GLO Discussion Paper No. 562

Occupational Sorting and Wage Gaps of Refugees*

Christopher F Baum (Boston College and DIW Berlin)
Hans Lööf (Royal Institute of Technology, Stockholm)
Andreas Stephan (Jönköping University and DIW Berlin)
Klaus F. Zimmermann† (UNU-MERIT, Maastricht University, CEPR and GLO)

June 17, 2020

Abstract

Refugee workers start low and adjust slowly to the wages of comparable natives. The innovative approach in this study using unique Swedish employer-employee data shows that the observed wage gap between established refugees and comparable natives is mainly caused by occupational sorting into cognitive and manual tasks. Within occupations, it can be largely explained by differences in work experience. The identification strategy relies on a control group of matched natives with the same characteristics as the refugees, using panel data for 2003–2013 to capture unobserved heterogeneity.

JEL: C23, F22, J24, J6, O15

Keywords: refugees, wage earnings gap, Blinder—Oaxaca decomposition, employer-employee data, coarsened exact matching, correlated random effects model

*We thank participants at the following seminars and conferences for comments and suggestions on earlier versions of the paper: KTO-OFCE-GREDEG 2016, Sophia Antipolis, AFSE 2017, Université Côte d'Azur, Nice, WRSA 56th Annual Meeting 2017, Santa Fe, The International Conference on Immigration and Labour Market 2017, Gothenburg, The 11th Computational and Financial Econometrics CFE 2017, London, International Workshop on Computational Economics and Econometrics IWcee 2017, National Research Council, Rome, Asian Development Bank 2017, Manila, EcoMod Conference 2017, University of Ljubljana, Växjö university 2018, Portuguese Stata Conference 2020, Porto and University of Minho, Braga, Swedish Ministry of Employment 2020, Stockholm.

†Corresponding author: klaus.f.zimmermann@gmail.com. Author contact emails: kit.baum@bc.edu, hans.loof@indek.kth.se, Andreas.Stephan@ju.se

1 Introduction

The labor market consequences of refugee immigration have been a major concern in the public in many countries around the globe, and have also caused lively debates in the economics literature (Card, 1990; Peri and Yasenov, 2019; Borjas and Monras, 2017; Clemens and Hunt, 2019; Foged and Peri, 2016; Tumen, 2015, 2016; Balkan and Tumen, 2016). For the receiving countries, a crucial concern is the ability of migrants to integrate well in their new society and become productive members of the workforce. This paper addresses the question of what we can learn from earlier waves of refugees in order to better understand labor market integration for current and future flows of refugees.

The broad conclusion one can draw from an extensive literature is that the employment effect is negative and associated with slow integration of refugees into the host country labor market in comparison to other groups of immigrants and natives: see Dumont, Liebig, Peschner, Tanay and Xenogiani (2016) and Zimmermann (2017). This line of research includes Fasani, Frattini and Minale (2018) for the EU; Åslund, Forslund and Liljeberg (2017); Luik, Emilsson and Bevelander (2018) for Sweden; Sarvimäki (2017) for Finland; Schultz-Nielsen (2017) for Denmark ; Bakker, Dagevos and Engbersen (2017) for Holland and Ruiz and Vargas-Silva (2018) for the UK.

While refugees' employment probabilities may adjust to those of the natives after 15–20 years in the receiving country, wages may not converge at all which leads to a debate on inequality and productivity concerns of refugee immigration. Therefore, labor market experience, occupational sorting and the wage performance of established refugee workers are promising new research topics. Successful migrants in the labor market also help to avoid negative attitudes of the natives against foreigners (Bauer, Lofstrom and Zimmermann, 2000).

The present study examines effects of occupational sorting on wage differentials of refugees and reveals underlying driving factors. It contributes to the literature on the productivity of refugee workers, as captured by wage income, by exploiting high quality Swedish labor market data, applying recent findings from the skill biased technical change literature, and combining the occupational sorting approach with an appropriate matching technique and identification strategy.

As a consequence of the country's refugee-friendly migration policy in recent decades, Sweden has the largest share of the population with a refugee background of any European nation. Sweden also allows asylum seekers to work immediately after the application process for refugee status is lodged, while most other European countries have substantially longer waiting periods (Constant and Zimmermann, 2016; Zimmermann, 2017). Sweden is therefore a good case study for the topic. In 2015 more than 162,000 asylum seekers filed applications in Sweden, which along with Germany (477,000) and Hungary (177,000) were the preferred European destinations for a wave of mainly Syrian and Afghan asylum seekers. The previous largest wave of refugees to Sweden occurred in the 1990s during the Yugoslav collapse, division of the country, civil war, terror and ethnic cleansing in the 'Bosnian War'. This refugee wave peaked in 1992 with 84,000 asylum seekers (Constant and Zimmermann, 2016). A total of more than 100,000 former Yugoslavs, predominantly Bosnians, received a new homeland in Sweden.

During the 1980s, Sweden was also an attractive European destination for many asylum seekers.

A refugee as defined in this paper is an asylum seeker whose request for refugee status in Sweden, according to the framework for the international regime of refugee protection, has been approved and therefore has full access to the labor market. Unlike most European countries (Constant and Zimmermann, 2016), the vast majority of refugees who successfully applied for permission to stay in Sweden before 2016 received permanent status.[1] Our study is restricted to refugees born between 1954 and 1980 who entered Sweden before 1997. In total, we study about 100,000 unique refugee workers, and follow their labor market performance during the period 2003–2013. The groups analyzed are European refugees arriving in the 1990s, non-European refugees entering Sweden in the 1990s, and all pre-1990 refugees.

We use very detailed population-level administrative register data that contains information on occupations, work history and wages for 27 fixed cohorts of individuals over 20 years in combination with administrative firm level data as an employer-employee panel. The data, covering the full population of firms and employees in Sweden, enable us to study both the impact of individual workers' characteristics and workplace-related circumstances on workers' wage earnings.

The empirical analysis is conducted for established workers, defined as those earning at least 60% of the median monthly wage for the relevant occupation, cov-

[1]https://www.asylumineurope.org/reports/country/sweden/content-international-protection/status-and-residence/residence-permit. This has changed significantly in 2016 with a move to a more temporary legislation and practice.

ering only refugee migrants who managed to basically integrate into the Swedish employment system. Are there still wage differentials after successful integration? To identify those potential wage earnings differentials, we employ a coarsened exact matching (CEM) approach where a control group of native-born individuals from the full population is chosen having the same characteristics as the refugee immigrants. Those characteristics include age, gender, marital status, number of children, education and place of living.

We study occupational sorting by delineating occupational categories along 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 the skill intensity of occupational tasks and wage earnings. Whereas most previous studies have compared refugee outcomes directly with those of natives, our matching approach facilitates identification of the causal impact of refugee background on the workers' observed wage earnings, considering all available other important characteristics including their educational background. The paper examines the determinants of 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 routine, (3) manual non-routine, and (4) manual routine.

The empirical estimates show that, ceteris paribus, refugee immigrants are significantly less likely to work in the better-paying cognitive non-routine task categories, but 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 initial category. Our results suggest that an early sorting into low-skilled manual occupations after arriving in the host country may hamper a future transition to better paying occupations.

We then 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. In a robustness test, we apply several IV approaches and account for selectivity bias. Based on the wage earnings equations, which documents the existence of a wage gap, we apply the Blinder–Oaxaca technique (Blinder, 1973; Oaxaca, 1973) 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. On average, there is 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) or persistent wage discrimination against refugees are responsible for the observed wage gap.

Surprisingly, while the wage earnings of refugees are lower than those of natives 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.

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 by early occupational sorting. 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 observed shortage of skilled labor.

The paper is structured as follows. In Section 2, we briefly introduce the policy background for our research focus in Sweden, present the data and descriptive statistics. The empirical analysis is carried out in Section 3 followed by a robustness study in Section 4. Section 5 concludes.

2 Background

2.1 The Swedish refugee and labor market policy context

The purpose of the paper is to shed more light on refugees' wage performance by analyzing the impact of occupational sorting on the observed wage gap between refugee immigrants and native-born workers. Our research agenda is the systematic and representative longitudinal analysis of refugees' labor market integration in a knowledge-based economy. This links two strands of the labor market literature, (i) migration economics and (ii) technological change and skills. We are able to study the labor market performance of refugee workers over the decade 2003–2013, who entered the country before 1997 with a permanent status and their occupational orientation.

There were several policy changes in Swedish migration policy during the period for our study that might have affected the conditions for labor market integration conditional on the time of arrival. One change concerns teaching of the Swedish language (Swedish for immigrants, SFI) which is a key integration issue. While in the 1970–1980s, the education included a broad set of aspects such as civil rights, obligations and participation in both society the working life, since 1990 there has been a stronger focus on employability. Another change concerns settlement policies. Between 1987 and 1991, 90% of newly arrived asylum seekers were mandatorily placed in municipalities with plenty of vacant housing rather than those with a high demand for employment. When refugees were granted a residence permit, they were allowed to move freely, and a large proportion chose to move when given the opportunity. This implies a significant potential to adjust to labor market needs.

To compare wages for refugees and matched native workers, we adopt the occupational classification scheme of the skill biased technical change (SBTC) literature based on Autor, Levy and Murnane (2003), Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018). This literature highlights the increasing wage gap between non-routine and routine tasks, and in particular an increasing gap between cognitive and manual work tasks as a consequence of technical change and increased skill intensity. Broadly, non-routine cognitive tasks require problem-solving skills, critical thinking and decision making, with technology as an important complement to skills. Routine-based occupational tasks are those performed through step-by-step guidelines or specific rules. It is assumed that routine manual tasks and routine cognitive tasks can relatively easily be replaced with technology and are therefore expected to be a substitute for technological innovation.

In the early 2000s, the fraction of Swedish employment related to routine manual tasks (production, craft and repair, operators, fabricators and laborers) and routine cognitive tasks (sales, office and administrative support) was close to 40%. This share decreased to about 35% in 2013. Similar to many other OECD economies, a large proportion of the Swedish labor force is involved in non-routine analytic work. In 2003, 42% of the labor force was associated with non-routine cognitive tasks (professionals, associate professionals, managers and technicians). By 2013, this share had increased slightly. About one in five workers were occupied by non-routine manual tasks (personal care, staff services, protective services, food service and cleaning services) during the period of our analysis.

Occupational sorting, in combination with low occupational mobility, might have significant economic consequences for refugees' labor market integration. Migrants often cannot enter particular skilled occupations due to their education, prior experience or licensing requirements. It might also be too late to acquire additional professional education or licensure. Hence, if refugees are stuck in particular categories, it is likely that wage gaps persist. 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.

2.2 Data

The data for the analysis were provided by Statistics Sweden and contain extensive information on all individuals in Sweden born between 1954 and 1980 as well as variables related to all firms in Sweden, accessed through the remote MONA (microdata online access) delivery system. Appendix A discusses the various sources of the data in more detail. The variables constructed from these sources include population groups (natives, various refugee groups), demographics (gender, age, marital status, preschool children), education, citizenship, work characteristics (occupational tasks, work experience, wage), firm characteristics (industry, firm size) and geographics (muncipalities, rural areas, regions), and are described in more detail in Table 1.

The information on the migration background of a person is used to identify all refugee immigrants who arrived in Sweden before 1997 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 origin. We delineate the first two groups because one could assume that European refugee immigrants may be subject to less discrimination in the labor market than non-European refugees.

In order to make a valid comparison of the wage earnings of refugees with those of natives, a control cohort of native-born workers with similar characteristics to the refugee cohorts with regard to important characteristics is created. We include only persons born in Sweden with no more than one parent born abroad in the comparison group of natives. The control cohort is constructed by employing coarsened exact matching (CEM) (Iacus, King and Porro, 2012; Blackwell, Iacus, King and Porro, 2009; King, Lucas and Nielsen, 2017) where refugees constitute the "treatment" group and the "control" group is created from the native born. The CEM procedure balances the cohorts of natives and refugees for the following variables: gender, education, citizenship, number of children, region where the person lives (district) and birth year (see Table 2). For the former variables an exact match is performed, while for birth year coarsened matching is applied. Table 2 shows that the resulting measure of imbalance is very small.

The three refugee groups defined above, designated as cohorts 3, 4, and 5, constitute our fixed cohorts for analysis. The two comparison groups of natives contain randomly selected natives (cohort 1) and the CEM-matched sample (cohort 2). We observe the labor market outcomes of these five cohorts over the period 2003–2013.

Following Acemoglu and Autor (2011), we classify all workers into task categories, defined in Table 3: (1) cognitive non-routine work tasks (professionals, managers and technicians), (2) cognitive routine tasks (office and administrative support and sales), (3) manual non-routine tasks (personal care, personal service, protective service, food and cleaning) and finally (4) manual routine tasks (production, craft, repair, operators, fabricators and laborers).

The self-employed are excluded from all chosen samples as they exhibit quite different behavior than the standard workers who are the focus of our analysis. We further concentrate on individuals that earn at least 60% of median wage earnings, differentiated by gender, considering them as established in the labor market. How do established refugee workers differ from comparable natives?

2.3 Descriptive findings

Table 4 shows that over the period 2003–2013, on average 85% 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%. Table 4 also reveals that about 88% of employed individuals of the matched native cohort are established in the labor market, while the shares for the refugee cohorts are lower with non-European refugees being lowest with about 75%. In all groups the share of individuals with Swedish citizenship is lowest for pre-1990 refugees with 92%, while for natives it is more than 99%.

Table 5 reports how workers in population groups are distributed across occupational task groups. Among matched natives, about 49% of workers work with cognitive non-routine tasks. Closest to this share are pre-1990 refugees with 34%. The lowest share is observed for European refugees, while individuals from this group are most likely to work with manual routine tasks (42% vs. 24% for the matched natives). Among the non-European refugees, most work with manual non-routine tasks (38% vs. 15% among matched natives).

Table 6 displays the average normalized wage earnings for the different population groups across occupational task groups, scaled to median wages in each year. There are significant differences for the first occupational task category: cognitive non-routine tasks. While the matched group of natives have wages 57% higher than median wage in the cognitive non-routine occupations, European refugees have only 25% higher wages, while non-European and pre-1990 refugees have 34% and 38% higher wages, respectively. However, for manual non-routine tasks these two groups have higher wages than native born workers.

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

Table 8 shows the variable 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 6% of matched natives have this degree. However, the difference for the master's degree is smaller, 10.5% vs. 9%. Refugees are less likely to work in micro firms (9 and 11% vs. 17% for matched natives), but more likely to work in medium sized firms. They are less likely to work in knowledge intensive services (KIS: e.g., in financial sectors) but more likely to work in low-tech manufacturing or other low-tech service sectors. Non-European and pre-1990 refugees live to a larger extent in metro regions (more than 61%) where European refugees are more similar to matched natives.

Table 9 shows the variable means for those who work in cognitive non-routine occupations. We see that for refugees, a greater share of women work in this task category, and refugees have on average more formal education compared to their peers. More than 31% have a master's degree, whereas the corresponding figure for matched natives is only 17%. Refugees in these 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 Empirical analysis

This section reports our empirical analysis in three steps. First, we estimate the likelihood of a worker being sorted into a specific occupational task category. Wage differentials between native workers and refugees within each wage task category are then calculated. In the final analysis, these wage differences are decomposed into explained and unexplained parts. We use panel data with variables from the period 2003–2013 along with prior information. The refugee sample of almost 100,000 individuals is matched with a similar-sized group of native individuals. The reference group consisting of randomly selected native individuals is also of the same size. In the econometric analysis, the total number of worker-year differs between the groups, reflecting disparities in labor market participation. The robustness section tests the sensitivity of the basic results for alternative definitions of workers' established status. We employ a multinomial logit approach to estimate occupational sorting, and a correlated random effects model for the wage analysis.

The analysis in the sequel is based on the merged samples for the five groups defined above: the two comparison groups of natives, randomly selected natives (cohort 1) and the CEM-matched sample (cohort 2), and the three refugee worker groups, European refugees (cohort 3), non-European refugees (cohort 4) and pre-1990 refugees (cohort 5). The individual cohort sizes are provided in Table 8. The total sample of worker-years in the regressions below is 1,936,101.

3.1 Occupational sorting

We employ a multinomial logit (MNL) model to analyze 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. Table 10 presents the average marginal effects (AMEs) from this estimation. We find that the choice of 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 tasks. The likelihood to work in cognitive non-routine occupations increases with experience and education, while for manual non-routine tasks we find the opposite.

While controlling for all of the background variables, we find that refugees are significantly less likely to work with cognitive non-routine tasks in comparison to the CEM-matched sample of natives. 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 displays marginal effects from interactions with year dummies. It is based on a 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, and industry classification. Refugees' probability to hold a non-routine cognitive job was about 15% to 20% lower, than that of natives in 2003, and the gap is only moderately reduced by 2013. Note that the reference category contains randomly selected natives so that we can illustrate the differences between the matched native-born and the three refugee cohorts. As is evident from the figure, there is almost no difference between matched natives and random natives. 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 is 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, institutional or legal constraints, or other unobserved variables and individual characteristics.

3.2 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 model in that it enables estimation of the effects of time-invariant variables such as a worker 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 those 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 corresponds 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 denotes 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 $\hat{\beta}_b$ have a direct interpretation, we prefer the hybrid model formulation over the CRE specification. While the within estimate $\hat{\beta}_w$ shows the effect of a time-varying variable on the outcome for an individual, the between estimate $\hat{\beta}_b$ can be interpreted as the long-term impact of that variable.

Table 11 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 the 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.

Columns 1–5 of Table 11 report several notable estimates. First, women earn on average 27% less than men, all else equal, and in the various occupational groups between 15 and 34% less than men. The effects for the various cohorts are much less pronounced. Overall, European refugees earn about 2.3% more than matched natives over all occupations, while non-European refugees earn about 3.3% less. Pre-1990 refugees earn on average 5.4% less than the matched natives. The differences between matched natives and refugees are most apparent for cognitive non-routine tasks. European refugees earn 5% less than matched natives, and non-European and pre-1990 refugees earn about 11.0–11.4% less. All refugees have about 4.2–4.6% higher earnings than matched natives in manual non-routine task categories, perhaps due to overqualification.

While the short-term effect of switching to cognitive non-routine tasks from manual routine tasks is only 4.2% on average, the between estimates show that the long-term difference is 35%. 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 task 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 27% 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, reflecting a worker changing task category, is less pronounced. In Figure 2, the effect from a task category is interacted with the year dummies to examine how the connection 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.

3.3 Wage Discrimination

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)

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

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) 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 results above, using matched natives as the reference group and the respective refugee group as the comparison group. The results are shown in Tables 12 to 15. The lower part of each table separates estimate wage differences into an explained and an unexplained part. Our analysis of the contribution of the explanatory variables to the explained difference shows that it is mainly due to differences in accumulated work experience of refugees and natives (see Table 8).

Over all occupations, as shown in the first column of Tables 12 to 15, the unexplained wage difference between refugees and matched natives are relatively small: 2.1% lower wages for all refugees in Table 12, 3.1% higher for European refugees in Table 13, 5.1% lower for non-European refugees in Table 14, and 5.1% lower relative wages for pre-1990 refugees in Table 15. Larger unexplained wage differences are found for cognitive non-routine task categories (column 2), where the unexplained differences are 11.9% lower for all refugees (Table 12), 7.4% lower for European refugees (Table 13), 13.6% lower for non-European refugees (Table 14) and the unexplained gap is 9.6% for pre-1990-refugees (Table 15).

Tables 16 and 17 present Blinder–Oaxaca wage decomposition results separately for male and female refugees. While the wage gap between native and refugee males is more than 30%, the relative wage difference in only 8% for females. The model predicts well for both genders in column 1 of Tables 16 and 17, which reports results for the combined four occupational categories. However, there are two noticeable deviations from this finding when we consider the individual categories. Column 2 of Table 16 shows that more than 60% of the wage differences between males in non-routine cognitive task are unexplained, with a similar result in column 4 of Table 17 for females in the non-routine manual group. Table 16 reports that male refugees in non-routine cognitive occupations have lower wages compared to the model's prediction, and Table 17 shows that female refugees in non-routine task categories earn higher wages than predicted.

Tables 18 and 19 delineate the cognitive non-routine task into twelve subgroups, and show that the estimated relative wage gap varies between 28% lower wages (electronics and telecommunication engineers) and 10% higher wages (non-specialist nurses). The tables also reveal that the unexplained part of the wage differences is significantly larger than the explained part for several of the cognitive non-routine subgroups. How might this be interpreted?

The results might be indicative of wage discrimination in the labor market. However, as the unexplained part is not uniformly negative, other factors matter. Refugees earn higher wages than predicted by the model in the education and health care sectors, while we find the opposite among technicians, engineers and public administrators. It is possible to trace a public–private sector dimension in this difference between the work task which could imply greater discrimination in the private sector. Another tentative explanation is unobserved abilities related to the impact of ongoing technological change on the demand for labor. Freeman, Ganguli and Handel (2020) find that the within–occupation impact of technological changes dominated changes between occupations in the U.S. economy over the period 2005–2015. If this pattern is also relevant for the Swedish economy, which is likely, it can be assumed that workers with larger ability are more prone to switch to new, more productive and higher-paid job tasks within the cognitive non-routine group.

For the three other occupation categories in tables 12, 13, 14 and 15, the wage gap between natives and refugees is substantially smaller compared to cognitive non-routine tasks, and the explained wage differences are generally larger than the unexplained differences. Notably, all three refugee categories in the study earn more than natives in manual non-routine occupations, and that the unexplained differences are significantly larger than the explained differences. Similar to our discussion above, unobserved ability might contribute to the results. If this is the case, refugees may have higher ability compared to natives in non-routine manual job tasks.

4 Robustness checks and discussion

As years of labor market experience is a key determinant to the differences in wage income between natives and refugees in our results, as a first robustness check we considered the sensitivity of results to an alternative definition. In the regression analysis, we count experience as the number of years when an individual has labor income, starting with 1993. Obviously there may be problems with this measure as it does not capture the intensity of work effort. We therefore imposed a restriction on *establishment* on the labor market, defined as wage earnings above a 60% threshold of monthly median labor income in that industry. As a robustness test we reestimated the Blinder–Oaxaca decompositions without this restriction, defining work experience as the number of years when an individual is established, and found that the unexplained wage differences between natives and refugees increase, but that the relevance of experience prevailed.

An additional robustness check for the worker's experience variable was to consider only individuals with employment during the period 1998–2013 in the empirical analysis. The justification for this test is the large initial difference in the employment rate between refugees and other immigrants. It takes several years for refugees to establish themselves in the labor market. Comparing the result for experience over the full period 1993–2013, we once again found reduced explanatory power for work experience.

Our interpretation of the two sensitivity tests is that labor market experience is the most significant factor influencing the relative wages for refugee immigrants. This also seems to apply to the years when the connection to the labor market has been weak, which is more common among refugees.

There are two potential concerns regarding these analyses. The first is that accumulated work experience might be endogenous, affected by unobserved factors such as ability or motivation. Furthermore, it is plausible that accumulated work experience is affected by wage income. To address this concern, we implemented several instrumental variables (IV) approaches. The first instrument we use in these tests is the occurrence of having twin children. Twin children can be found 850 times in our sample.[2] We define two instruments for the tests: having twin children of ages 0–3 years and having twin children of ages 4–6 years. As expected, we find that having twins in the age between 4 and 6 years also reduces work experience, but to a significant lower extent compared to having twins between 0–3 years old. The Hansen J test of overidentifying restrictions supports the validity of the IVs at conventional levels, and weak instruments tests are satis-

[2]While our dataset does not provide direct information on having twins, we infer their presence indirectly from the change of the number of children with ages 0–3 years. If this change is 2 or more in a year, we classify this is as an indication of having or adopting twin children. Although Sweden allows for generous benefits while being on parental leave, having small children below the general school age of 7 years reduces accumulated work experience, in particular for women. This effect is even stronger with twins, so that having twins exerts a negative shock to work experience. As one can assume that adding twins to the family is generally a random event, this satisfies the IV exogeneity assumption.

factory. Note that these IV estimations indicate only very mild levels of potential endogeneity of experience, with p-values of endogeneity tests between 2.5% and 8.0%.[3]

For the refugee cohorts we are able to conduct additional endogeneity tests regarding work experience. For these cohorts we utilize the fact that the asylum decision was granted in different quarters of the year for various persons, as the length of processing times vary. There is also a seasonal tendency in the total number of asylum decisions, with fewer decisions in summer and more at the end of the year. Interestingly, the quarter of positive asylum decision also affects the accumulated work experience in later years. Persons that have obtained their asylum decision in the first quarter of the year have on average about half a year more accumulated work experience compared to refugees who obtained their decision in the third or fourth quarters of the year. We base the test of endogeneity of work experience on using the CRE model for wage income and inserting the residuals from the first-stage regression as an additional regressor. By doing so, this regression equation equation becomes a control function approach. As the coefficient on the residual is not significant, there is no evidence supporting the endogeneity of experience from these tests using the quarter of asylum decision as exogenous variation.

A second potential concern is that we might overestimate the effect of belonging to occupational task group 1. A person in this group might have earned a higher wage than others in other task groups, leading to a selection of persons

[3] The IV–GMM estimations have been performed with Stata's `xtivreg2` command and are available from the authors upon request.

with higher ability into task group 1. We address this concern by using a model that predicts whether a person is working in task group 1 or not. As an excluded instrument, we use the initial random allocation of refugees to regions, which is the region where an asylum seeker was first registered in Sweden. To reduce their impact on metropolitan areas, arriving refugees were located across smaller cities and rural districts of Sweden.

For natives, we use the municipality where a person was registered in 1990. For younger individuals, this could be the municipality where the person is born. We classify the municipalities into the six categories shown in Table 1. Probit model results highlight that persons that were initially located in metropolitan or densely populated regions have respectively a 52% and 31% percent higher probability to work in task group 1 in later years compared to persons initially located in remote regions. The results show that the error terms of the selection equation and the wage outcome equation have a low negative and significant correlation. More importantly, in the full model, the coefficient of belonging to task group 1 on wage income increases from 4.8 to 6.4 percent. This suggests that we most likely do not overestimate, but rather underestimate, the effect of belonging to task group 1 on wage.[4] However, the difference in point estimates between these models is not statistically significant.

As a further robustness check, we consider the impact of applying the coarsened exact matching (CEM) approach vis-a-vis the more common propensity score

[4] In this case, we use Roodman's `cmp` Stata command (Roodman, 2011) to estimate a probit model that explains the likelihood of a person to work in task group 1 jointly with the wage income equation. The results are available from the authors upon request.

matching (Caliendo and Kopeinig, 2008). We obtained qualitatively similar results.

Finally, we also compare the Blinder–Oaxaca decomposition for refugee-immigrants and other immigrants. We applied CEM again to define a matched sample of foreign-born non-refugee immigrants using the same criteria. These foreign-born workers from home countries outside of the Nordic countries and the EU emigrated to Sweden during the same period when the refugee immigrants arrived in Sweden. The results of the Blinder–Oaxaca decomposition are shown in Table 20. While the wage incomes in most task groups are very similar to those of refugees, there is a remarkable and significant difference for cognitive non-routine tasks, where foreign-born non-refugees earn about 8% more than the corresponding refugee immigrants. This difference, however, is less than the observed difference of 25% between refugees and natives for cognitive non-routine tasks. Only 4.5% of the difference remains unexplained in the Blinder–Oaxaca decomposition, whereas 12% of the difference between natives and refugees remains unexplained. Regarding individual characteristics, it is worth noting that for this task group the average work experience of about 10 years is very similar between those two groups of immigrants. Also, that the share of immigrants that work with cognitive non-routine tasks is very similar (26 vs. 27%) in both immigrant groups.

How can we understand the wage differences between refugee immigrants and other immigrants occupied with cognitive non-routine tasks? A tentative explanation may be that other immigrants to a large extent consist of labor market immigrants and immigrants with a Swedish degree who arrived as students. Probably these immigrants are better integrated on arrival into the Swedish economy in the form of recruited specialists or well-qualified students, and therefore might be less exposed to the discrimination that may be most noticeable within cognitive non-routine occupations.

5 Conclusions

Previous research has found that refugee migrants integrate slowly into the labor market and have lower wages than natives during the adjustment period, indicating a productivity problem. This paper studies long-term wage differences between established refugees and comparable natives in Sweden over the period 2003–2013. For this analysis, we were able to exploit comprehensive administrative register employer-employee data to compare wages for occupational task groups for individuals with similar socioeconomic characteristics within and across industries. Established refugee workers have a job, they earn a decent salary, but why do they still earn a lower salary than comparable natives?

Employing an innovative matching approach for identifying the causal effects, we find that the observed wage gap between established refugees and their native counterpart in Sweden is mainly explained by two factors. The first is occupational sorting into different tasks. The predicted probability of refugee immigrants of working in higher-paid cognitive non-routine 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 of working in manual occupational task categories, where they tend to remain. Mobility across occupational categories is low for both native-born workers and refugee workers, but is relatively lower for refugee workers.

The second potential explanation of wage differentials relates to personal characteristics. On average, native-born workers have more accumulated work experience. Refugees may have difficulty in gaining relevant work experience, particularly during the process of achieving permanent status. 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 reflect missing personal characteristics or institutional constraints on occupational mobility.

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) and the role of cognitive and non-cognitive skills of refugee migrants for occupational allocations and wage formation.

References

Acemoglu, D. and Autor, D. (2011), 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.

Acemoglu, D. and Restrepo, P. (2018), 'The race between man and machine: Implications of technology for growth, factor shares, and employment', *American Economic Review* **108**(6), 1488–1542.

Åslund, O., Forslund, A. and Liljeberg, L. (2017), Labour market entry of non-labour migrants–Swedish evidence, *in* B. Bratsberg, O. Raaum, K. Røed and O. Åslund, eds, 'Nordic Economic Policy Review: Labour Market Integration in the Nordic Countries', Nordisk Ministerråd, pp. 115–158.

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.

Bakker, L., Dagevos, J. and Engbersen, G. (2017), 'Explaining the refugee gap: a longitudinal study on labour market participation of refugees in the Netherlands', *Journal of Ethnic and Migration Studies* **43**(11), 1775–1791.

Balkan, B. and Tumen, S. (2016), 'Immigration and prices: quasi-experimental evidence from Syrian refugees in Turkey', *Journal of Population Economics* **29**(3), 657–686.

Bauer, T. K., Lofstrom, M. and Zimmermann, K. F. (2000), 'Immigration policy, assimilation of immigrants and natives' sentiments towards immigrants: evidence from 12 OECD countries', *Swedish Economic Policy Review* **7**, 11–53.

Blackwell, M., Iacus, S. M., King, G. and Porro, G. (2009), 'CEM: Coarsened exact matching in Stata', *Stata Journal* **9**(4), 524–546.

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*

Borjas, G. J. and Monras, J. (2017), 'The labour market consequences of refugee supply shocks', *Economic Policy* **32**(91), 361–413.

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*

Card, D. (1990), 'The impact of the Mariel boatlift on the Miami labor market', *ILR Review* **43**(2), 245–257.

Clemens, M. A. and Hunt, J. (2019), 'The labor market effects of refugee waves: reconciling conflicting results', *ILR Review* **72**(4), 818–857.

Constant, A. F. and Zimmermann, K. F. (2016), 'Towards a new European refugee policy that works', *CESifo DICE Report* **14**(4), 3–8.

Dumont, J., Liebig, T., Peschner, J., Tanay, F. and Xenogiani, T. (2016), How are refugees faring on the labour market in Europe?, OECD Working Paper 1/2016.

Fasani, F., Frattini, T. and Minale, L. (2018), (The Struggle for) Refugee Integration into the Labour Market: Evidence from Europe, IZA Discussion Paper 11333.

Foged, M. and Peri, G. (2016), 'Immigrants' effect on native workers: New analysis on longitudinal data', *American Economic Journal: Applied Economics* **8**(2), 1–34.

Freeman, R. B., Ganguli, I. and Handel, M. J. (2020), Within-occupation changes dominate changes in what workers do: A shift-share decomposition, 2005–2015, *in* 'AEA Papers and Proceedings', Vol. 110, American Economic Association, pp. 394–399.

Groes, F., Kircher, P. and Manovskii, I. (2015), 'The u-shapes of occupational mobility', *The Review of Economic Studies* **82**(2), 659–692.

Iacus, S. M., King, G. and Porro, G. (2012), 'Causal inference without balance checking: Coarsened exact matching', *Political Analysis* **20**(1), 1–24.

Jann, B. (2008), 'The Blinder–Oaxaca decomposition for linear regression models', *Stata Journal* **8**(4), 453–479.

King, G., Lucas, C. and Nielsen, R. A. (2017), 'The Balance-Sample Size Frontier in Matching Methods for Causal Inference', *American Journal of Political Science* **61**(2), 473–489.

Luik, M.-A., Emilsson, H. and Bevelander, P. (2018), 'The male immigrant–native employment gap in Sweden: migrant admission categories and human capital', *Journal of Population Research* **35**(4), 363–398.

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*

Peri, G. and Yasenov, V. (2019), ‘The labor market effects of a refugee wave: Synthetic control method meets the Mariel boatlift’, *Journal of Human Resources* **54**(2), 267–309.

Roodman, D. (2011), ‘Fitting fully observed recursive mixed-process models with cmp’, *Stata Journal* **11**(2), 159–206.

Ruiz, I. and Vargas-Silva, C. (2018), ‘Differences in labour market outcomes between natives, refugees and other migrants in the UK’, *Journal of Economic Geography* **18**(4), 855–885.

Sarvimäki, M. (2017), Labor market integration of refugees in Finland, *in* B. Bratsberg, O. Raaum, K. Røed and O. Åslund, eds, ‘Nordic Economic Policy Review: Labour Market Integration in the Nordic Countries’, Nordisk Ministerråd, pp. 91–114.

Schultz-Nielsen, M. L. (2017), Labor market integration of refugees in Denmark, *in* B. Bratsberg, O. Raaum, K. Røed and O. Åslund, eds, ‘Nordic Economic Policy Review: Labour Market Integration in the Nordic Countries’, Nordisk Ministerråd, pp. 55–89.

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.

Tumen, S. (2015), ‘The use of natural experiments in migration research’, *IZA World of Labor* .

Tumen, S. (2016), 'The economic impact of Syrian refugees on host countries: Quasi-experimental evidence from Turkey', *American Economic Review* **106**(5), 456–60.

Wooldridge, J. M. (2010), *Econometric Analysis of Cross Section and Panel Data*, 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*

Zimmermann, K. F. (2017), Refugee and Migrant Labor Market Integration: Europe in Need of a New Policy Agenda, *in* R. Bauböck and M. Tripkovic, eds, 'The integration of migrants and refugees: an EUI forum on migration, citizenship and demography', European University Institute, pp. 88–100.

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 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, organizational classifications, locations, 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: 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**
citizenship	Swedish citizenship: 1=yes, **0=no**
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**
region	aggregated from the 21 counties, 1=Stockholm, 2=Scania, 3=Västra Götaland, 4=south, **5=middle and north Sweden**

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

Table 2: Coarsened Exact Matching (CEM) Summary (native and refugee individuals)

Number of strata: 20114
Number of matched strata: 9644

Refugee	0	1
All	2,603,815	101,453
Matched	99,882	99,882
Unmatched	2,503,933	1,571

Multivariate L1 distance: .03862558

Univariate imbalance:

	L1	mean	min	25%	50%	75%	max
female	0	0	0	0	0	0	0
married	0	0	0	0	0	0	0
educ	0	0	0	0	0	0	.
kids0_3	0	0	0	0	0	0	0
kids4_6	0	0	0	0	0	0	0
region	0	0	0	0	0	0	0
birthyear	.00723	.001	0	0	0	0	0

Notes: The upper panel of the table reports the number of individuals that are matched, while the lower panel reports univariate imbalance measures. Refugees arrived in Sweden before 1996 and all individuals are born between 1954 and 1980.

Table 3: Occupational task classifications following Acemoglu and Autor (2011)

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 4: CEM: Employment, labor market establishment, Swedish citizenship, 2003–2013

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
fraction employed	0.845	0.843	0.717	0.597	0.650
of which					
fraction established	0.888	0.882	0.870	0.749	0.794
fraction citizens	0.993	0.992	0.993	0.940	0.917
person-year obs	1,079,632	1,079,622	392,528	333,044	320,474

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, conditional on being employed. 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	0.519	0.487	0.201	0.269	0.344
cognitive routine	0.121	0.124	0.091	0.087	0.085
manual non-routine	0.151	0.151	0.287	0.378	0.324
manual routine	0.209	0.238	0.421	0.266	0.247
observations	753,561	735,772	238,621	138,942	153,932

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	1.443	1.570	1.250	1.342	1.381
cognitive routine	0.991	1.003	0.960	0.982	1.005
manual non-routine	0.874	0.881	0.865	0.923	0.930
manual routine	1.118	1.122	1.059	1.036	1.079
observations	753,561	735,772	238,621	138,942	153,932

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	13.721	14.220	9.605	9.290	11.098
female	0.475	0.385	0.475	0.371	0.395
age	41.575	42.961	41.937	42.224	43.632
married	0.491	0.328	0.270	0.237	0.255
kids age 0-3	0.152	0.124	0.131	0.184	0.139
kids age 4-6	0.146	0.135	0.130	0.180	0.135
educ primary	0.081	0.169	0.123	0.167	0.155
educ secondary	0.495	0.490	0.578	0.416	0.464
educ tertiary	0.193	0.189	0.170	0.207	0.166
educ bachelor	0.114	0.057	0.050	0.069	0.088
educ master	0.105	0.085	0.074	0.128	0.114
educ doctoral	0.012	0.009	0.005	0.011	0.014
fsize micro 1-9	0.149	0.165	0.087	0.115	0.113
fsize small 10-49	0.312	0.313	0.267	0.240	0.236
fsize medium 50-249	0.302	0.292	0.394	0.354	0.336
fsize large 250-999	0.212	0.204	0.226	0.251	0.262
fsize big>=1000	0.025	0.026	0.026	0.039	0.052
manu high-tech	0.014	0.015	0.020	0.022	0.026
manu medium	0.109	0.114	0.221	0.103	0.120
manu low	0.051	0.058	0.095	0.051	0.053
kis high-tech	0.049	0.050	0.014	0.023	0.031
kis market	0.124	0.126	0.087	0.094	0.096
serv other	0.654	0.637	0.564	0.708	0.674
muni metro/city	0.353	0.430	0.323	0.613	0.629
muni dense close city	0.429	0.372	0.463	0.308	0.286
muni rural close city	0.079	0.088	0.105	0.031	0.042
muni dense remote	0.076	0.066	0.059	0.026	0.023
muni rural remote	0.050	0.038	0.046	0.021	0.019
muni rural very remote	0.013	0.007	0.004	0.001	0.001
observations	753,561	735,772	238,621	138,942	153,932

Notes: Only established persons; see Table 4.

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

	natives	matched natives	European refugees	non-European refugees	pre-1990 refugees
experience	13.823	14.573	9.964	9.831	11.384
female	0.497	0.361	0.544	0.395	0.410
age	41.775	43.654	41.117	42.412	42.915
married	0.431	0.287	0.305	0.223	0.255
kids age 0-3	0.181	0.139	0.169	0.194	0.163
kids age 4-6	0.168	0.146	0.142	0.171	0.142
educ primary	0.028	0.071	0.013	0.024	0.026
educ secondary	0.261	0.323	0.181	0.120	0.160
educ tertiary	0.287	0.309	0.267	0.238	0.257
educ bachelor	0.206	0.110	0.210	0.197	0.219
educ master	0.195	0.169	0.308	0.387	0.299
educ doctoral	0.022	0.018	0.021	0.034	0.039
fsize micro 1-9	0.129	0.152	0.093	0.101	0.109
fsize small 10-49	0.291	0.291	0.250	0.225	0.223
fsize medium 50-249	0.313	0.296	0.349	0.325	0.292
fsize large 250-999	0.236	0.229	0.269	0.276	0.287
fsize big>=1000	0.031	0.032	0.039	0.072	0.090
manu high-tech	0.020	0.024	0.031	0.043	0.048
manu medium	0.081	0.090	0.106	0.057	0.065
manu low	0.029	0.034	0.021	0.011	0.015
kis high-tech	0.078	0.084	0.044	0.057	0.070
kis market	0.175	0.187	0.123	0.114	0.124
serv other	0.617	0.580	0.676	0.719	0.677
muni metro/city	0.447	0.531	0.457	0.640	0.673
muni dense close city	0.400	0.335	0.414	0.305	0.271
muni rural close city	0.053	0.056	0.060	0.023	0.023
muni dense remote	0.058	0.050	0.044	0.020	0.018
muni rural remote	0.034	0.025	0.020	0.011	0.014
muni rural very remote	0.008	0.004	0.005	0.001	0.001
observations	383,412	350,468	47,238	36,260	51,772

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
matched natives	0.011***	-0.003***	-0.002***	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]
European refugees	-0.168***	-0.026***	0.076***	0.117***
	[0.001]	[0.001]	[0.001]	[0.001]
non-European refugees	-0.195***	-0.029***	0.173***	0.051***
	[0.001]	[0.001]	[0.001]	[0.001]
pre-1990 refugees	-0.125***	-0.033***	0.134***	0.025***
	[0.001]	[0.001]	[0.001]	[0.001]
female	0.014***	0.076***	0.155***	-0.245***
	[0.001]	[0.000]	[0.000]	[0.001]
citizenship	0.048***	-0.002	-0.048***	0.001
	[0.003]	[0.002]	[0.002]	[0.002]
experience	0.005***	-0.000	-0.005***	-0.000
	[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]
secondary school	0.077***	-0.014***	-0.015***	-0.048***
	[0.001]	[0.001]	[0.001]	[0.001]
tertiary school	0.378***	-0.053***	-0.138***	-0.187***
	[0.001]	[0.001]	[0.001]	[0.001]
2 yrs college degree	0.621***	-0.095***	-0.253***	-0.273***
	[0.001]	[0.001]	[0.002]	[0.002]
university degree	0.668***	-0.078***	-0.283***	-0.308***
	[0.001]	[0.001]	[0.002]	[0.002]
doctoral degree	0.699***	-0.150***	-0.248***	-0.301***
	[0.005]	[0.007]	[0.006]	[0.007]
married	-0.016***	0.003***	0.004***	0.008***
	[0.000]	[0.000]	[0.000]	[0.000]
kid age 0-3: 1	0.027***	-0.003***	-0.015***	-0.009***
	[0.001]	[0.001]	[0.001]	[0.001]
kids age 0-3: 2	0.040***	-0.007***	-0.019***	-0.014***
	[0.002]	[0.002]	[0.002]	[0.002]
kid age 4-6: 2	0.017***	-0.004***	-0.007***	-0.006***
	[0.001]	[0.001]	[0.001]	[0.001]
kids age 4-6: 1	0.016***	-0.005**	-0.008***	-0.004*

cont.

	(1) cogn non-rout	(2) cogn rout	(3) man non-rout	(4) man rout
	[0.002]	[0.002]	[0.002]	[0.002]
age <30	-0.014***	0.060***	-0.048***	0.002
	[0.002]	[0.001]	[0.002]	[0.002]
age 30-34	0.026***	0.036***	-0.055***	-0.006***
	[0.002]	[0.001]	[0.001]	[0.001]
age 35-39	0.033***	0.020***	-0.050***	-0.003**
	[0.001]	[0.001]	[0.001]	[0.001]
age 40-44	0.031***	0.011***	-0.040***	-0.002
	[0.001]	[0.001]	[0.001]	[0.001]
age 45-49	0.022***	0.006***	-0.027***	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]
age 50-54	0.013***	0.002	-0.013***	-0.002
	[0.001]	[0.001]	[0.001]	[0.001]
fsize micro 1-9	0.009***	0.071***	-0.147***	0.067***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize small 10-49	-0.008***	0.048***	-0.090***	0.050***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize medium 50-249	-0.006***	0.022***	-0.051***	0.035***
	[0.002]	[0.002]	[0.002]	[0.002]
fsize large 250-999	0.002	0.021***	-0.060***	0.037***
	[0.002]	[0.002]	[0.002]	[0.002]
ind high-tech	0.205***	-0.015***	-0.392***	0.202***
	[0.003]	[0.003]	[0.007]	[0.003]
ind medium-high	0.095***	0.025***	-0.357***	0.238***
	[0.001]	[0.001]	[0.002]	[0.001]
ind medium-low	-0.001	-0.013***	-0.190***	0.204***
	[0.001]	[0.001]	[0.001]	[0.001]
ind low-tech	0.261***	0.103***	-0.238***	-0.125***
	[0.002]	[0.001]	[0.003]	[0.002]
ind KIS	0.144***	-0.014***	-0.062***	-0.069***
	[0.001]	[0.001]	[0.001]	[0.001]
muni metro/city	0.103***	0.032***	-0.066***	-0.070***
	[0.003]	[0.003]	[0.002]	[0.003]
muni dense close city	0.050***	0.015***	-0.044***	-0.021***
	[0.003]	[0.003]	[0.002]	[0.003]
muni rural close city	0.011***	0.004	-0.028***	0.014***
	[0.003]	[0.003]	[0.003]	[0.003]

cont.

	(1) cogn non-rout	(2) cogn rout	(3) man non-rout	(4) man rout
muni dense remote	0.021***	-0.000	-0.027***	0.005**
	[0.003]	[0.003]	[0.003]	[0.003]
muni rural remote	0.018***	-0.004	-0.022***	0.009***
	[0.003]	[0.003]	[0.003]	[0.003]
observations	1,936,101			
df (model)	144			
χ^2	1,743,143			
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					
matched native	0.018***	0.026***	-0.004	-0.002	-0.001
	[0.004]	[0.007]	[0.003]	[0.002]	[0.002]
European refug	0.036***	-0.031***	0.021***	0.048***	0.016***
	[0.004]	[0.008]	[0.005]	[0.003]	[0.003]
non-European refug	-0.021***	-0.078***	-0.013*	0.055***	-0.023***
	[0.004]	[0.010]	[0.008]	[0.004]	[0.004]
pre-1990 refug	-0.041***	-0.091***	0.003	0.047***	-0.020***
	[0.005]	[0.009]	[0.008]	[0.004]	[0.004]
female	-0.269***	-0.348***	-0.151***	-0.146***	-0.146***
	[0.004]	[0.006]	[0.003]	[0.003]	[0.003]
time-varying regressors (within estimates)					
non-rout cogn (w)	0.047***				
	[0.002]				
rout cogn (w)	-0.008***				
	[0.003]				
non-rout man (w)	-0.026***				
	[0.003]				
experience (w)	0.070***	0.125***	0.058***	0.031***	0.041***
	[0.002]	[0.005]	[0.004]	[0.002]	[0.003]
experience^2 (w)	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
married (w)	-0.005***	-0.009***	-0.004***	-0.002*	-0.003***
	[0.001]	[0.003]	[0.001]	[0.001]	[0.001]
kid age 0-3: 1 (w)	-0.078***	-0.115***	-0.061***	-0.049***	-0.041***
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]
kids age 0-3: 2 (w)	-0.140***	-0.201***	-0.102***	-0.090***	-0.070***
	[0.004]	[0.007]	[0.006]	[0.006]	[0.005]
kid age 4-6: 2 (w)	-0.017***	-0.023***	-0.020***	-0.019***	-0.016***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]
kids age 4-6: 1 (w)	-0.033***	-0.050***	-0.026***	-0.024***	-0.032***
	[0.005]	[0.009]	[0.010]	[0.005]	[0.005]
educ effects (w)	yes	yes	yes	yes	yes
age effects (w)	yes	yes	yes	yes	yes
firm size effects (w)	yes	yes	yes	yes	yes

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
industry effects (w)	yes	yes	yes	yes	yes
region effects (w)	yes	yes	yes	yes	yes
citizenship effect (w)	yes	yes	yes	yes	yes
time-varying regressors (between estimates)					
non-rout cogn (b)	0.342***				
	[0.004]				
rout cogn (b)	0.018***				
	[0.004]				
non-rout man (b)	0.035***				
	[0.005]				
experience (b)	-0.027***	-0.048***	-0.019***	-0.001	-0.008***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]
experience^2 (b)	0.002***	0.004***	0.002***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
age <30 (b)	-0.051***	-0.208***	-0.021	0.029***	0.052***
	[0.014]	[0.029]	[0.019]	[0.010]	[0.012]
age 30-34 (b)	-0.045***	-0.083***	0.022	0.049***	0.054***
	[0.013]	[0.029]	[0.018]	[0.009]	[0.011]
age 35-39 (b)	-0.027**	-0.083***	-0.001	0.037***	0.039***
	[0.013]	[0.028]	[0.018]	[0.009]	[0.010]
age 40-44 (b)	0.052***	0.059*	0.046**	0.050***	0.056***
	[0.014]	[0.030]	[0.018]	[0.008]	[0.010]
age 45-49 (b)	0.047***	0.071**	0.015	0.042***	0.039***
	[0.013]	[0.028]	[0.016]	[0.008]	[0.009]
age 50-54 (b)	0.032*	0.064*	-0.020	0.025**	0.030**
	[0.017]	[0.038]	[0.023]	[0.011]	[0.013]
married (b)	-0.000	-0.007***	-0.001	0.001	-0.001
	[0.001]	[0.003]	[0.002]	[0.001]	[0.001]
educ secondary (b)	0.038***	0.064***	0.023***	0.028***	0.023***
	[0.002]	[0.009]	[0.005]	[0.003]	[0.002]
educ tertiary (b)	0.066***	0.174***	0.075***	0.053***	0.062***
	[0.004]	[0.009]	[0.006]	[0.004]	[0.004]
educ bachelor (b)	0.139***	0.334***	0.135***	0.107***	0.062***
	[0.013]	[0.018]	[0.013]	[0.009]	[0.010]
educ master (b)	0.326***	0.493***	0.210***	0.130***	0.095***
	[0.008]	[0.012]	[0.015]	[0.013]	[0.013]
educ doctoral (b)	0.480***	0.596***	0.177***	0.120***	0.064*

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
	[0.024]	[0.026]	[0.066]	[0.043]	[0.035]
muni metro/city (b)	0.161***	0.271***	0.116***	0.055***	0.048***
	[0.009]	[0.021]	[0.017]	[0.008]	[0.009]
muni dense close city (b)	0.026***	0.040*	0.041**	0.014*	0.021**
	[0.009]	[0.022]	[0.017]	[0.008]	[0.009]
muni rural close city (b)	0.009	0.015	0.006	-0.003	-0.002
	[0.009]	[0.022]	[0.017]	[0.008]	[0.009]
muni dense remote (b)	0.007	0.008	0.010	0.003	0.013
	[0.009]	[0.022]	[0.018]	[0.009]	[0.009]
muni rural remote (b)	-0.011	-0.018	-0.009	-0.007	-0.018**
	[0.009]	[0.022]	[0.018]	[0.009]	[0.009]
fsize micro 1-9 (b)	-0.142***	-0.216***	0.046***	-0.041***	-0.179***
	[0.011]	[0.019]	[0.010]	[0.008]	[0.010]
fsize small 10-49 (b)	-0.066***	-0.076***	0.096***	-0.035***	-0.107***
	[0.012]	[0.022]	[0.010]	[0.007]	[0.010]
fsize medium 50-249 (b)	-0.076***	-0.110***	0.100***	-0.030***	-0.088***
	[0.011]	[0.018]	[0.010]	[0.007]	[0.010]
fsize large 250-999 (b)	0.008	0.007	0.117***	0.009	-0.022**
	[0.011]	[0.019]	[0.011]	[0.008]	[0.010]
ind high-tech (b)	0.343***	0.398***	0.121***	0.167***	0.020**
	[0.025]	[0.036]	[0.030]	[0.062]	[0.010]
ind medium-high (b)	0.137***	0.200***	0.095***	0.116***	0.010***
	[0.005]	[0.011]	[0.006]	[0.015]	[0.003]
ind medium-low (b)	0.139***	0.295***	0.066***	-0.064***	0.013***
	[0.012]	[0.043]	[0.010]	[0.008]	[0.004]
ind low-tech (b)	0.257***	0.323***	0.017	0.058***	-0.013
	[0.009]	[0.011]	[0.011]	[0.022]	[0.013]
ind KIS (b)	0.268***	0.396***	0.081***	0.020***	-0.024***
	[0.008]	[0.011]	[0.007]	[0.006]	[0.006]
Swedish citizenship	0.037***	0.050**	0.034**	0.041***	0.009
	[0.008]	[0.022]	[0.016]	[0.007]	[0.009]
Constant	1.057***	1.491***	0.827***	0.789***	1.088***
	[0.027]	[0.064]	[0.046]	[0.026]	[0.033]
year effects (b)	yes	yes	yes	yes	yes
kids age 0-3 (b)	yes	yes	yes	yes	yes
kids age 4-6 (b)	yes	yes	yes	yes	yes
observations	1,937,909	852,355	214,165	362,093	483,155

cont.

Dep var: *wage*	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
σ_u	0.762	1.098	0.271	0.224	0.364
σ_ϵ	0.744	1.070	0.264	0.218	0.355
ρ	0.346	0.310	0.487	0.450	0.238
individuals	231,828	111,277	36,444	54,354	65,621
df(model)	97	91	91	91	91
R^2 (w)	0.005	0.005	0.013	0.012	0.006
R^2 (b)	0.236	0.172	0.176	0.170	0.140

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 all refugees, 2003–2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.318***	1.596***	1.032***	0.897***	1.146***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
refugees	1.092***	1.345***	1.000***	0.918***	1.082***
	[0.001]	[0.004]	[0.004]	[0.002]	[0.002]
difference	0.226***	0.251***	0.032***	-0.021***	0.064***
	[0.003]	[0.006]	[0.004]	[0.002]	[0.002]
explained	0.205***	0.132***	0.037***	0.022***	0.072***
	[0.004]	[0.008]	[0.004]	[0.003]	[0.003]
unexplained	0.021***	0.119***	-0.005	-0.044***	-0.007*
	[0.005]	[0.009]	[0.006]	[0.004]	[0.004]
N matched natives	706,115	343,808	85,632	102,008	165,575
N refugees	506,922	131,899	43,292	155,749	168,346
Total obs	1,213,037	475,707	128,924	257,757	333,921

Notes: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimations based on correlated random effects model eq. (1). Reference group matched natives. Wage earnings relative to median wage earnings in respective year.

Table 13: Twofold Blinder–Oaxaca wage decomposition for European refugees, 2003–2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.318***	1.596***	1.032***	0.897***	1.146***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
European refugees	1.056***	1.268***	0.982***	0.882***	1.083***
	[0.002]	[0.005]	[0.004]	[0.002]	[0.002]
difference	0.262***	0.328***	0.051***	0.015***	0.063***
	[0.003]	[0.007]	[0.005]	[0.003]	[0.003]
explained	0.293***	0.255***	0.077***	0.061***	0.091***
	[0.005]	[0.008]	[0.004]	[0.003]	[0.003]
unexplained	-0.031***	0.074***	-0.026***	-0.046***	-0.028***
	[0.005]	[0.011]	[0.006]	[0.004]	[0.004]
N matched natives	706,115	343,808	85,632	102,008	165,575
N European refugees	229,373	46,093	20,455	62,657	97,196
Total obs	935,488	389,901	106,087	164,665	262,771

Notes: Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimations based on correlated random effects model eq. (1). Reference group matched natives. Wage earnings relative to median wage earnings in respective year.

Table 14: Twofold Blinder–Oaxaca wage decomposition for non-European refugees, 2003–2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.318***	1.596***	1.032***	0.897***	1.146***
	[0.002]	[0.004]	[0.002]	[0.002]	[0.002]
non-European refugees	1.090***	1.360***	1.004***	0.940***	1.056***
	[0.003]	[0.007]	[0.007]	[0.003]	[0.003]
difference	0.228***	0.236***	0.029***	-0.043***	0.090***
	[0.004]	[0.008]	[0.008]	[0.003]	[0.004]
explained	0.177***	0.100***	0.002	0.003	0.069***
	[0.005]	[0.010]	[0.006]	[0.003]	[0.004]
unexplained	0.051***	0.136***	0.027***	-0.046***	0.021***
	[0.006]	[0.012]	[0.009]	[0.005]	[0.006]
N matched natives	706,115	343,808	85,632	102,008	165,575
N non-European refugees	130,551	35,200	10,910	47,227	34,890
Total obs	836,666	379,008	96,542	149,235	200,465

Notes: see Table 12.

Table 15: Twofold Blinder-Oaxaca wage decomposition for pre-1990 refugees, 2003–2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched natives	1.318***	1.595***	1.036***	0.900***	1.145***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]
before 1990s refugees	1.151***	1.405***	1.029***	0.949***	1.103***
	[0.003]	[0.007]	[0.008]	[0.003]	[0.004]
difference	0.167***	0.190***	0.007	-0.049***	0.042***
	[0.004]	[0.008]	[0.008]	[0.004]	[0.004]
explained	0.135***	0.094***	0.047***	0.014***	0.039***
	[0.004]	[0.007]	[0.004]	[0.003]	[0.003]
unexplained	0.032***	0.096***	-0.040***	-0.064***	0.004
	[0.005]	[0.010]	[0.009]	[0.005]	[0.005]
N matched natives	706,115	343,808	85,632	102,008	165,575
N pre-1990 refugees	146,998	50,606	11,927	45,865	36,260
Total obs	853,113	394,414	97,559	147,873	201,835

Notes: see Table 12.

Table 16: Two-fold Blinder-Oaxaca wage decomposition for male refugees

	(1) All	(2) Non-rout cogn	(3) Rout cogn	(4) Non-rout man	(5) Rout man
matched natives men	1.477***	1.783***	1.155***	1.052***	1.164***
	[0.004]	[0.006]	[0.005]	[0.004]	[0.002]
refugees men	1.172***	1.467***	1.068***	1.013***	1.100***
	[0.002]	[0.006]	[0.005]	[0.003]	[0.002]
difference	0.305***	0.316***	0.087***	0.038***	0.064***
	[0.004]	[0.009]	[0.007]	[0.005]	[0.002]
explained	0.266***	0.123***	0.078***	0.071***	0.068***
	[0.008]	[0.014]	[0.009]	[0.007]	[0.004]
unexplained	0.039***	0.194***	0.009	-0.032***	-0.004
	[0.009]	[0.016]	[0.011]	[0.009]	[0.004]
N matched natives men	431,783	219,591	33,658	24,748	148,889
N refugees men	292,704	72,212	23,154	51,147	141,484
Total obs	724,487	291,803	56,812	75,895	290,373

Notes: see Table 12.

Table 17: Two-fold Blinder-Oaxaca wage decomposition for female refugees

	(1) All	(2) Non-rout cogn	(3) Rout cogn	(4) Non-rout man	(5) Rout man
matched natives women	1.067***	1.265***	0.953***	0.847***	0.986***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.005]
refugees women	0.983***	1.199***	0.924***	0.872***	0.985***
	[0.002]	[0.004]	[0.005]	[0.002]	[0.005]
difference	0.084***	0.066***	0.029***	-0.025***	0.000
	[0.003]	[0.006]	[0.005]	[0.002]	[0.007]
explained	0.122***	0.064***	0.055***	0.026***	0.025***
	[0.003]	[0.006]	[0.005]	[0.003]	[0.008]
unexplained	-0.038***	0.002	-0.026***	-0.051***	-0.025**
	[0.004]	[0.008]	[0.007]	[0.004]	[0.010]
N matched natives women	274,332	124,217	51,974	77,260	16,686
N refugees women	214,218	59,687	20,138	104,601	26,862
Total obs	488,550	183,904	72,112	181,861	43,548

Notes: see Table 12.

Table 18: Two-fold Blinder-Oaxaca wage decomposition for the most frequent occupations (cognitive non-routine tasks), panel 1

	(1) 21.31	(2) 23.30	(3) 33.10	(4) 31.21	(5) 22.21	(6) 24.70
matched natives	1.733***	1.040***	0.929***	1.472***	2.473***	1.408***
	[0.011]	[0.004]	[0.004]	[0.010]	[0.027]	[0.009]
refugees	1.565***	1.021***	0.939***	1.335***	2.528***	1.191***
	[0.012]	[0.005]	[0.005]	[0.017]	[0.026]	[0.010]
difference	0.168***	0.019***	-0.010	0.137***	-0.055	0.217***
	[0.016]	[0.007]	[0.007]	[0.019]	[0.037]	[0.014]
explained	0.181***	0.012*	0.030***	0.119***	0.249***	0.169***
	[0.022]	[0.007]	[0.008]	[0.020]	[0.038]	[0.017]
unexplained	-0.013	0.006	-0.040***	0.019	-0.304***	0.048**
	[0.026]	[0.009]	[0.010]	[0.026]	[0.051]	[0.021]
N matched natives	15,763	9,814	11,662	9,394	4,562	7,153
N refugees	6,314	7,997	5,274	3,236	8,193	3,569
Total obs	22,077	17,811	16,936	12,630	12,755	10,722

Notes: see Table 12. Occupational codes: 21.31: Computer systems designers and analysts, 23.30: Nursing associate professionals, 33.10: Primary education teaching associate professionals, 31.21: Computer assistants, 22.21: Medical doctors, 24.70: Public administration.

Table 19: Two-fold Blinder-Oaxaca wage decomposition for occupations (cognitive non-routine tasks), panel 2

	(1) 32.39	(2) 31.19	(3) 34.31	(4) 31.15	(5) 21.44	(6) 31.14
matched natives	1.081***	1.484***	1.240***	1.461***	2.031***	1.666***
	[0.006]	[0.010]	[0.012]	[0.012]	[0.031]	[0.016]
refugees	1.178***	1.369***	1.095***	1.414***	1.751***	1.561***
	[0.009]	[0.017]	[0.017]	[0.025]	[0.018]	[0.019]
difference	-0.097***	0.115***	0.145***	0.047*	0.279***	0.105***
	[0.011]	[0.019]	[0.021]	[0.028]	[0.036]	[0.025]
explained	0.027***	-0.009	0.090***	0.029	0.136**	0.030
	[0.009]	[0.022]	[0.023]	[0.031]	[0.064]	[0.042]
unexplained	-0.124***	0.124***	0.055*	0.017	0.143**	0.074
	[0.013]	[0.029]	[0.030]	[0.041]	[0.073]	[0.048]
N matched natives	5,393	6,999	7,044	5,773	3,732	4,978
N refugees	4,816	2,600	2,326	2,462	3,406	2,045
Total obs	10,209	9,599	9,370	8,235	7,138	7,023

Notes: see Table 12. Occupational codes: 32.39: Non-specialist nurses, 31.19: Physical and engineering science technicians not elsewhere classified, 34.31: Administrative secretaries and related associate professionals, 31.15: Mechanical engineering technicians, 21.44: Electronics and telecommunications engineers, 31.14 Electronics and telecommunications technicians.

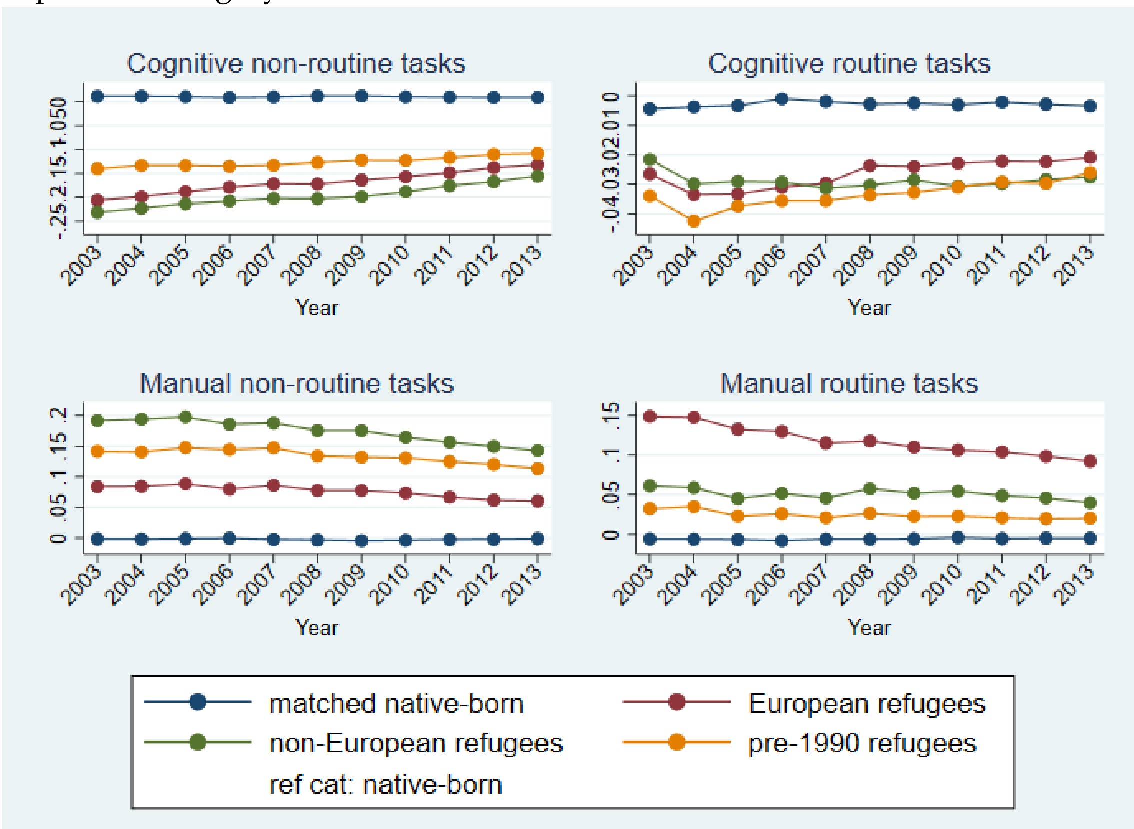
Table 20: Robustness test: Twofold Blinder-Oaxaca wage decomposition for refugees vs. foreign-born immigrants, 2003–2013

	(1) all occup	(2) cogn non-rout	(3) cogn rout	(4) man non-rout	(5) man rout
matched foreign-born	1.095***	1.408***	1.008***	0.904***	1.086***
	[0.002]	[0.005]	[0.004]	[0.002]	[0.002]
refugees	1.085***	1.331***	0.999***	0.917***	1.080***
	[0.001]	[0.004]	[0.004]	[0.002]	[0.002]
difference	0.010***	0.077***	0.009*	-0.013***	0.007**
	[0.002]	[0.006]	[0.005]	[0.002]	[0.003]
explained	0.002***	0.032***	0.016***	0.003***	-0.001
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
unexplained	0.008***	0.045***	-0.007	-0.017***	0.008***
	[0.002]	[0.006]	[0.005]	[0.002]	[0.003]
N matched foreign-born	404,232	103,967	37,438	142,820	113,405
N refugees	456,890	119,991	40,201	145,906	143,731
Total obs	861,122	223,958	77,639	288,726	257,136

Notes: see Table 12.

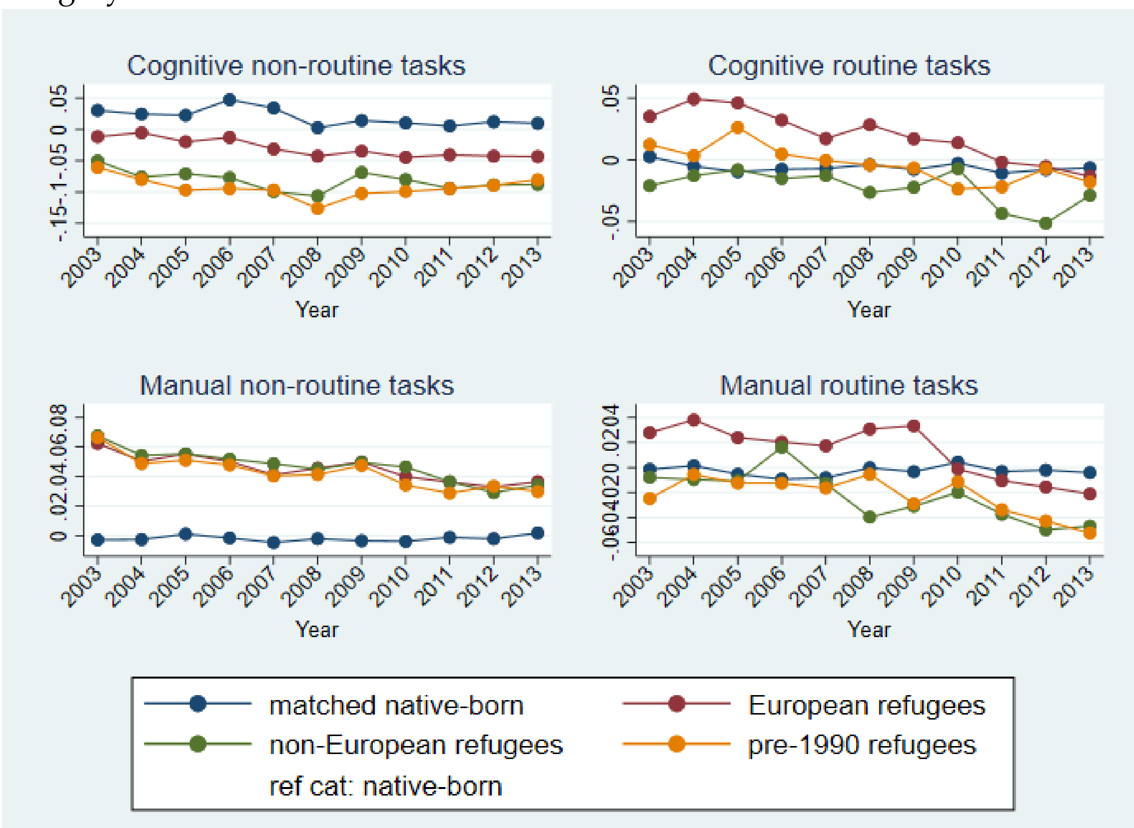
C Figures

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 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, Swedish citizenship, size of work establishment, industry classification.