans Lööf, Andreas Stephan

Boston College Working Papers in Economics, 2018

Originally posted on: http://ideas.repec.org/p/boc/bocoec/963.html

Refugee immigrants, occupational sorting and wage gaps

Christopher F Baum (Boston College and DIW Berlin)
Hans Lööf* (Royal Institute of Technology, Stockholm)
Andreas Stephan (Jönköping University and DIW Berlin)

October 11, 2018

Abstract

This paper analyzes wage income differences between native born workers and refugee immigrants in Sweden within occupations delineated in accordance with the augmented canonical model of occupational assignment. The identification strategy is based on a control group of matched native born persons with similar characteristics as the refugees and by using panel data methods capturing unobserved heterogeneity. The econometric results from a Swedish employer-employee panel data set document a narrowed wage gap over time, showing that the remaining difference can be explained to a large extent by the sorting into different types of occupations. Based on a Blinder–Oaxaca decomposition, we find a persistent wage gap in cognitive non-routine occupations but also, surprisingly, task categories where refugees have higher earning than natives.

Keywords: refugee immigration, income gap, employer-employee data, Blinder–Oaxaca decomposition

JEL: C23, F22, J24, J6, O15

*Corresponding author: hans.loof@indek.kth.se

1 Introduction

In the end of 2017, there were more than 25 million refugees fleeing armed conflict or persecution worldwide (United Nations, 2016). Economic integration of refugees creates challenges for receiving countries. Refugees and other humanitarian immigrants (people with protection status) differ in several aspects from labor force migrants. Forced immigrants are expected to face greater difficulties of integrating into the new environment given their background and the language and cultural barriers they might encounter in the country where they arrive. Furthermore, they might be insecure over the long-term perspective of staying in their new home country and might be therefore less willing to invest in their assimilation. But conditional on permission of grant to stay, refugees might have an incentive to more rapidly integrate in the new home country compared to labor immigrants, resulting in a narrowed wage gap (Chin and Cortes, 2015).

An empirical regularity established in the literature is that refugee immigrants as a category in the labor market tend to be to be overrepresented in low paid jobs (Colic-Peisker and Tilbury, 2006), earn lower wages than observationally equivalent natives (Dustmann, Glitz and Vogel, 2010; Dustmann, Frattini and Preston, 2012; Llull, 2017), and that these differences tend to abate over time (Connor, 2010). There is also evidence of discrimination in the labor market where natives often are preferred in better-paying occupations (Grand and Szulkin, 2002). What distinguishes refugees from other immigrants in these respects is that they usually have a worse starting point, but show better development in the longer term (Chin and Cortes, 2015). However, evidence on the relative wages of refugee-immigrants is limited, mainly due to the lack of representative data for empirical analysis.

The purpose of our paper is to shed more light on refugees' wage performance by analyzing the impact of occupational sorting on the observed wage gap between refugee[1] and native workers. We adopt the occupational classification scheme of the skill biased technical change literature based on Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011*a*) to compare wages for refugees and matched native workers. This literature highlights the increasing wage gap between non-routine and routine tasks, and in particular an increasing gap between cognitive and manual work task as a consequence of technical change and increased skill intensity. Occupational sorting, in combination with low occupational mobility, might have significant economic consequences for the labor market integration of refugees. Yamaguchi (2012) shows in a model of occupational sorting based on cognitive and manual skill endowments that productivity differences of workers increase with task complexity as skills are more relevant in occupations involving complex tasks.

To identify the causal wage earnings differentials, we employ a matching approach where a control group of native-born individuals from the full population is formed having the same characteristics as the refugee immigrants. Those characteristics include age, gender, marital status, number of children, education and place of living. In order to being able to test whether cultural distances and also length of stay in Sweden might matter for the observed wage gap of refugees, we identify three population groups of refugees: pre-1990 refugees who arrived between 1980 and 1989 in Sweden, European refugees who arrived 1990–1996, and non-European refugees who also arrived during 1990–1996. Nearly nine out of ten refugees arriving before 1990 were non-Europeans, and the majority of the refugees arriving in the 1990s came from the former Yugoslavia (Europe).

In a first step, we study occupational sorting by using a multinomial logit model that describes the likelihood that a person's occupation is associated with one of four occupational task categories: (1) cognitive non-routine, (2) cognitive

[1] A refugee in our study is an asylum seeker whose request for refugee status, according to the framework for the international regime of refugee protection, has been approved and therefore received permanent permission to stay in Sweden.

routine, (3) manual non-routine, (4) manual routine. In addition to a person's characteristics and those of her workplace, we include indicator variables indicating the assignment to a specific fixed cohort (population group), which is either the control group of matched natives or refugee immigrants from one of the three groups described above.

The empirical results show that, ceteris paribus, refugee immigrants are significantly less likely to work in the better paying cognitive non-routine task categories, but significantly more likely to work in one of the two manual task groups. While Groes, Kircher and Manovskii (2015) find that job mobility in general is higher both at the top and bottom of the distribution of wage earnings, we provide evidence that mobility across occupational task categories is low, implying that the majority of workers typically remain in their category. In the context of refugees, these findings imply that an early sorting into low skilled manual occupations after arriving in the host country hampers a future transition to better paying occupations. It also shows evidence of discrimination against refugees in that given similar personal characteristics, natives are more likely to be employed in comparison to refugees in certain occupations or sectors.

In a second step of the analysis, we estimate a wage equation by using the correlated random effects panel approach (Mundlak, 1978; Wooldridge, 2010). This approach allows us to control for unobserved heterogeneity at the individual level while including the effects of time-invariant regressors such as group membership. Based on the wage earnings equation, we apply the Blinder–Oaxaca technique to decompose observed differences in wage earnings into explained and unexplained components. Even 15 to 20 years after arrival in Sweden, we find that accumulated work experience is the decisive explanatory factor for the observed wage differential. There is on average a four year difference in work experience between refugees and the control group of matched natives. However, a sizable unexplained gap remains for cognitive non-routine occupations.

This points out that either omitted variables (e.g., social or psychological factors) are responsible for the observed wage gap, or as suggested in previous literature, there is persistent wage discrimination against refugees. Surprisingly, while the wage earnings of refugees are lower in occupations with cognitive non-routine tasks, it is similar or even significantly higher than the wage of matched natives in occupations with manual non-routine tasks. This holds in particular for non-European refugees and those arriving before 1990. In these occupations, refugees perform better than predicted by their personal characteristics.

In this paper, we contribute to the literature on the productivity of refugee workers as captured by wage income by exploiting high quality data, applying recent findings from the skill biased technical change literature, and combining the occupational sorting approach and a matching technique. We use very detailed and population-level Swedish administrative register data that contains information on occupations and work history over 20 years in combination with administrative firm level data as an employer-employee panel. This enables us to study both the impact of individual workers' characteristics and workplace-related circumstances on workers' wage earnings. To study occupational sorting, we delineate occupational categories into two dimensions: routine vs. non-routine work and manual vs cognitive tasks. The information on a person's occupation allows us to study the context between skill intensity of occupational tasks and wage earnings. Whereas most previous studies have compared refugee outcomes directly with those of natives, we employ a matching approach that facilitates identification of the causal impact of refugee background on the workers' observed wage earnings considering all other important characteristics including their educational background. Individual wages for 27 fixed cohorts are analyzed in a panel data setting.

Our main findings imply that the wage earnings gap between refugee immigrants and native-born workers is mainly caused by occupational sorting into cognitive and manual tasks. Within occupations, it can be largely explained by differences in work experience. However, an unexplained part of the wage gap remains which might be caused by wage discrimination of refugees in the labor market.

Our findings have important policy implications. First, as occupational sorting is accompanied by increasing wage differentials for high-skilled and low-skilled workers while occupational mobility is limited, increasing wage inequality in the long run is implied. Second, as many companies are raising concerns about the difficulties of recruiting competent and qualified personnel, refugee workers might have unexploited skill potentials that could be used to reduce the shortage of skilled labor in many developed economies.

The remainder of this paper is organized as follows. Section 2 provides an overview of the data, reports summary statistics and introduces our empirical approach. Section 3 presents the econometric results and Section 4 concludes.

2 Empirical Approach

The data for the analysis are provided by Statistics Sweden (SCB) and contain extensive information on all individuals in Sweden born between 1954 and 1980, as well as variables related to all firms in Sweden. Information on the variables used in the empirical analyses is provided in Table 2. Details on the databases are provided in Appendix A.

The information on migration background of a person is used to identify all refugee immigrants who arrived to Sweden before 1997 and who have been granted asylum. We distinguish between three refugee groups: (1) those from European countries arriving during the period 1990–1996, (2) those from non-European countries arriving during the same period and (3) those arriving in Sweden between 1980–1989 without classifying their country of emigration. This three groups define our fixed cohorts, for which we observe the labor market outcomes of these cohorts over the period 2003–2013.

Following Acemoglu and Autor (2011*b*), we classify a person's occupational task category as shown in Table 1. The task categories are (1) cognitive non-routine work tasks (professionals, managers and technicians), (2) cognitive routine tasks (office and administrative support and sales), (3) manual non-routine (personal care, personal service, protective service, food and cleaning) and finally (4) manual routine tasks (production, craft, repair, operators, fabricators and laborers).

In order to make a valid comparison of the wage earnings of refugees with those of natives, a control cohort of native born persons with similar characteristics to the refugee cohorts with regard to important characteristics is created. This is achieved by employing propensity score matching (Caliendo and Kopeinig, 2008) where refugees constitute the "treatment" group and the "control" group is created from the native born. The matching approach balances the two cohorts of natives and refugees for the following variables: gender, education, civil status, children, region where the person lives (district) and birth year (see Table 3).

In further analysis, rather than treating all refugee immigrants in one group, we separate the refugees into two socio-geographic categories: European (cohort 3) and non-European (cohort 4), as well as a group arriving in 1980–1989 (cohort 5). The comparison groups are randomly selected natives (cohort 1) and the matched sample (cohort 2). We do so because one could assume that European refugee immigrants could be less discriminated against the labor market compared to non-European refugees.

2.1 Descriptive Results

Table 3 shows that the share of women in the refugee cohorts is 41%, while for the unmatched sample this share is 49%. After matching, both cohorts include about the same share of women. About 57% of the refugee cohort individuals are married while 36% of the natives are married. Higher shares of refugees live in one of the larger cities (Stockholm, Gothenburg and Malmo) in comparison to natives. Fewer refugees hold a bachelor's degree (3.1% vs. 7.6%) but the share with a master's degree is similar between the cohorts (about 5.5%). The same is true for doctoral degrees (about 0.5% for both groups).

Table 4 shows that over the period 2003–2013, on average 82% of the matched natives were employed, while 72% of the European refugees and 60% of non-European refugees were employed. The employment rate of the pre-1990 refugee cohort is 65%. The following analyses of wage earnings will be based on individuals that earn at least 60% of median wage earnings, differentiated by gender.

Table 4 also shows that about 70% of individuals of matched cohort are established in the labor market,[2] while the shares for the refugee cohorts are lower with non-European refugees being lowest with about 47%. The Table also shows that in all groups the share of individuals with Swedish citizenship is at least 90%, and for natives it is 96%. A higher share of citizenship indicates that individuals in that cohort are planning to stay in the longer term.

Table 5 reports how workers in population groups are distributed across occupational task groups. Among matched natives, about 46% of workers work with cognitive non-routine tasks, and closest to this share are pre-1990 refugees with 33% in this task category. The lowest share is observed for European refugees while individuals from this group are most likely to work with manual routine tasks (41% vs. 25% for the matched natives). Among the non-European refugees, most work with manual non-routine tasks (39% vs. 17% among matched natives).

Table 6 displays the average wage earning for the different population groups across occupational task groups. There are significant differences for the first occupational task categories, cognitive non-routine tasks. While the matched group

[2] A person is defined as being established on the labor market if the monthly wage earnings exceed 60% of monthly median wage earnings, differentiated by gender.

of natives have wages 53% higher than median wage in the cognitive non-routine occupations, European refugees only have 23% higher wages. This is somewhat better for non-European and pre-1990 refugees who have 33% and 36% higher wages respectively. However, for manual non-routine tasks these two groups have higher wages than natives.

Table 7 shows the frequency of occupations with cognitive non-routine task for the different population groups. While for natives technical and commercial sales representatives is the most frequent occupation, for European and non-European refugee nursing associate professionals is the most frequently observed. For the pre-1990 refugees, medical doctors constitute the largest group with cognitive non-routine occupation.

Table 8 shows the variables' means for the various groups. There are differences in work experience of about four years between natives and refugees. One can see that among natives 11% have a bachelor's degree, while only 5.5% of matched natives have this degree. However, the difference for master's degree is smaller, 10% vs. 8.3%. Refugees are less likely to work in micro firms (10 and 14% vs. 17%) for matched natives, but more likely to work in medium sized firms. They are less likely to work in market knowledge intensive services (e.g., financial sectors) but more likely to work in low-tech manufacturing or other service sectors (low-tech). Non-European and pre-1900 refugees live to a larger extent in metro regions (more than 60%) where European refugees are most similar to matched natives.

Table 9 shows the variables' means for those who work in cognitive non-routine occupations. We see that for refugees it is a higher share of women that work in this task category, and refugees have on average higher formal education degrees compared to their peers. More than 30% have a master's degree, where the corresponding figure for matched natives is only 17.5%. Refugees in this occupations are also more likely to work in very large firms. Finally, they are underrepresented in high-tech knowledge-intensive services (KIS) but overrepresented in high-tech manufacturing.

3 Econometric Results

With the first econometric model, we investigate how likely it is that a person is employed in one of the broadly defined occupational task categories. We use a multinomial logit (MNL) model to predict the probability that a person is employed in occupational task category k, using gender, marital status, population group, experience, education and age as explanatory variables. In Table 10 the marginal effects from this estimation are reported. We find that task category is significantly related to gender: women are significantly overrepresented in task categories 1 and 2, and in particular in category 3 (manual non-routine tasks), and are significantly underrepresented in task category 4, manual routine. The likelihood to work in cognitive non-routine occupations increases with experience and education, but for manual non-routine tasks we find the opposite. While controlling for all the background variables, we find that refugees are significantly less likely to work with cognitive non-routine tasks. On the other hand they are much more likely to work with manual tasks, in particular in those occupations with routine tasks. In addition, workers living in cities or metropolitan regions are more likely to be employed in cognitive non-routine occupations, as are those who work in high-tech knowledge intensive services.

Figure 1 shows marginal effects from interactions with the time effects. Refugees' probability to hold a non-routine cognitive job was about 15% to 20% lower, cet.par., compared to natives in 2003, and the gap is only moderately reduced by 2013. Note that the reference category is natives, and there is almost no difference between matched natives and this reference category, despite that matched natives have by design very similar characteristics as the refugee immigrants. In contrast, refugee immigrants are significantly more likely to work in occupations involving manual tasks, in particular those with manual non-routine tasks. The difference for manual routine tasks in smaller; European refugees are more likely to work in those occupations.

One tentative conclusion from these results is that refugees face obstacles entering the higher paying cognitive task occupations. This can be due to discrimination on the labor market, so that refugees do not obtain the more attractive jobs.

3.1 Wage earnings

Using the correlated random effects (CRE) approach (Mundlak, 1978; Wooldridge, 2010), we estimate the determinants of wage earnings for each of the occupational task categories. The CRE approach has the advantage over a fixed effects approach in that it enables estimation of the effects of time-invariant variables such as belonging to a specific cohort. Furthermore, it relaxes the restrictive assumptions of the random effects model in that the unobserved heterogeneity term need not be uncorrelated with other explanatory variables, as their correlations are modeled.

Formally, the CRE model can be written as follows (Schunck, 2013; Schunck and Perales, 2017):

$$y_{it} = \beta_0 + \beta_w x_{it} + \beta_2 c_i + \pi \bar{x}_i + \mu_i + \epsilon_{it} \tag{1}$$

where y_{it} is normalized monthly wage earnings of person i, β_w correspond to the within estimates, $\bar{x}_i$ are group specific means of variables and π indicates the difference between within and between estimates, $\pi = \beta_w - \beta_b$. μ_i denote individual random effects uncorrelated with the error term ϵ_{it} and the other explanatory variables x_{it} of the model. It is worth noting that if $H_0 : \pi = 0$ cannot be rejected , a pure random effects model would be appropriate. Under the alternative $H_1 : \pi \neq 0$, the data support the CRE specification. This is an augmented regression model test which is equivalent to a Hausman test on the random versus fixed effects specification.

As Schunck (2013) has pointed out, the CRE model is numerically equivalent to a so-called hybrid model formulation from which both within and between estimates can be obtained:

$$y_{it} = \beta_0 + \beta_w(x_{it} - \bar{x}_i) + \beta_2 c_i + \beta_b \bar{x}_i + \mu_i + \epsilon_{it}. \tag{2}$$

Because the between group estimates have a direct interpretation, we prefer the hybrid model formulation over the CRE specification. While the within estimate shows the effect of a variable which varies over time on the outcome for an individual, the between estimates can be interpreted as the long-term impact of that variable.

Table 6 displays the estimation results. Due to space constraints not all coefficients are reported. (w) or (b) after variable names indicates within or between estimates. We estimate the model first for all occupations, including occupational task category as a time varying control variable, yielding both within and between estimates. We then estimate the model separately for each task category.

One result that is worth pointing out is that women earn on average between 13% to 29% less than men, all else equal. The effects for the various cohorts is much less pronounced. Overall, European refugees earn the same as matched natives over all occupations, while non-European refugees earn about 3.5% less. Pre-1990 refugees earn on average 4.8% less than the matched natives. While we find only minor differences for the remaining three occupational categories, the differences are most apparent for cognitive non-routine tasks. European refugees earn 6.9% less than matched natives, cet.par., and non-European and pre-European earn about 9.5–9.9% less. On the other hand, surprisingly, all refugees have about 3% higher earnings than matched natives in manual non-cognitive task categories.

While the short-term effect of switching to cognitive non-routine tasks is only 4.3% in average (relative to manual routine tasks), the between estimates show that the long-term difference is 32%. Interestingly, only the cognitive non-routine tasks have such a higher wage compared to manual routine tasks, whereas there are only minor differences for the other occupational tasks groups. The effect of an additional year of experience is highest for cognitive non-routine tasks and lowest for manual non-routine tasks. Also, for cognitive non-routine tasks, the wage earnings are about 25% higher in municipalities located in larger cities and metropolitan areas compared to very remote areas.

It is also worth noting that the between R^2s are much higher compared to within R^2s. The difference between the first column and the other columns shows that the occupational task category has considerable explanatory power for explaining wage differences between individuals. The within effect, i.e. when a person changes task category, is less pronounced. In Figure 2, the effect from task category is interacted with the year indicators to see how the effect evolves over time. The first panel in the upper left corner shows that the difference between cohorts is persistent. In all other task categories the differences are negligible.

Finally, based on the CRE estimates reported in Table 11 we perform a Blinder–Oaxaca wage decomposition (Blinder, 1973; Oaxaca, 1973) to examine whether wage differences can be explained with different characteristics of native and refugee workers, or whether unexplained differences exist which would suggest wage discrimination.

We apply the so-called twofold decomposition, which is defined as (Jann, 2008)

$$R = \underbrace{[E(X_A) - E(X_B)]'\beta^*}_{\text{explained part}} + \underbrace{E(X_A)'(\beta_A - \beta^*) + E(X_B)'(\beta^* - \beta_B)}_{\text{unexplained part}} \quad (3)$$

where R is the difference in wage earnings between the groups and β^* has been estimated for a reference group, in our case for the matched natives. In our case we have $\beta_A = \beta^*$, so the second term disappears. Thus, the first term shows that differences in characteristics (endowments) do explain wage differences, while differences in coefficients imply unexplained wage differences.

We perform the Blinder–Oaxaca decomposition for each cohort over 2003–2013 using the CRE model outlined above, using matched natives as the reference group and the respective refugee group as comparison group. The results are shown in Tables 12 to 14.

Over all occupations, there are only minor unexplained wage difference between refugees and matched natives, with an almost negligible -1% for European refugees, but larger for non-European (4.6%) and pre-1990 refugees (2.8%). An analysis of contribution of the various variables to the explained difference shows that it is mainly due to differences in accumulated work experience of refugees and natives (see Table 8). However, larger unexplained differences are found for cognitive non-routine task categories, where the unexplained differences are 8% and 12% respectively. Thus, this result might be indicative of wage discrimination in the labor market. On the other hand, for manual non-routine tasks, we find that refugees earn higher wages than predicted by the model.

4 Conclusions

In the industrial world with its aging population, international migration now accounts for the entire net increase in the labor force. A major concern for the receiving country is the productivity impact of immigration. An empirical regularity established in the literature is that refugee immigrants earn lower wages than observationally equivalent natives in the short run. This paper studies wage differences between refugees and natives in Sweden over the period 2003–2013. We exploit full-population administrative register employer-employee data to compare wages for occupational task groups for individuals with similar socioeconomic characteristics within and across industries.

Employing a matching approach for identifying the causal effects, we find that the observed wage gap between refugees and natives is mainly explained by two factors. The first is occupational sorting into different work tasks. The marginal probability of refugee immigrants to work in higher paid cognitive non-routine occupational jobs is significantly lower, even after controlling for a number of individual characteristics such as education and work experience. Refugee immigrants have a significantly higher probability to work in manual occupational task categories, where they tend to remain. Mobility across occupational categories is limited for both native-born workers and refugee workers, but is lower for refugee workers. The second key explanation of wage differentials are personal characteristics. Native-born workers have, on average, more accumulated work experience. Holding other factors equal—age, gender, family status, education, place of residence, company size, industry, and job task—refugees have less work experience, which explains a large part of the wage disparity. However, a significant part of the wage gap remains unexplained, which might suggest wage discrimination.

Our findings have important policy implications with respect to both income inequality and economic efficiency. Occupational sorting is accompanied by increasing wage differentials for high-skilled and low-skilled workers while occupational mobility is limited. This may counteract the long-run process of narrowing wage gaps due to reduced differences in work experience. Further, as many companies face difficulties in recruiting competent and qualified personnel, refugee workers may have unexploited skill potentials that could be used to reduce the shortage of skilled labor in many developed economies facing the demographic challenges of an increasing ratio of pensioners to workers.

Areas for further research on economic integration of refugee immigrants include a deeper analysis of cognitive non-routinized occupations with respect to STEM workers (Science, Technology, Engineering & Mathematics). Despite the fact that many immigrants have a STEM background, the knowledge regarding their contribution to technological change and innovation in their new home countries is limited. This applies in particular to refugee immigrants.

References

Acemoglu, D. and Autor, D. (2011*a*), Skills, tasks and technologies: Implications for employment and earnings, *in* 'Handbook of labor economics', Vol. 4, Elsevier, pp. 1043–1171.

Acemoglu, D. and Autor, D. (2011*b*), Skills, tasks and technologies: Implications for employment and earnings, *in* D. Card and O. Ashenfelter, eds, 'Handbook of Labor Economics', Vol. 4b, Elsevier, pp. 1043–1171.

Autor, D. H., Levy, F. and Murnane, R. J. (2003), 'The skill content of recent technological change: An empirical exploration', *Quarterly Journal of Economics* **118**(4), 1279–1333.

Blinder, A. S. (1973), 'Wage discrimination: Reduced form and structural estimates', *The Journal of Human Resources* **8**(4), 436–455.
URL: *http://www.jstor.org/stable/144855*

Caliendo, M. and Kopeinig, S. (2008), 'Some practical guidance for the implementation of propensity score matching', *Journal of Economic Surveys* **22**(1), 31–72.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6419.2007.00527.x*

Chin, A. and Cortes, K. E. (2015), The refugee/asylum seeker, *in* 'Handbook of the economics of international migration', Vol. 1, Elsevier, pp. 585–658.

Colic-Peisker, V. and Tilbury, F. (2006), 'Employment niches for recent refugees: Segmented labour market in twenty-first century Australia', *Journal of Refugee Studies* **19**(2), 203–229.

Connor, P. (2010), 'Explaining the refugee gap: Economic outcomes of refugees versus other immigrants', *Journal of Refugee Studies* **23**(3), 377–397.

Dustmann, C., Frattini, T. and Preston, I. P. (2012), 'The effect of immigration along the distribution of wages', *Review of Economic Studies* **80**(1), 145–173.

Dustmann, C., Glitz, A. and Vogel, T. (2010), 'Employment, wages, and the economic cycle: Differences between immigrants and natives', *European Economic Review* **54**(1), 1–17.

Grand, C. l. and Szulkin, R. (2002), 'Permanent disadvantage or gradual integration: explaining the immigrant–native earnings gap in Sweden', *Labour* **16**(1), 37–64.

Groes, F., Kircher, P. and Manovskii, I. (2015), 'The u-shapes of occupational mobility', *The Review of Economic Studies* **82**(2), 659–692.
URL: *http://dx.doi.org/10.1093/restud/rdu037*

Jann, B. (2008), 'The Blinder–Oaxaca decomposition for linear regression models', *Stata Journal* **8**(4), 453–479.
URL: *https://ideas.repec.org/a/tsj/stataj/v8y2008i4p453-479.html*

Llull, J. (2017), 'The effect of immigration on wages: exploiting exogenous variation at the national level', *Journal of Human Resources* pp. 0315–7032R2.

Mundlak, Y. (1978), 'On the pooling of time series and cross section data', *Econometrica* **46**(1), 69–85.
URL: *http://www.jstor.org/stable/1913646*

Oaxaca, R. (1973), 'Male-female wage differentials in urban labor markets', *International Economic Review* **14**(3), 693–709.
URL: *http://www.jstor.org/stable/2525981*

Schunck, R. (2013), 'Within and between estimates in random-effects models: Advantages and drawbacks of correlated random effects and hybrid models', *Stata Journal* **13**(1), 65–76.
URL: *http://www.stata-journal.com/article.html?article=st0283*

Schunck, R. and Perales, F. (2017), 'Within- and between-cluster effects in generalized linear mixed models: A discussion of approaches and the xthybrid command', *Stata Journal* **17**(1), 89–115.
URL: *https://EconPapers.repec.org/RePEc:tsj:stataj:v:17:y:2017:i:1:p:89-115*

Wooldridge, J. M. (2010), *Econometric Analysis of Cross Section and Panel Data*, Vol. 1 of *MIT Press Books*, 2nd edn, The MIT Press.
URL: *https://ideas.repec.org/b/mtp/titles/0262232197.html*

Yamaguchi, S. (2012), 'Tasks and Heterogeneous Human Capital', *Journal of Labor Economics* **30**(1), 1–53.
URL: *https://ideas.repec.org/a/ucp/jlabec/doi10.1086-662066.html*

A Statistics Sweden database descriptions

A few countries provide administrative register data that allows for microeconometric analysis of refugees' interaction with the host economies. One of these countries is Sweden, where all individuals and firms can be linked to a wide range of administrative registers with long time series via unique identification codes. The data, provided by Statistics Sweden, contain information whether the individuals are natives or immigrants. In the latter case, the reason for immigration is also reported, which allows to identify refugees.

We employ several full population-level databases including LISA: Longitudinal integration database for health insurance and labor market studies; RAKS: Register based activity statistics; FAD: The dynamics of firms and workplaces; RAMS, Register based labor market statistics; STATIV: A longitudinal database for integration studies and MOA: Migration and asylum statistics. Additional databases are databases on trade statistics, patents (PATSTAT), databases on firm and establishment statistics (firm register, corporation register, organizational classification) and work tasks (SSYK codes). All databases are retrieved from Statistics Sweden and accessed through the remote MONA (Microdata online access) delivery system.

The LISA, RAKS and STATIV databases provide individual-level data on personal characteristics, education, employment, labor income, immigration status, and occupation. We consider data from the period 1990–2013. We include Swedish-born and foreign-born refugee-immigrant workers who were born between 1954 and 1980. Registers for plants, firms, corporations, trade, organizational classifications, locations, patents and job tasks provide data on workplaces over the period 1997–2013, which means that the cohorts we study in the employee-employer data are between 17 and 43 years of age in the beginning of the period, and between 33 and 59 years in the end of the period. As the population of refugee-immigrants varies greatly across Sweden, we include labor market regions in the econometric analysis.

B Tables

Table 1: Occupational task classifications

Work tasks	ISCO-88/SSYK 96
Cognitive non-routine	
Professionals	21-24
Managers	12-13
Technicians and Associate professionals	31-34
Cognitive routine	
Office and Administrative Support	41
Sales	42-52
Manual non-routine	
Personal Care, Personal Service, Protective Service	51
Food, Cleaning Service	91
Manual routine	
Production, Craft and Repair	71-74
Operators, Fabricators and Laborers	81-83, 93

Table 2: Variable descriptions

Variable	Definition
occupational task category	1= cognitive non-routine tasks, 2=cognitive routine tasks, 3=manual non-routine tasks, **4=manual routine tasks**
population group	**1=native-born**, 2=matched control group of native-born, 3=European refugees, 4=non-European refugees, 5=pre-1990 refugees
educ	highest educational attainment: **1=primary school**, 2=secondary school, 3=tertiary education (below university degree), 4=bachelor's degree, 5=master's degree, 6=doctoral degree
female	1=women, **0=men**
age	current year minus birth year. In regression models, age is included as categorical variable, 1=age <30, 2=age 30-34, 3=age 35-39, 4=age 40-44, 5=age 45-49, 6=age 50-54, **7=age 55-59**
married	marital status: 1=married, **0=unmarried**
kids age 0-3	number of children with age 0-3 years, winsorized at 2, ref category **0 children**
kids age 4-6	number of children with age 4-6 years, winsorized at 2, ref category **0 children**
wage	monthly wage earnings relative to median monthly wage earnings in respective year differentiated by gender
experience	cumulative number of years with labor income as main source of income
ind	1=high-tech manufacturing, 2=medium-tech manufacturing, 3=low-tech manufacturing, 4=high-tech knowledge intensive services (kis), 5=market kis, **6=less knowledge intensive services**
fsize	number of firm's employees, 1=micro$<$1-9, 2=small 10-49, 3=medium 50-249, 4=large 250-999, **5=big$\geq$1000 employees**
muni	settlement type of municipality where a person's workplace is located, 1= metropolitan area/larger city, 2=densely populated, close to larger city, 3=rural region close to larger city, 4=densely populated remote region, 5=rural remotely located region, **6=rural very remotely located region**

Notes: reference category of a categorical variable is shown in **bold.**

Table 3: Tests of balancing assumption after propensity score matching

		Mean			%reduct	t-test	V(T)/
Variable		Refugees	Natives	%bias	bias	t	p>t
female	U	0.411	0.493	-16.6	-51.1	0	
	M	0.411	0.411	-0.1	99.6	-0.15	0.880
married	U	0.569	0.358	43.3	136.45	0	
	M	0.569	0.570	0	99.9	-0.1	0.924
educ secondary	U	0.496	0.520	-4.7	-14.56	0	
	M	0.496	0.497	-0.1	98.6	-0.15	0.882
educ tertiary	U	0.187	0.211	-6	-18.08	0	.
	M	0.187	0.187	0.1	99	0.14	0.890
educ bachelor	U	0.031	0.076	-20.2	-53.37	0	
	M	0.031	0.031	0	99.9	-0.06	0.948
educ master	U	0.055	0.059	-1.6	-5.02	0	
	M	0.055	0.055	-0.1	95.8	-0.16	0.875
educ doctoral	U	0.005	0.008	-3.6	-10.12	0	
	M	0.005	0.005	0.2	93.4	0.61	0.545
kids age 0-3: 1	U	0.164	0.149	4	12.55	0	
	M	0.164	0.164	-0.1	97.1	-0.25	0.804
kids age 0-3: 2	U	0.036	0.031	2.8	9.08	0	
	M	0.036	0.034	1.1	61.4	2.37	0.018
kids age 4-6: 1	U	0.163	0.126	10.6	34.52	0	
	M	0.163	0.164	-0.2	98	-0.45	0.653
kids age 4-6: 2	U	0.023	0.014	6.8	24.02	0	
	M	0.023	0.021	1.3	80.9	2.64	0.008
birthyear 1960	U	0.052	0.036	8.1	27.53	0	
	M	0.052	0.052	0.1	98.7	0.21	0.832
birthyear 1961	U	0.049	0.036	6.5	21.6	0	
	M	0.049	0.049	0	99.6	-0.05	0.959
birthyear 1962	U	0.053	0.037	7.8	26.37	0	
	M	0.053	0.053	0	99.7	-0.05	0.960
birthyear 1963	U	0.052	0.039	6.2	20.49	0	
	M	0.052	0.052	-0.1	98.8	-0.15	0.879
birthyear 1964	U	0.053	0.042	5	16.37	0	
	M	0.053	0.053	0	99.3	-0.07	0.944
region Stockholm	U	0.269	0.230	9.1	28.96	0	
	M	0.269	0.269	0	99.6	-0.09	0.931
region Gothenburg	U	0.176	0.126	14	46.64	0	
	M	0.176	0.176	0	99.8	-0.06	0.953
region Malmö	U	0.209	0.170	10	32.27	0	
	M	0.209	0.209	0	100	0	1

Notes: Sample means unmatched (U) and matched (M) based on 1:1 propensity score matching without replacement. probit model for year 2002 using 99,247 refugees and 3,070,343 natives. Variables region denotes a person's living region. For birth years 1954-1980 and 21 regions only selected categories are reported. All categories are balanced between refugees and natives after matching.

Table 4: Employment, labor market establishment, Swedish citizenship, 2003-2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
employed	0.823	0.820	0.720	0.600	0.651
established	0.718	0.703	0.658	0.472	0.531
citizenship	0.961	0.955	0.942	0.901	0.914
observations	1,068,318	1,064,859	390,326	330,723	319,342

Notes: A person is defined as being established on the labor market if monthly wage earnings $\geq$ 0.6 monthly median wage earnings, differentiated by gender. Citizenship indicates being a Swedish citizen.

Table 5: Share of workers from population group j in occupational task category k, 2003-2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
cognitive non-routine	0.494	0.458	0.196	0.256	0.330
cognitive routine	0.121	0.124	0.092	0.088	0.088
manual non-routine	0.172	0.174	0.298	0.387	0.334
manual routine	0.213	0.245	0.414	0.269	0.249
observations	766,597	748,821	257,029	155,943	169,708

Notes: Only employed persons established on the labor market, see Table 4.

Table 6: Normalized wage earnings for population group j in occupational task category k, 2003-2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
cognitive non-routine	1.402	1.531	1.230	1.326	1.363
cognitive routine	0.977	0.991	0.965	0.995	1.006
manual non-routine	0.873	0.878	0.864	0.925	0.930
manual routine	1.103	1.105	1.061	1.048	1.078
observations	766,597	748,821	257,029	155,943	169,708

Notes: Wage earnings relative to median wage earnings in respective year. Only established persons, see Table 4.

Table 7: The 10 most frequent occupations by population group within the cognitive non-routine task category (%)

natives		matched natives		European refugees		non-European refugees		pre-1990 refugees	
Technical and commercial sales representatives (3415)	5.37	Technical and commercial sales representatives (3415)	7.03	Nursing associate professionals (2330)	6.19	Nursing associate professionals (2330)	9.83	Medical doctors (2221)	5.57
Primary education teaching associate professionals (3310)	5.33	Computer systems designers and analysts (2131)	4.87	Primary education teaching associate professionals (3310)	4.81	Medical doctors (2221)	8.96	Computer systems designers and analysts (2131)	5.55
Nursing associate professionals (2330)	4.87	Primary education teaching associate professionals (3310)	3.99	Medical doctors (2221)	4.48	Computer systems designers and analysts (2131)	4.70	Nursing associate professionals (2330)	5.51
Computer systems designers and analysts (2131)	4.67	Nursing associate professionals (2330)	3.24	Computer systems designers and analysts (2131)	4.14	Primary education teaching associate professionals (3310)	4.24	Non-specialist nurses (3239)	4.17
Public administration (2470)	2.76	Computer assistants (3121)	2.94	Non-specialist nurses (3239)	3.78	Non-specialist nurses (3239)	3.32	Primary education teaching associate professionals (3310)	4.00
Non-specialist nurses (3239)	2.69	Public administration (2470)	2.33	Public administration (2470)	3.76	Electronics and telecommunications engineers (2144)	2.99	Electronics and telecommunications engineers (2144)	3.12
Administrative secretaries and related associate professionals (3431)	2.43	Physical and engineering science technicians not elsewhere classified (3119)	2.25	Physical and engineering science technicians not elsewhere classified (3119)	3.21	Public administration (2470)	2.94	Computer assistants (3121)	2.94
Computer assistants (3121)	2.42	Administrative secretaries and related associate professionals (3431)	2.06	Mechanical engineering technicians (3115)	3.08	Social service worker (2492)	2.86	Biomedical analytics (3240)	2.63
Medical doctors (2221)	1.92	Mechanical engineering technicians (3115)	1.96	Social service worker (2492)	2.84	Computer assistants (3121)	2.53	Public administration (2470)	2.59
College, university and higher education teaching professionals (2310)	1.81	Directors and chief executives (1210)	1.92	Government social benefits officials (3443)	2.84	General managers in wholesale and retail trade (1314)	2.31	College, university and higher education teaching professionals (2310)	2.20
Cumulative %	34.25		32.58		39.12		44.69		38.30

Notes: Occupation codes using SSYK 96 classification.

Table 8: Variable means for population groups, 2003-2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
experience	13.4	13.8	9.5	9.1	10.9
female	0.487	0.393	0.479	0.369	0.395
age	41.5	42.9	41.9	42.2	43.6
married	0.453	0.594	0.731	0.608	0.572
kids age 0-3	0.157	0.131	0.137	0.195	0.144
kids age 4-6	0.146	0.136	0.132	0.188	0.138
educ primary	0.090	0.165	0.128	0.173	0.161
educ secondary	0.495	0.499	0.576	0.420	0.469
educ tertiary	0.192	0.190	0.171	0.210	0.166
educ bachelor	0.110	0.055	0.048	0.066	0.083
educ master	0.101	0.083	0.071	0.120	0.108
educ doctoral	0.013	0.008	0.005	0.011	0.013
fsize micro 1-9	0.162	0.174	0.100	0.145	0.141
fsize small 10-49	0.302	0.300	0.265	0.234	0.232
fsize medium 50-249	0.299	0.295	0.390	0.343	0.327
fsize large 250-999	0.210	0.204	0.221	0.242	0.252
fsize big$\geq$1000	0.027	0.027	0.025	0.036	0.049
manu high-tech	0.014	0.016	0.019	0.020	0.024
manu medium	0.106	0.118	0.211	0.094	0.111
manu low	0.051	0.057	0.094	0.050	0.053
kis high-tech	0.045	0.047	0.013	0.022	0.030
kis market	0.123	0.123	0.089	0.095	0.097
serv other	0.661	0.639	0.574	0.720	0.685
metro/city	0.373	0.432	0.322	0.611	0.625
dense close city	0.414	0.382	0.465	0.311	0.290
rural close city	0.078	0.086	0.104	0.031	0.041
dense remote	0.074	0.060	0.059	0.026	0.023
rural remote	0.049	0.034	0.045	0.021	0.019
rural very remote	0.011	0.005	0.004	0.001	0.002
observations	766,597	748,821	257,029	155,943	169,708

Notes: Only established persons, Table 4.

Table 9: Variable means for population groups in occupational task category cognitive non-routine, 2003-2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
experience	13.6	14.4	9.9	9.8	11.3
female	0.506	0.365	0.545	0.395	0.411
age	41.7	43.7	41.0	42.4	42.9
married	0.516	0.632	0.681	0.633	0.591
kids age 0-3	0.186	0.143	0.177	0.201	0.166
kids age 4-6	0.166	0.143	0.144	0.175	0.144
educ primary	0.028	0.062	0.015	0.027	0.029
educ secondary	0.257	0.320	0.184	0.126	0.165
educ tertiary	0.286	0.313	0.267	0.241	0.258
educ bachelor	0.207	0.112	0.210	0.196	0.216
educ master	0.196	0.175	0.303	0.377	0.294
educ doctoral	0.026	0.018	0.021	0.034	0.038
fsize micro 1-9	0.136	0.154	0.099	0.116	0.121
fsize small 10-49	0.285	0.283	0.250	0.223	0.222
fsize medium 50-249	0.308	0.302	0.348	0.323	0.289
fsize large 250-999	0.237	0.228	0.264	0.268	0.280
fsize big$\geq$1000	0.033	0.033	0.038	0.069	0.088
manu high-tech	0.021	0.025	0.030	0.041	0.046
manu medium	0.078	0.094	0.103	0.054	0.062
manu low	0.028	0.033	0.021	0.010	0.015
kis high-tech	0.075	0.083	0.044	0.055	0.069
kis market	0.173	0.184	0.122	0.115	0.125
serv other	0.624	0.581	0.680	0.725	0.682
muni metro/city	0.462	0.527	0.456	0.635	0.669
muni dense close city	0.385	0.347	0.414	0.309	0.273
muni rural close city	0.054	0.055	0.061	0.024	0.023
muni dense remote	0.058	0.046	0.044	0.020	0.019
muni rural remote	0.034	0.022	0.020	0.012	0.014
observations	368,833	333,369	49,219	38,316	54,152

Notes: See Table 8.

Table 10: Marginal effects of being employed in occupational task category k, MNL model

	(1) cogn non-rout	(2) cogn rout	(3) man non-rout	(4) man rout
female	0.012***	0.071***	0.161***	-0.245***
	[0.001]	[0.000]	[0.000]	[0.001]
matched natives	0.005***	-0.000	-0.001**	-0.003***
	[0.001]	[0.001]	[0.001]	[0.001]
European refugees	-0.147***	-0.020***	0.058***	0.110***
	[0.001]	[0.001]	[0.001]	[0.001]
non-European refugees	-0.169***	-0.022***	0.146***	0.046***
	[0.001]	[0.001]	[0.001]	[0.001]
pre-1990 refugees	-0.104***	-0.027***	0.114***	0.017***
	[0.001]	[0.001]	[0.001]	[0.001]
experience	0.011***	0.001***	-0.010***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
experience^2	0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
educ secondary	0.082***	-0.006***	-0.030***	-0.047***
	[0.001]	[0.001]	[0.001]	[0.001]
educ tertiary	0.369***	-0.039***	-0.152***	-0.178***
	[0.001]	[0.001]	[0.001]	[0.001]
educ bachelor	0.613***	-0.078***	-0.277***	-0.258***
	[0.001]	[0.001]	[0.002]	[0.002]
educ master	0.659***	-0.065***	-0.309***	-0.285***
	[0.001]	[0.001]	[0.002]	[0.002]
educ doctoral	0.682***	-0.127***	-0.257***	-0.298***
	[0.004]	[0.006]	[0.006]	[0.006]
married	0.034***	-0.005***	-0.012***	-0.018***
	[0.001]	[0.000]	[0.001]	[0.001]
kids age 0-3: 1	0.017***	-0.002***	-0.009***	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]
kids age 0-3: 2	0.023***	-0.007***	-0.009***	-0.007***
	[0.002]	[0.002]	[0.002]	[0.002]
kids age 4-6: 1	0.010***	-0.005***	-0.004***	-0.001*
	[0.001]	[0.001]	[0.001]	[0.001]
kids age 4-6: 2	0.010***	-0.009***	-0.004*	0.003
	[0.002]	[0.002]	[0.002]	[0.002]
age <30	0.022***	0.062***	-0.067***	-0.016***
	[0.002]	[0.001]	[0.002]	[0.002]
age 30-34	0.052***	0.036***	-0.068***	-0.020***
	[0.002]	[0.001]	[0.001]	[0.001]
age 35-39	0.049***	0.018***	-0.056***	-0.011***
	[0.001]	[0.001]	[0.001]	[0.001]
age 40-44	0.043***	0.008***	-0.044***	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]
age 45-49	0.031***	0.001	-0.029***	-0.004***
	[0.001]	[0.001]	[0.001]	[0.001]

cont.

	(1) cogn non-rout	(2) cogn rout	(3) man non-rout	(4) man rout
age 50-54	0.017***	-0.001	-0.012***	-0.004***
	[0.001]	[0.001]	[0.001]	[0.001]
fsize micro 1-9	0.003	0.073***	-0.156***	0.081***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize small 10-49	-0.009***	0.051***	-0.098***	0.056***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize medium 50-249	-0.009***	0.022***	-0.057***	0.044***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize large 250-999	-0.003	0.022***	-0.066***	0.046***
	[0.002]	[0.002]	[0.002]	[0.002]
muni metro/city	0.069***	0.034***	-0.040***	-0.063***
	[0.003]	[0.003]	[0.003]	[0.003]
muni dense close city	0.025***	0.020***	-0.028***	-0.018***
	[0.003]	[0.003]	[0.003]	[0.003]
muni rural close city	-0.006*	0.007**	-0.014***	0.013***
	[0.003]	[0.003]	[0.003]	[0.003]
muni dense remote	0.005	0.004	-0.012***	0.003
	[0.003]	[0.003]	[0.003]	[0.003]
muni rural remote	0.002	0.000	-0.013***	0.011***
	[0.003]	[0.003]	[0.003]	[0.003]
manu high-tech	0.210***	-0.011***	-0.425***	0.226***
	[0.003]	[0.003]	[0.007]	[0.003]
manu medium-tech	0.097***	0.024***	-0.381***	0.260***
	[0.001]	[0.001]	[0.002]	[0.001]
manu low-tech	-0.010***	-0.012***	-0.192***	0.215***
	[0.001]	[0.001]	[0.001]	[0.001]
kis high-tech	0.261***	0.106***	-0.235***	-0.132***
	[0.002]	[0.001]	[0.003]	[0.002]
kis low-tech	0.138***	-0.013***	-0.055***	-0.070***
	[0.001]	[0.001]	[0.001]	[0.001]
observations	1,996,658			
df (model)	141			
pseudo R^2	0.34			
χ^2	1786968.2			
p-value	0.000			

Notes: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Determinants of wage earnings by occupational category, correlated random effects model

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
time-invariant regressors					
female	-0.225***	-0.294***	-0.137***	-0.135***	-0.129***

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
	[0.003]	[0.004]	[0.003]	[0.002]	[0.003]
matched native	0.016***	0.024***	-0.003	-0.000	-0.004*
	[0.003]	[0.005]	[0.003]	[0.002]	[0.002]
European refugee	0.017***	-0.045***	0.016***	0.031***	0.002
	[0.003]	[0.006]	[0.006]	[0.003]	[0.003]
non-European refugee	-0.019***	-0.070***	-0.011	0.034***	-0.028***
	[0.004]	[0.008]	[0.008]	[0.004]	[0.004]
pre-1990 refugee	-0.032***	-0.074***	0.002	0.035***	-0.022***
	[0.004]	[0.007]	[0.007]	[0.004]	[0.004]
time-variant regressors (within estimates)					
cognitive non-routine (w)	0.043***	—	—	—	—
	[0.003]				
cognitive routine (w)	-0.009***	—	—	—	—
	[0.003]				
manual non-routine (w)	-0.028***	—	—	—	—
	[0.003]				
occupational task effects (w)	yes	—	—	—	—
experience (w)	0.058***	0.106***	0.047***	0.020***	0.041***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.003]
experience^2 (w)	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
kid age 0-3: 1 (w)	-0.027***	-0.048***	-0.021***	-0.022***	-0.008***
	[0.002]	[0.003]	[0.004]	[0.002]	[0.002]
kids age 0-3: 2 (w)	-0.047***	-0.082***	-0.035***	-0.027***	-0.015***
	[0.003]	[0.006]	[0.007]	[0.005]	[0.004]
age <30	-0.004	-0.007	0.022	-0.008	-0.009
	[0.008]	[0.017]	[0.016]	[0.009]	[0.012]
age 30-34	0.034***	0.057***	0.042***	0.008	0.013
	[0.007]	[0.015]	[0.013]	[0.007]	[0.010]
age 35-39	0.057***	0.093***	0.052***	0.011*	0.021***
	[0.006]	[0.013]	[0.011]	[0.006]	[0.008]
age 40-44	0.070***	0.114***	0.048***	0.020***	0.026***
	[0.005]	[0.011]	[0.009]	[0.005]	[0.006]
age 45-49	0.064***	0.107***	0.042***	0.019***	0.020***
	[0.004]	[0.009]	[0.007]	[0.004]	[0.005]
age 50-54	0.038***	0.064***	0.024***	0.011***	0.009**
	[0.004]	[0.008]	[0.005]	[0.003]	[0.004]
year effects (w)	yes	yes	yes	yes	yes
educ effects (w)	yes	yes	yes	yes	yes
firm size effects (w)	yes	yes	yes	yes	yes
industry effects (w)	yes	yes	yes	yes	yes
region effects (w)	yes	yes	yes	yes	yes
time-variant regressors (between estimates)					
non-rout cogn (b)	0.313***	—	—	—	—
	[0.004]				
rout cogn (b)	-0.000	—	—	—	—

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
	[0.003]				
non-rout man (b)	0.003	—	—	—	—
	[0.003]				
experience (b)	-0.028***	-0.036***	-0.024***	-0.005***	-0.015***
	[0.001]	[0.004]	[0.003]	[0.001]	[0.002]
experience^2 (b)	0.002***	0.003***	0.002***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
educ secondary (b)	0.030***	0.046***	0.016***	0.021***	0.023***
	[0.002]	[0.008]	[0.004]	[0.003]	[0.002]
educ tertiary (b)	0.040***	0.139***	0.057***	0.040***	0.048***
	[0.003]	[0.009]	[0.006]	[0.004]	[0.004]
educ bachelor (b)	0.101***	0.276***	0.119***	0.076***	0.055***
	[0.008]	[0.012]	[0.011]	[0.008]	[0.010]
educ master (b)	0.303***	0.461***	0.143***	0.102***	0.085***
	[0.008]	[0.012]	[0.010]	[0.009]	[0.012]
educ doctoral (b)	0.443***	0.554***	0.180***	0.090***	0.022
	[0.025]	[0.028]	[0.051]	[0.032]	[0.023]
married (b)	0.041***	0.087***	0.016***	-0.008***	0.013***
	[0.003]	[0.005]	[0.004]	[0.002]	[0.002]
muni metro/city (b)	0.135***	0.245***	0.112***	0.038**	0.026**
	[0.009]	[0.018]	[0.011]	[0.015]	[0.011]
muni dense close city (b)	0.020**	0.039**	0.040***	-0.001	0.001
	[0.009]	[0.018]	[0.011]	[0.015]	[0.011]
muni rural close city (b)	0.003	0.004	0.015	-0.016	-0.018
	[0.009]	[0.019]	[0.012]	[0.015]	[0.011]
muni dense remote (b)	0.002	0.004	0.016	-0.016	-0.004
	[0.009]	[0.019]	[0.013]	[0.015]	[0.012]
muni rural remote (b)	-0.008	0.003	-0.005	-0.022	-0.032***
	[0.009]	[0.019]	[0.013]	[0.015]	[0.012]
manu high-tech (b)	0.311***	0.363***	0.149***	0.203***	0.018**
	[0.019]	[0.025]	[0.024]	[0.051]	[0.008]
manu medium-tech (b)	0.127***	0.191***	0.099***	0.140***	0.016***
	[0.005]	[0.011]	[0.007]	[0.014]	[0.003]
manu low-tech (b)	0.102***	0.194***	0.088***	-0.051***	0.006
	[0.006]	[0.018]	[0.011]	[0.009]	[0.004]
kis high-tech (b)	0.272***	0.346***	0.062***	0.103***	0.015
	[0.010]	[0.012]	[0.011]	[0.019]	[0.014]
kis market (b)	0.229***	0.345***	0.100***	0.031***	0.001
	[0.007]	[0.009]	[0.007]	[0.006]	[0.007]
fsize micro 1-9 (b)	-0.139***	-0.226***	0.015	-0.021**	-0.178***
	[0.010]	[0.017]	[0.016]	[0.011]	[0.009]
fsize small 10-49 (b)	-0.067***	-0.073***	0.059***	-0.033***	-0.121***
	[0.010]	[0.017]	[0.016]	[0.010]	[0.009]
fsize medium 50-249 (b)	-0.072***	-0.104***	0.071***	-0.026**	-0.103***
	[0.010]	[0.017]	[0.016]	[0.010]	[0.009]
fsize large 250-999 (b)	0.008	0.013	0.091***	0.003	-0.040***

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
	[0.011]	[0.018]	[0.016]	[0.010]	[0.009]
constant	1.263***	1.638***	1.107***	0.939***	1.373***
	[0.046]	[0.109]	[0.096]	[0.030]	[0.071]
year effects (b)	yes	yes	yes	yes	yes
kids age 0-3 effects (b)	yes	yes	yes	yes	yes
kids age 4-6 effects (b)	yes	yes	yes	yes	yes
age effects (b)	yes	yes	yes	yes	yes
observations	1,996,658	833,162	228,688	421,224	513,584
σ_u	0.475	0.627	0.289	0.247	0.228
σ_ϵ	0.520	0.699	0.314	0.263	0.388
ρ	0.454	0.446	0.458	0.468	0.257
individuals	246,014	115,774	46,470	72,396	77,028
df(model) (w/b)	95	89	89	89	89
R^2 (w)	0.006	0.008	0.005	0.003	0.004
R^2 (b)	0.257	0.199	0.112	0.092	0.082

Notes: Cluster-robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wage earnings relative to median wage earnings in respective year. (w) indicates within, (b) indicates between.

Table 12: Twofold Blinder-Oaxaca wage decomposition for European refugees, years 2003-2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.245***	1.514***	1.003***	0.878***	1.103***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
European refugees	1.027***	1.216***	0.968***	0.866***	1.060***
	[0.002]	[0.005]	[0.005]	[0.003]	[0.003]
difference	0.218***	0.298***	0.035***	0.012***	0.043***
	[0.003]	[0.006]	[0.006]	[0.003]	[0.003]
explained	0.227***	0.218***	0.058***	0.041***	0.053***
	[0.004]	[0.007]	[0.004]	[0.002]	[0.003]
unexplained	-0.009*	0.080***	-0.023***	-0.028***	-0.011**
	[0.005]	[0.009]	[0.006]	[0.004]	[0.004]
N matched natives	713,968	329,469	89,113	120,534	174,852
N European refugees	245,810	48,607	22,902	70,837	103,464
Total obs	959,778	378,076	112,015	191,371	278,316

Notes: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimations based on correlated random effects model eq. Reference group matched natives. Wage earnings relative to median wage earnings in respective year.

Table 13: Twofold Blinder-Oaxaca wage decomposition for non-European refugees, years 2003-2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.245***	1.514***	1.003***	0.878***	1.103***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
non-European refugees	1.065***	1.310***	0.993***	0.922***	1.045***
	[0.003]	[0.006]	[0.008]	[0.003]	[0.004]
difference	0.181***	0.204***	0.009	-0.044***	0.057***
	[0.003]	[0.007]	[0.009]	[0.003]	[0.004]
explained	0.135***	0.087***	-0.009**	-0.014***	0.033***
	[0.004]	[0.008]	[0.005]	[0.002]	[0.003]
unexplained	0.046***	0.117***	0.019*	-0.030***	0.025***
	[0.005]	[0.010]	[0.010]	[0.004]	[0.005]
N matched natives	713,968	329,469	89,113	120,534	174,852
N non-European ref	145,550	37,670	13,012	55,031	39,837
Total obs	859,518	367,139	102,125	175,565	214,689

Notes: see Table 12.

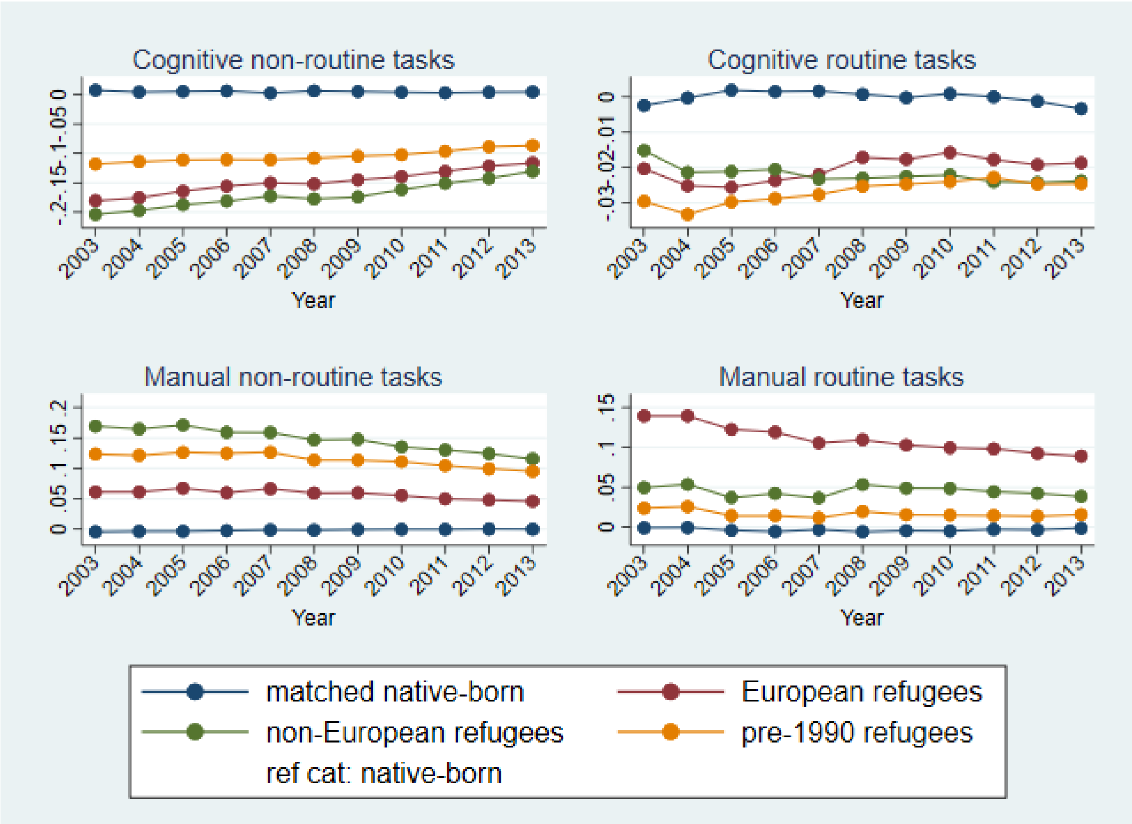
Table 14: Two-fold Blinder-Oaxaca wage decomposition for pre-1990 refugees, years 2003-2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.247***	1.514***	1.007***	0.882***	1.101***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
before 1990s refugees	1.116***	1.350***	1.011***	0.933***	1.077***
	[0.003]	[0.006]	[0.007]	[0.004]	[0.004]
difference	0.131***	0.164***	-0.004	-0.051***	0.025***
	[0.004]	[0.007]	[0.007]	[0.004]	[0.004]
explained	0.103***	0.083***	0.035***	-0.001	0.018***
	[0.003]	[0.006]	[0.003]	[0.002]	[0.002]
unexplained	0.028***	0.081***	-0.039***	-0.050***	0.006
	[0.004]	[0.009]	[0.008]	[0.004]	[0.004]
N matched natives	713,968	329,469	89,113	120,534	174,852
N pre-1990 refugees	160,722	53,528	14,182	52,497	40,515
Total obs	874,690	382,997	103,295	173,031	215,367

Notes: see Table 12.

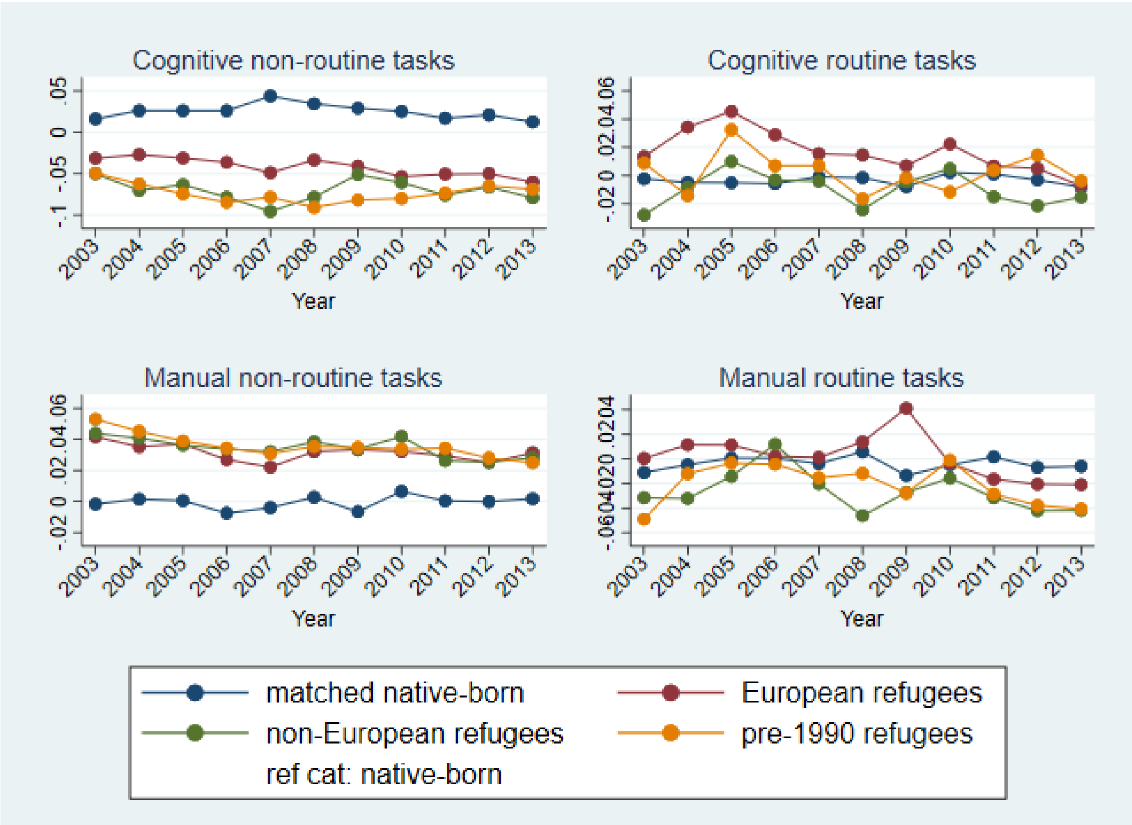
C Figures

Figure 1: Marginal effect of population group on the probability to belong to occupational category k



Notes: Marginal effects from a multinomial logit model with the following control variables: year, gender, municipality of work, marital status, number of children, age category, experience, highest education qualification attained, size of work establishment, industry classification.

Figure 2: Marginal effect of population group on wage earnings in occupational category k



Notes: Marginal effects from a correlated random effects model with wage as the dependent variable and the following control variables: year, gender, municipality of work, marital status, number of children, age category, experience, highest education qualification attained, size of work establishment, industry classification.