Migrant Labour and Integration in the Russian Federation

Ivan Privalko, PhD

November 18, 2022

Abstract

This article compares the labour market outcomes of migrants in Russia to the non-migrant population. It explores the importance of human capital theory and integration theory as mechanisms for gaps between migrants and non-migrants in work status, work contracts, and wages. The paper offers two unique facets, relevant to migration researchers. First, it considers internal migration as a distinct category, one that is separate from non-migrants or people who are immobile from their place of birth within the country under study. Second, it uses an index which combines the person's age and their duration in the host country, two measures which are highly correlated, as a control for estimating outcomes. We find that migrants have high levels of employment but that certain groups are disproportionally likely to fall into unofficial employment. We further find that migrants report higher earnings than non-migrants, as do internal migrants. These findings highlight a type of reservation wage that could be associated with migration into Russia. Educational background, demographic characteristics, and duration in the country did not explain these migrant gaps, suggesting unexplained penalties and premiums may exist for certain groups of migrants which go beyond their resources and characteristics. The paper highlights the importance of migrant labour in Russia's economy.

1 Introduction

Countries throughout Europe have increased their reliance on migrant labour (?, ?, ?, ?). Despite this demand, authors find gaps in labour market outcomes between migrants and non-migrants which close as migrants spend more time in their host country. This finding is routinely reported in European cases and is a theoretically important rebuttal of discrimination hypotheses, where comparable, migrant, human capital is seen as inferior by employers when compared to similar, host country, human capital.

There have been few studies of migrants using Russian data, and little is known about the migrant composition of the country overall. This is especially relevant given the high disapproval that people in Russia have of liberal migration policies, although these attitudes are improving. The Levada Centre, Russia's institute of Social Attitudes, reports that 68% of respondents believe that the government should limit the flow of migrant workers into Russia, while 45% of respondents do not believe that migrant labour is useful for the country and society (Levada Centre, 2022). Further, given Russia's war with Ukraine, media outlets report a migrant exodus from the country, claiming that migrant workers face "layoffs, lower wages, and fewer job prospects" (The Moscow Times, 2022). Given the importance of migrant labour to Russia's economy, we will consider the level of migrant integration up to 2020. Overall, this paper considers migrant outcomes in Russia and asks if time spent in the Russian Federation is a relevant predictor of labour migrant integration, above what can be explained using simple human capital and demographic factors. More importantly, international relations between Russia and many of its neighbouring countries have changed for the worse. One consequence of this will be a gap in Russia's labour market in positions which were previously filled by migrants from former Soviet states. Since such migrants are highly skilled, this is an issue for policy-makers.

Using data from the Russian Longitudinal Monitoring Survey, we will compare migrants' employment, unemployment, and pay to non-migrants in Russia. We will also compare migrants alongside internal migrant groups, or people who have moved from other Russian regions to the region where they are surveyed, to non-mobile Russians. Specifically, we consider nine migrant categories; people from other parts of Russia, Ukraine, Belarus, a category for Azerbaijan, Armenia, and Georgia, a category for Kazakhstan and Kyrgyzstan, a category for Latvia, Lithuania, and Estonia, a category for Moldova, and a residual migrant category. We use data from 2015-2020 and estimate migrant differences using binary logistic regression and a nested model design (for unemployment). We estimate differences in pay using ordinary least squares regression with a nested model design, and clustered standard errors. Regarding controls, we consider measures tied to human capital, social integration (for example a duration measure for time spent in Russia, and whether the person is a Russian national), and a set of demographic factors (like age and gender) which are associated with differences between migrants and non-migrants.

We find that migrants make up over 7% of the Russian labour market, and that migrant groups perform well in terms of employment and earnings. However, this effect is largely dependent on duration in the country, with recent migrants faring worse than more established groups. In such cases, a selection process may be tied to Russia's migration policy. Regarding public policy, the Russian labour market depends strongly on migrants, especially those from Ukraine and Belarus, who report high employment levels, and high earnings among the employed. Although Russian policy is focused on attracting returning non-migrants from Europe and the US, the success of such policies is not clear, and retention of migrants (who make up a significant share of the country's labour market) should remain a priority. The retention of migrants will likely remain a challenge for the Russian Federation.

2 Review

2.1 Three theories on migrant and non-migrant differences

In this section, we will outline three frameworks for considering migrant and non-migrant differences in labour market outcomes; human capital, discrimination, and integration as a social process.

In the first framework, migrant differences in labour market outcomes are often explained by differences in Human Capital (?, ?, ?). Here, factors like age, labour market experience, education, and language ability are more important than migrant status or country of birth (?, ?, ?, ?). Given that migrants are often younger and less experienced than non-migrant groups, their level of experience and efficiency explains basic differences in labour market outcomes rather than their country of birth. In this framework, measures of skill and efficiency, as well as certain demographic measures should explain away any difference between migrants and non-migrants in labour market outcomes like pay.

The second framework suggests that differences between migrants and non-migrants stem from taste-based discrimination or statistical discrimination. In this view discrimination (either taste (?, ?) or signal (?, ?)) where migrants' educational qualifications, skills, and experience are (incorrectly) perceived as lesser than non-migrants educational qualifications, skills, and experience explain the difference between migrants and non-migrants. On the former, taste-based discrimination is exogenous to the labour market, and works through the preferences of the employer. On the latter, employers' experiences of guessing a given job applicant's efficiency or a given worker's productivity cause them to do two things. First, to consider the observable characteristic like ethnicity, race, and country of birth as a surrogate for unobservable characteristics like productivity, and efficiency which causes the productivity differences. Second, to see their perception of the group's average levels of efficiency as applicable to an individual job applicant or worker. This is a market-based explanation which does not require tastes for discrimination. For example, employers often see learning credentials from another country as less valid than learning credentials obtained in the employer's country. A more subtle example is the perception that work experience in another country is less applicable than the experience gained in the employer's country. In this framework, group differences in labour market outcomes should remain, even after correcting for Human Capital measures.

The final framework sees integration as a social process, where migrants' socio-cultural integration is key to their labour market success (?, ?, ?, ?). These researchers claim that time spent in the host country, beyond a person's age or a person's labour market experience, captures the slow process of integration, as migrants learn more about the labour market, build networks, and develop "weak ties" (?, ?, ?). Since migrants who arrive in host countries have limited networks, they are at a disadvantage in finding work, finding highly paid work, and matching their skills to their earnings. In this framework, differences between migrants and non-migrants should be weaker once time in the country has been considered, given this process.

2.2 Empirical findings on migrant gaps

Empirical work has tested many of the theories listed above. On measures of human capital and efficiency, education is a key factor in the integration process as it can play a decisive role in improving economic and social outcomes (?, ?, ?). Across Organisation for Economic Co-operation and Development (OECD) countries, those with higher educational attainment report better physical health and improved socio-emotional well-being; they are also more likely to be active participants in their societies. Higher levels of education are associated with improved labour market outcomes – both much lower unemployment rates and higher occupational attainment for migrants in Ireland for example (?, ?, ?). Measures like language ability, which could also be taken as measures of wider social integration, are also important for measures of human capital among potential workers (?, ?, ?, ?, ?, ?).

However, authors routinely find estimates which confirm the presence of either taste or statistical discrimination. In job application experiments, employers often show a preference for non-migrant workers when hiring staff (?, ?, ?, ?, ?). This effect remains even when human capital (?, ?, ?, ?) and volunteer status is controlled for (?, ?). Quillian, especially notes that although levels of discrimination against white immigrants are low, they are present in all sampled countries, suggesting a universal barrier for migrant workers with comparable human capital. Elsewhere, using data on race and ethnicity, authors show that although white migrants again experience low levels of discrimination, non-white migrants in majority-white societies experience higher levels of discrimination (?, ?), in that they experience a penalty beyond what can be explained by Human Capital measures.

Authors in the UK have shown that gaps between white migrants and white non-migrant groups can be closed by controlling compositional and geographical factors, but that differences between non-white migrants and UK-born workers, persist even after a range of controls are considered (?, ?). This gap again suggests some level of discrimination or taste-based preferences among employers or consumers against non-white workers of a similar background to their UK counterparts. Similar gaps emerge in Irish research, where black adults are significantly less likely to be employed when compared to white Irish adults (?, ?, ?). Asian non-Irish people do not differ from white non-migrants in terms of employment rates, and Asian Irish are more likely to work in professional-managerial occupations than white Irish (?, ?). Additional qualitative data further shows that black non-Irish respondents report higher rates of discrimination in both recruitment and the workplace when compared to non-migrant Irish respondents (?, ?).

Beyond human capital and discrimination, the authors also find support for the integration hypothesis. Previous research shows that time spent in the country is negatively correlated with unemployment status, and positively correlated with occupational attainment (?, ?). Elsewhere, time spent in the host country increases a migrant's chance of acquiring skills (?, ?), and further acquiring a job (?, ?), which also closes some of the initial jobs between migrant groups.

3 Methodology

3.1 Sample

We use five rounds of the Russian Longitudinal Monitoring Survey (RLMS) throughout, which is a representative sample of Russian households. It has been collected annually since its inception in the 1990s and curated by the Carolina Population Center at the University of North Carolina at Chapel Hill and the Demoscope team at the Higher School of Economics in Russia.

3.2 Measures and Definitions

We use five groups of measures throughout our analysis; a respondent's labour market outcomes, a respondent's country of birth, their demographic characteristics, their measures of human capital, and their level of integration into the Russian Federation to date.

Regarding outcomes, we use three specific measures, whether the respondent is employed, whether the job where they are employed is an official position and their mean monthly wage. Our employment measure is a subset of the wider measure for economic status, respondents are asked to '...talk about your primary work at present. Respondents who are 'currently working' and respondents who are 'on paid leave' either maternity leave or 'another form of paid leave' are considered employed. Respondents who are 'on unpaid leave' or respondents who are 'not currently working' are not considered employed. We also consider group differences in unofficial forms of employment. This measure is collected when respondents describe their work contract, specifically, they are asked 'Are you employed in this job officially, in other words, by labour book, labour agreement, or contract?' We create a binary measure for this analysis, comparing official and unofficial employment types. Finally, our last outcome considers the mean monthly wages of the respondent. Specifically, respondents are asked 'How much money did you receive in the last 30 days from your primary job after taxes? If you received all or part of the money in foreign currency, please convert that into rubles and report the total.'

For the person's country of birth, respondents are first asked 'Were you born in the place of your current residence or elsewhere?' splitting the answers into 'in another place and 'in the place where I live now. Subsequently, they are asked 'In what republic of the former USSR were you born?' followed by a list of 16 country categories. We will combine these two measures to compare internal and external migrants and a reference category for an immobile migrant group. Specifically, we will compare people born in the following groups:

- Russia, no mobility
- Other Russia
- Ukraine
- Belarus

- Azerbaijan, Armenia, or Georgia
- Kazakhstan, Kyrgyzstan
- Latvia, Lithuania, or Estonia
- Moldova
- Tajikistan, Turkmenistan, or Uzbekistan
- Other

Regarding a person's demographic characteristics, we consider their age, gender, and their marital status. For marital status, we combine respondents who are separated, widowed, and divorced into one category. As a result, we compare respondents who are never married, to those who are married, cohabiting, and separated.

For measures of human capital, we consider the person's education, occupation, and their job tenure (the duration of time, in years, that the person has spent with a given employer). For education, we take the respondent's longitudinal measure of education. which contains 24 categories of educational attainment. We assign everyone with a third-level degree 'Institute, University or Academy diploma' or higher a value of 1. We assign everyone without such a degree a value of 0. Regarding occupations, we consider the one-digit ISCO coding for occupations in the sample. Regarding job tenure, respondents are asked 'Since what year and month have you been working at this place? If you left and then returned to this enterprise, give the date you last returned.' Focusing on the year, we subtract this value from the survey year to get a measure of company tenure.

Regarding measures of integration, we consider whether the person is a Russian national and their duration in Russia. This last measure is highly correlated with age, and so we record this measure as a categorical index, which captures age and duration together. Nationality is asked explicitly, respondents are presented with the question 'What nationality do you consider yourself?' and answer accordingly. Our measure of duration in Russia relies on two separate measures. The first is the year of arrival, where respondents are asked 'What year did you establish a permanent residence in the Russian Federation?' If the person was born in Russia, we assign their year of birth to their year of arrival, to include non-migrants in our analysis. If the person's year of birth is missing, we do not include them in our analysis. Once these measures are established, we create a measure for the duration in Russia, subtracting the year of arrival from the current survey year. Unfortunately, the correlation between age and gender is highly strong and highly significant (Pearsons's corr= 0.934). In the appendix presented below, we highlight the level of collinearity between both of these measures (we list the VIF values for models which contain both measures separately). As a result, we combine both age and duration into a categorical index which greatly reduces this collinearity. Specifically, we consider whether each age category in our four-category scale (15-30, 31-50, 51-65, 65 and over) has a value of duration that is either the same as age or lower than age, giving us an eight category measure.

3.3 Estimation

We use two forms of estimation throughout, a binary logistic regression model and a logged ordinary least squares regression. Specifically, a binary logistic regression takes the form:

$$ln(p/1-p) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 ... + \beta_n x_n$$

Where $ln(p/1-p)$ is the odds ratio, containing the probability of being in employment (having an unofficial job) against the probability of not being in employment (not having an unofficial job). Further β_0 is the estimated constant, and β_1 is the estimated effect of variable x_1 (Country of birth, gender or nationality for example). Similarly, when estimating group differences in earnings, we consider an ordinary least squares regression, using a logged measure of monthly wages, which takes the form:

$$ln(y_i) = \beta_0 + \beta_1 x_i + \beta_2 x_2 ... + \beta_n x_+ \epsilon_i$$

Where $ln(y_i)$ is a measure of logged wages, β_0 is an estimated constant, β_1 is an estimated effect of a control (x_i) like country of birth or gender, and ϵ_i is an error term. Given the longitudinal sample used throughout the analysis, we use clustered standard errors which account for the repeat personal identification numbers in the data.

4 Results

This section has three parts, we first consider summary statistics overall and for migrant groups. We then present a binary logistic regression model for employment, followed by an OLS regression (with ID clustered standard errors) for earnings. Throughout we show that gaps in employment and earnings, between migrant groups, cannot be explained by human capital and integration factors, and that overall, migrants fare better in Russia's labour market than non-migrant groups.

4.1 Summary statistics

Table 1 lists summary statistics for working-age migrants, focusing on employment, occupational attainment, and education. Regarding employment, we find that immobile Russians have lower levels of employment (60%) when compared to the average rate for the population (62%), while mobile Russians have higher levels of employment (65%). Just one migrant group reports lower than average employment levels, those born in Latvia, Lithuania, or Estonia (50%). Employment levels are especially high among migrants born in Belarus (74%), Kazakhstan or Kyrgyzstan (70%), and Moldova (72%).

Despite higher levels of employment, there are differences in occupational attainment across migrant groups. While immobile Russians have lower rates of employment, they have average rates of occupational attainment (among those who work) (23%). Occupational attainment is slightly higher among migrants from Ukraine (28%), Latvia, Lithuania, or Estonia (30%), as well as migrants from Other countries (29%). Occupational attainment is especially low among migrants from Tajikistan, Turkmenistan, or Uzbekistan (16%).

Lastly, education levels differ between migrant categories, with migrants from Ukraine (37%) and Moldova (37%) having the highest rates of third-level education (as well as Other migrants (46%)). Migrants from Azerbaijan, Armenia, and Georgia report the lowest levels (21%) of educational attainment. Russian respondents report just 30% educational attainment among working-age respondents, either for mobile (29%) or immobile (30%) Russians.

	employed	unemployed	simple_isco	nationality	simple_ed
Russia no mobility	0.605	0.068	0.229	0.867	0.303
Other Russia	0.650	0.045	0.230	0.885	0.294
Ukraine	0.666	0.066	0.280	0.685	0.374
Belarus	0.745	0.065	0.218	0.567	0.341
Azerbaijan Armenia and Georgia	0.657	0.045	0.189	0.298	0.211
Kazakhstan Kyrgyzstan	0.706	0.036	0.219	0.875	0.308
Latvia Lithuania Estonia	0.498	0.033	0.301	0.922	0.148
Moldova	0.729	0.097	0.233	0.631	0.377
Tajikistan Turkmenistan and Uzbekistan	0.683	0.063	0.160	0.657	0.269
Other	0.604	0.082	0.293	0.630	0.462
Total	0.625	0.059	0.229	0.859	0.300

Working age respondents (15-64) only

Further, we consider basic group differences in wages, income, age and years in the country below for migrant and non-migrant groups (Table 2). Regarding wages, we find that Russian respondents for both groups are in line with the average wage. Migrants from Ukrainian (34,000+), Belarus (38,000+), Azerbaijan, Armenia, and Georgia (29,000+), and Moldova (29,000+) have higher wages in monthly wages (in rubles) when compared to non-migrant groups. Migrants from Tajikistan, Turkmenistan, and Uzbekistan (25,000+) are the only group to earn less on average.

	wages	income	age	duration
Russia no mobility	27447	21519	36	36
Other Russia	27800	25587	43	43
Ukraine	34647	31170	48	33
Belarus	38563	37707	46	30
Azerbaijan Armenia and Georgia	29069	23563	44	26
Kazakhstan Kyrgyzstan	28330	26548	44	29
Latvia Lithuania Estonia	28056	22634	49	39
Moldova	29142	29028	42	25
Tajikistan Turkmenistan and Uzbekistan	25784	22115	42	23
Other	27538	26644	42	28
Total	27759	23256	39	38

Working age respondents (15-64) only

Regarding the age of respondents, we find that migrant groups in Russia are typically slightly older than the average sample age (39). Migrants from Ukraine (48), and Latvia, Lithuania, and Estonia (49) are typically older than immobile Russians (36), and mobile Russians (43). Other migrant groups are typically younger than these first two groups, but they are typically older than the average in the sample.

4.2 Employment Models

We now turn to the first set of regression models which estimate the odds ratio of employment for different migrant groups. Broadly, we note that migrant differences emerge only for certain groups, but these cannot be explained by demographic, integration or human capital measures. In model 1 we present the basic differences in employment. Holding immobile Russians as the reference category, we note that three migrant groups have significantly higher odds of employment when compared to the reference group (Internal migrants, migrants from Kazakhstan and Kyrgyzstan, and migrants from Moldova).

In model 2 we consider the importance of Russian nationality, or perceived Russian nationality. Although we find that Russian nationals have higher odds of employment, as predicted by integration literature, we also note that the previous differences have not been explained by the nationality measure. Mobile Russians (1.1), and migrants from Kazakhstan or Kyrgyzstan (1.3) still have higher odds of employment when compared to immobile Russians. Beyond these differences, we find that migrants from Belarus (1.7) and Azerbaijan, Armenia or Georgia (1.5) have significantly higher odds of employment when compared to non-migrants, once we control for Russian nationality status. Importantly, no migrant groups list lower odds of employment compared to immobile Russian respondents. Although migrants from Latvia, Lithuania, or Estonia (0.7) have a negative estimate (¡1), this difference is not statistically significant. In general migrants report higher odds of employment.

In model 3 we consider demographic factors like gender, marital status, and an index which combines a person's age and their duration in the host country. We find typical results, in that men have higher odds of employment when compared to women (0.7), and that married (4.2) or cohabiting (3.7) respondents have higher odds of employment when compared to those who were never married. Regarding age, we note that employment is highest among those aged 31-50, which is typical, we also find that those with shorter durations in the country than their age have lower odds of employment within age brackets, although we test this more formally later. As before, these demographic factors do not explain differences between migrant groups, which persist as before. Migrants from Ukraine (1.5), Belarus (2.0), Azerbaijan, Armenia, or Georgia (1.6), Kazakhstan or Kyrgyzstan (1.3), Moldova (2.7), and Tajikistan, Turkmenistan or Uzbekistan (1.4) all report higher odds of employment when compared to immobile Russian respondents.

Finally, in model 4 we consider the impact of a third level education, Once again, the wider differences between migrants and non-migrant groups persist, with migrants having higher odds of employment. Here, too respondents with a third level education have significantly greater odds of holding work, when compared to respondents without a third level education.

	M1: Basic	M2: Add nationality	M3: Add demographics	M4: Add education
Binary outcome: employed				
Russia no mobility	1	1	1	1
Other Russia	1.101**	1.100**	1.062	1.077*
Ukraine	1.103	1.256	1.509*	1.417*
Belarus	1.384	1.776*	2.044*	1.684
Azerbaijan Armenia and Georgia	1.035	1.592***	1.653**	1.732**
Kazakhstan Kyrgyzstan	1.363**	1.373**	1.449*	1.415*
Latvia Lithuania Estonia	0.761	0.723	0.962	0.981
Moldova	1.986*	2.386**	2.702*	2.444*
Tajikistan Turkmenistan and Uzbekistan	1.286	1.466*	1.640*	1.583*
Other	1.140	1.310	1.248	1.061
Other nationality		1	1	1
Russian national		1.998***	1.997***	1.924***
male			1	1
female			0.703***	0.643***
Never married			1	1
Married			4.258***	4.021***
Cohabiting			3.772***	3.881***
separated widowed divorced			3.592***	3.563***
15-30 duration is age			1	1
15-30 duration lower than age			0.108***	0.126***
31-50 duration is age			2.039***	2.040***
31-50 duration lower than age			1.313	1.380*
51-65 duration is age			0.420***	0.452***
51-65 duration lower than age			0.405***	0.419***
No third level				1
Third level				2.414***
Observations	59172	59172	59172	59172
Pseudo R^2	0.001	0.010	0.144	0.165
AIC	76520.6	75791.2	65586.3	63963.9
BIC	76610.4	75890.0	65766.1	64152.7

Exponentiated coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the models above, we find that migrants of all country groups have either greater or comparable odds of employment when compared to non-migrants. Part of this effect may be a response Russia's emphasis on employment conditions for certain migrant rights. In this system migrants must be employed in order to remain in the country, if they are not Russian nationals. Before considering wages, we first estimate the predicted probability of employment in Model 4 for migrant groups, and second for our age and tenure index. Previously, we showed that migrants with shorter durations in Russia may have lower levels of employment for all age groups. We now test this formally using marginal effects.

We first note the marginal effect of different country groups, relative to immobile Russians. The results are presented as predicted probabilities with 95% Confidence Intervals. Several migrant groups have higher predicted employment, and none of the groups list lower employment probabilities than the reference group. However, we also noted that migrants who spent less time in Russia likely have a disadvantage in their employment outcomes. We consider this using index tying age and tenure together in the figure below.

For each age group, we compare respondents whose duration falls into roughly the same category as their age against respondents whose duration falls into a category that is lower than their age. Considering respondents aged 51-65, we find no marginal difference in the predicted probability of employment between migrants with longer durations in Russia and migrants with shorter durations in Russia. Considering respondents aged 31-50, we find a significant difference, with long duration migrants having a significantly higher chance of employment when compared to shorter duration migrants (6 percentage points). Considering respondents aged 15-30, we find a large significant difference, with long duration migrants haveing a significantly higher chance of employment when compared to lower duration migrants (42 percentage points). This result could stem from certain migrants travelling to Russia for an education, while Russian respondents may be more likely to balance education and work.

In general we find support for the integration hypothesis, that although migrants are more likely to be employed, those with lower durations in Russia see a penalty in terms of access to employment, especially when aged 15-30, and to a lesser extent 31-50.

4.3 Unofficial employment

We now turn to measures of unofficial employment contracts, where respondents are split into whether they work officially or unofficially. Unofficial working agreements are associated with lower pay and lower working conditions, due to limited regulation and limited bargaining power given to workers (?, ?). If certain migrants are more likely to fall into such agreements, they likely hold a disadvantage in the labour market.

In model 1 we establish the basic differences in unofficial employment between migrant groups. We note that Azerbaijan, Armenian, and Georgian migrants have higher odds of working unofficially for an employer when compared to immobile Russian respondents. This is also true for Moldovan migrants, and migrants from Tajikistan, Turkmenistan, and Uzbekistan.

In model 2 we consider the additional impact of nationality. This measure does not have an impact on the likelihood of working unofficially in itself, but explains some differences for certain migrant groups (Tajikistan, Turkmenistan, and Uzbekistan). In model 3, we add additional demographic factors like gender, marital status, and our factor capturing both age and duration in the country. We find that women are less likely to work unofficially, when compared to men. We also find that married respondents are less likely to work unofficially when compared to respondents who were never married. Cohabiting respondents in turn have higher odds of working unofficially when compared to respondents who were never married. Regarding migrant groups, this model still holds differences, with mobile Russian respondents reporting higher odds of unofficial work when we consider demographic factors. Lastly, model 4 considers the impact of a third level education. Those with a third level education have lower odds of working unofficially, when compared to those without a third level education. Importantly, this measure does not explain the gaps found between migrant groups in working unofficially, which remain in place.

Figure 1: Marginal COB effects for Employment

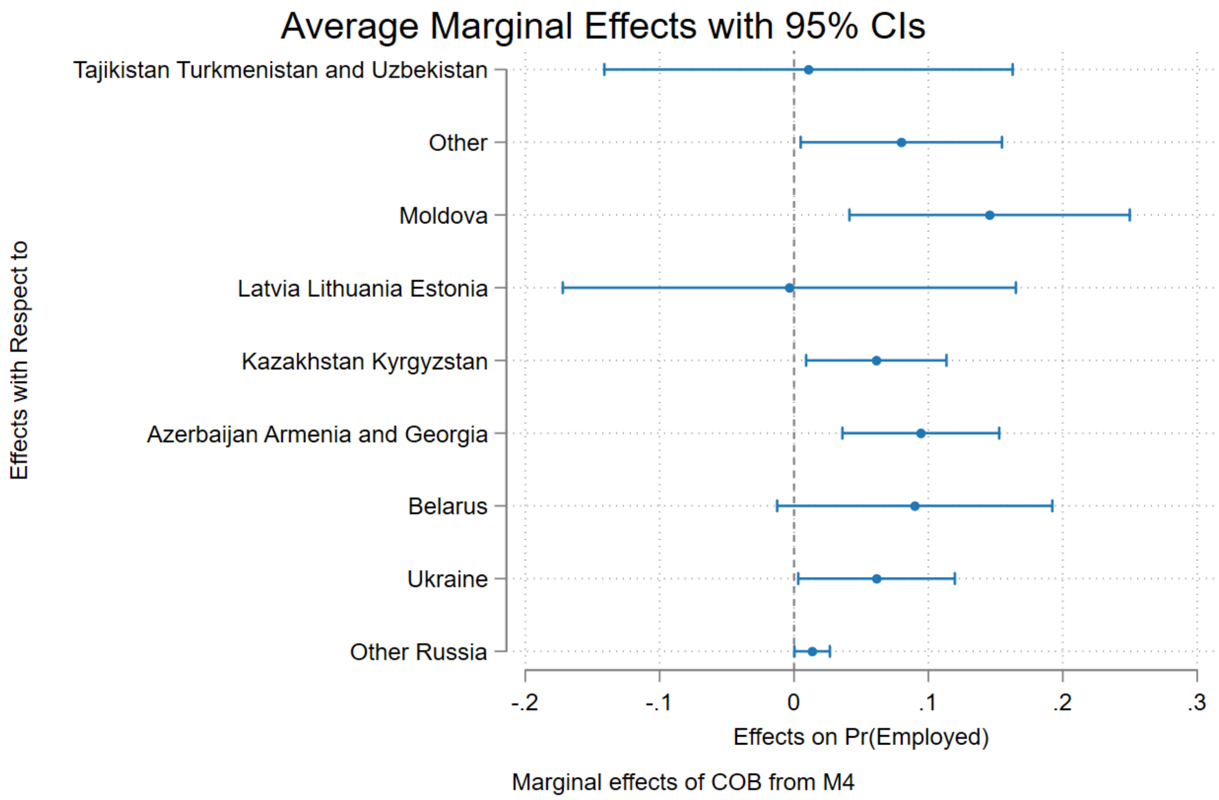
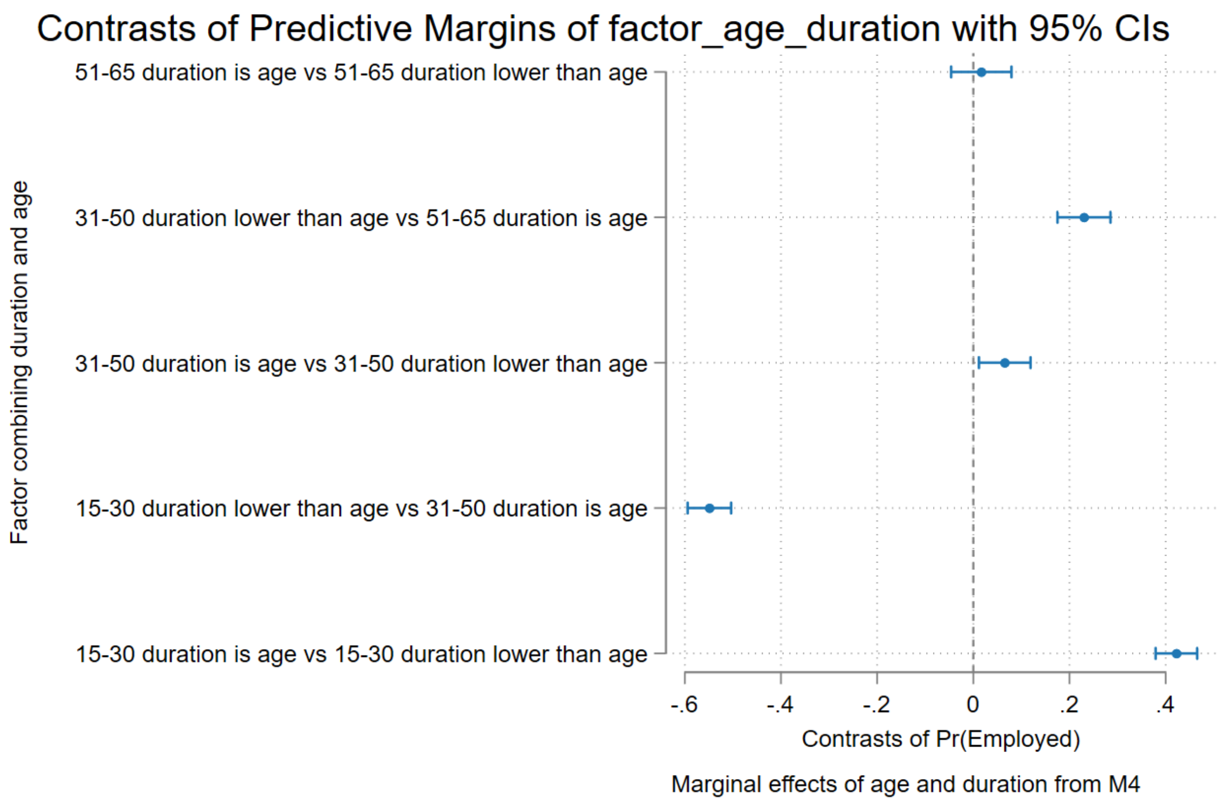


Figure 2: Marginal Age and Duration effects for Employment



	M1: Basic	M2: Add nationality	M3: Add demographics	M4: Add education
Binary variable: employed unofficially				
Russia no mobility	1	1	1	1
Other Russia	1.124	1.119	1.225**	1.210**
Ukraine	1.173	1.139	1.140	1.168
Belarus	1.135	1.086	1.117	1.223
Azerbaijan Armenia and Georgia	2.498***	2.302***	2.289**	2.127**
Kazakhstan Kyrgyzstan	1.416	1.401	1.300	1.288
Latvia Lithuania Estonia	0.320	0.320	0.299	0.264
Moldova	3.511***	3.394**	3.373**	3.681**
Tajikistan Turkmenistan and Uzbekistan	1.718*	1.666	1.637	1.567
Other	2.669	2.643	2.608	3.404*
Other nationality		1	1	1
Russian national		0.870	0.868	0.885
male			1	1
female			0.571***	0.643***
Never married			1	1
Married			0.510***	0.526***
Cohabiting			1.277*	1.188
separated widowed divorced			1.183	1.137
15-30 duration is age			1	1
15-30 duration lower than age			1.897	1.872
31-50 duration is age			0.832*	0.822*
31-50 duration lower than age			1.063	1.069
51-65 duration is age			0.780*	0.703***
51-65 duration lower than age			0.908	0.912
No third level				1
Third level				0.379***
Observations	34972	34972	34972	34972
Pseudo R^2	0.004	0.004	0.034	0.056
AIC	17712.7	17710.6	17197.9	16813.8
BIC	17797.3	17803.6	17367.2	16991.5

Exponentiated coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We note that certain migrant groups have higher odds of working in an unofficial position. However, these measure do not formally test our hypothesis regarding early arrivals, which we test using predicted probabilities using the estimates from Model 4. This is listed in the figure below. We do not find a statistically significant difference between early arrivals and more established groups in terms of unofficial employment. Although the estimates are not significant, it is the more established groups who are more likely to use unofficial employment contracts.

4.4 Wage models

Our final set of models considers monthly wages, checking for wage penalties which cannot be explained by demographics, occupational sorting, or education and tenure with the firm (human capital).

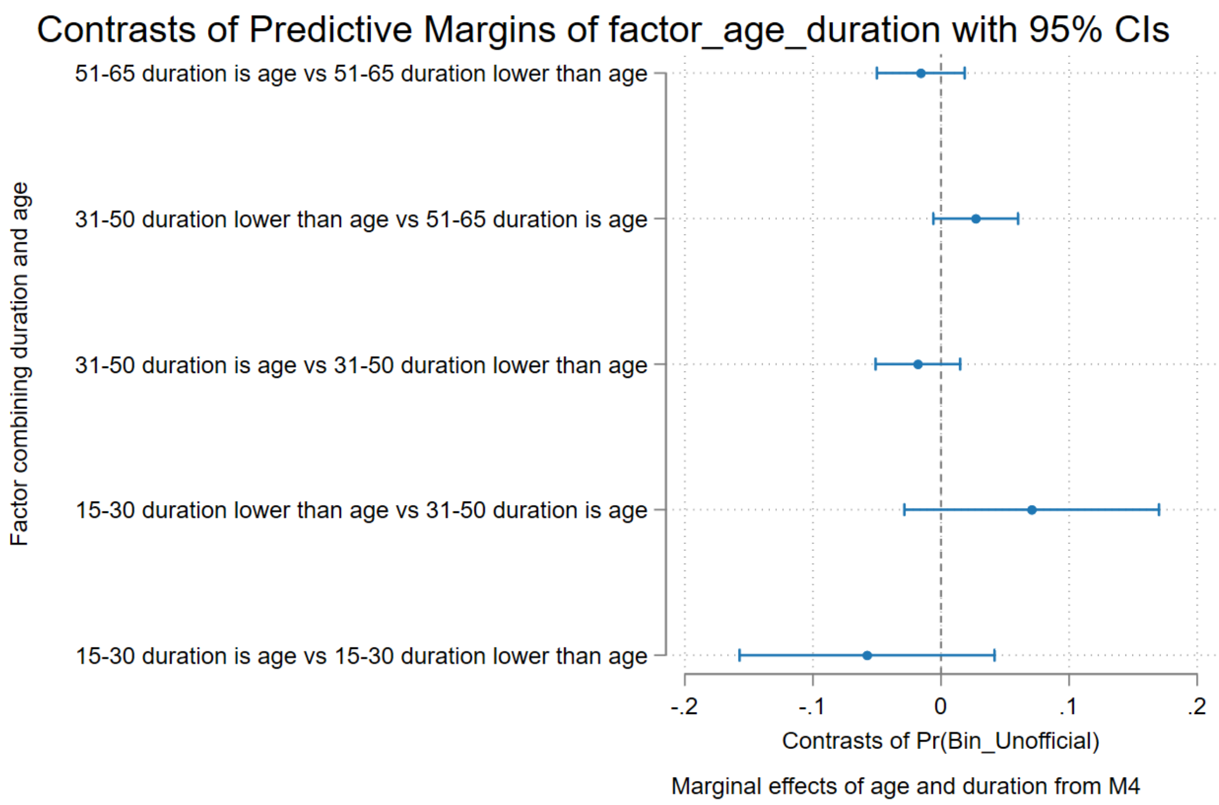
Model 1 establishes the basic differences between migrant groups, showing few significant estimates. Only migrants from Ukraine (1.2) and Belarus (1.6) have significantly different wages from Russian non-migrants, and these estimates list higher wages.

In model 2, we add measure of nationality and occupation. Here, we find significant differences between occupational groups, with Managers earning more than most occupational categories. However, this measure does not explain migrant group differences, and so we cannot say that migrant premiums come from their higher chances of working in a certain occupation. Ukrainians and Moldovans still hold a premium in terms of pay when compared to Russian non-migrants.

In model 3 we consider additional demographics, like gender, marital status, and our combined index of age and time spent in the country. These have their own impacts on wages, but importantly they do not explain the differences between migrant groups recorded earlier. Ukrainian and Moldovan migrants still see higher earnings, as do mobile Russians, once their demographic factors are held constant against non-mobile Russians.

Finally, Model 4 considers job tenure and education, with education being significantly associated with higher wages. Once again these estimates do not explain differences in earnings between Ukrainian migrants and Moldovan migrants. It is likely that migrants who are able to work in Russia, seek a pay premium, similar to mobile Russians who move from a separate part of the country. This premium acts as a reservation wages, where mobility has to be compensated in part by the employer.

Figure 3: Marginal Age and Duration effects for Unofficial Contracts



	(1) M1: Basic	(2) M2: Add Occupation and nationality	(3) M3: Add demographics	(4) M4: Add education and tenure
AFTER-TAX WAGES LAST 30D–JOB 1				
Russia no mobility	1	1	1	1
Other Russia	1.019	1.029	1.065***	1.067***
Ukraine	1.235***	1.241***	1.179*	1.171*
Belarus	1.622*	1.748*	1.886*	1.850*
Azerbaijan Armenia and Georgia	1.106	1.160**	1.065	1.067
Kazakhstan Kyrgyzstan	1.037	1.022	0.947	0.947
Latvia Lithuania Estonia	1.031	0.976	1.006	1.036
Moldova	1.006	1.071	1.010	0.968
Tajikistan Turkmenistan and Uzbekistan	0.971	0.991	0.905	0.919
Other	1.160	1.091	1.072	1.035
Armed forces occupations		0.939	0.811***	0.852**
Managers		1	1	1
Professionals		0.707***	0.794***	0.772***
Technicians and associate prefessionals		0.634***	0.688***	0.715***
Clerical support workers		0.535***	0.614***	0.654***
Servece and sales workers		0.464***	0.503***	0.559***
Skilled agricultural, forestry and fishery workers		0.726*	0.681**	0.732*
Craft and related trades workers		0.640***	0.571***	0.647***
Plant and machine operators, and assemblers		0.669***	0.595***	0.682***
Elementary occupations		0.387***	0.409***	0.471***
Other nationality		1	1	1
Russian national		1.053	1.064	1.063
male			1	1
female			0.676***	0.682***
Never married			1	1
Married			1.049*	1.040
Cohabiting			1.010	1.017
separated widowed divorced			1.057*	1.064*
15-30 duration is age			1	1
15-30 duration lower than age			1.058	1.065
31-50 duration is age			1.087***	1.085***
31-50 duration lower than age			1.222	1.234
51-65 duration is age			0.887***	0.909***
51-65 duration lower than age			0.953	0.963
j_tenure				1.004
j_tenure × j_tenure				1.000
No third level				1
Third level				1.259***
Observations	35519	35519	35519	35519
AIC	808729.0	805556.7	802924.1	802168.3
BIC	808813.8	805726.3	803170.0	802439.6

Exponentiated coefficients

We again consider the predicted earnings of migrants use marginal effects, formally testing our hypothesis regarding migrant groups using the estimates from Model 4. This is listed in the figure below. We do not find a statistically significant penalty in wages between migrants. In fact we find a significant pay premium for people who move from other parts of Russia, Ukraine, and Moldova.

We further test the Marginal effects of our age and duration index on earnings, and as with country of birth, we do not find seignficant differences in this measure.

Our three sets of models highlights some important differences. Regarding employment, migrants are more likely to be employed when compared to non-migrants. However, recent arrivals are less likely to be employed when compared to more established groups. Regarding unofficial employment, we find certain groups that are especially likely to hold these position, but recent arrivals did not hold a disadvantage on this measure. Finally, regarding pay, we found that migrants and internal migrants typically earned more than non-migrants, and we hypothesise that this effect stems from a reservation wage, where migrants try to compensate for the cost of moving, through wages.

5 Discussion

With reference to the three theoretical frameworks above, we find support a number of hypotheses. Thinking of human capital theory, our estimates for third level education routinely show that respondents with a college degree have more favourable labour market outcomes; having higher odds of employment, lower odds of unofficial employment, and higher earnings (?, ?, ?). We also find support for this theory in the index which combines age with duration, where older groups typically report higher earnings than younger groups (?, ?, ?). However, we do not find support for Human Capital theory in our estimate for job tenure, and further, Human Capital theory does not fully explain group differences between migrant and non-migrant groups.

We find limited support for the discrimination hypothesis (?, ?). Although migrants are more likely than non-migrants to be employed, certain groups have higher odds of falling into unofficial employment. Further, additional measures cannot explain why certain migrants fall into unofficial work, mainly migrants from other parts of Russia, migrants from Azerbaijan, Armenia, or Georgia, and migrants from Moldova, Tajikistan, Turkmenistan, and Uzbekistan. Despite comparable measures of human capital and comparable demographics, these workers remain more likely to work unofficially, when compared to immobile workers.

Lastly, we find some support for theories of integration (?, ?), where newer arrivals report lower employment when compared to more established groups. However this finding does not translate to lower earnings or higher chances of unofficial employment, beyond the gaps reported by COB group.

6 Conclusion

This paper outlined migrant gaps in employment, official employment, and wages using data from the Russian Federation. It considered three theoretical frameworks for explaining these gaps, and the estimated models offer some support for each of the three interpretations of migrant differences. Although migrant groups differ little in terms of employment rates, and even report higher employment levels when compared to non-migrants, migrants with a shorter duration in Russia report lower levels of employment. However, migrants have a higher likelihood of working in unofficial positions, which could carry penalties in terms of pay and working conditions. These differences do not translate in lower earnings for migrants, in fact many migrant groups including those from Belarus and Ukraine, report higher earnings, which could reflect a type of Reservation Wage that migrants look for, in order to move to Russia. These results help to understand the importance of migrant labour in Russia, and the impact they have on the Russian economy.

Future researchers should pay close attention to the participation of migrants in Russia's economy. As micro-level data from the time of COVID-19 lock-downs and the ongoing war in Ukraine becomes more available, it will be important to highlight the impact of exogenous shocks to migrants' time in Russia. These migrants and their labour are an important resource for the country, one that will likely withdraw over the years ahead. If true, policy makers will have to supplement their labour and their wider contributions to Russian society somehow, which will prove difficult.

Figure 4: Marginal COB effects for Wages

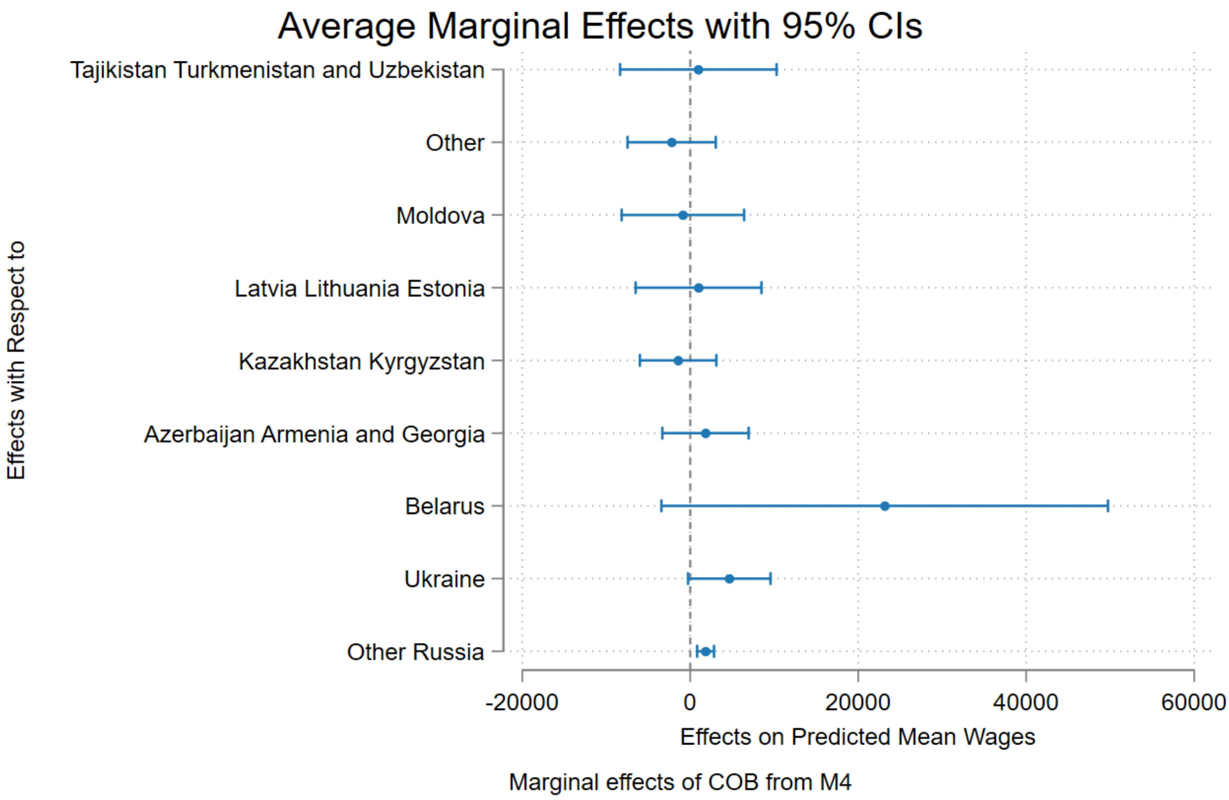
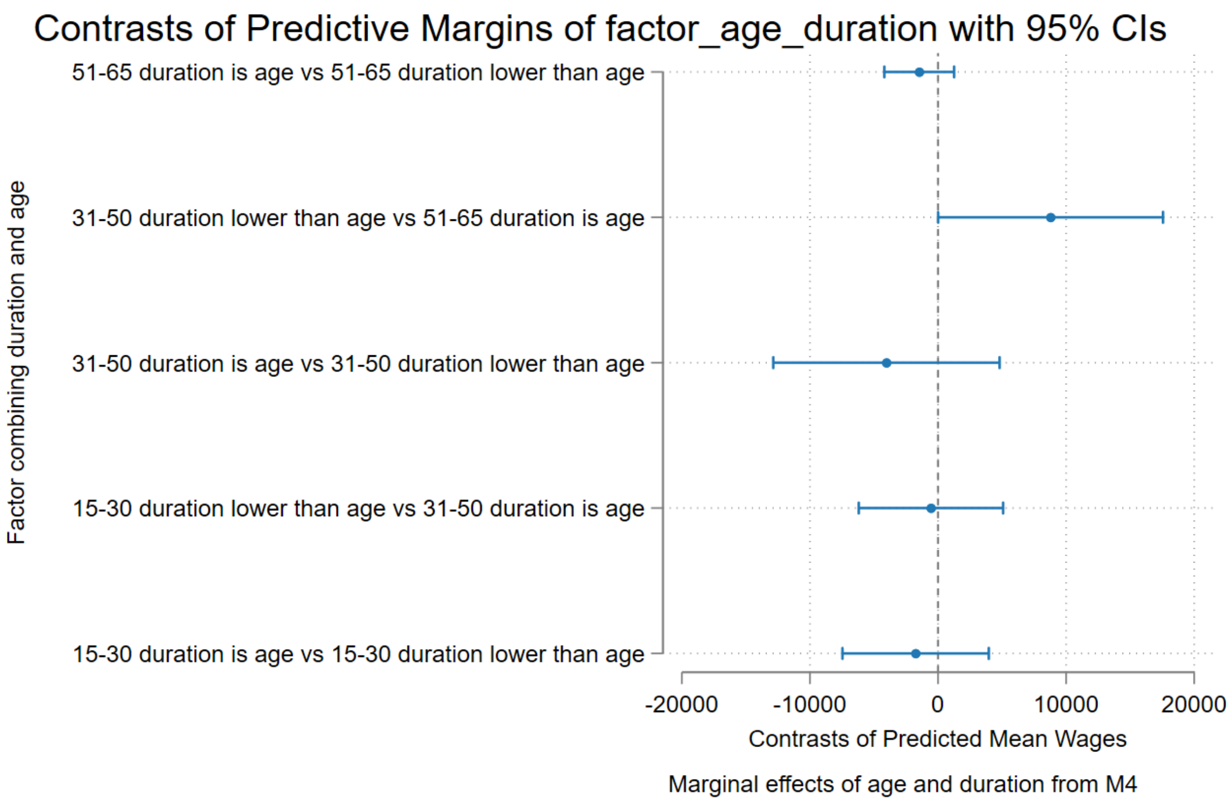


Figure 5: Marginal Age and Duration effects for Wages



A Post-estimation checks

Our initial models reported high collinearity between age and duration in the country. Below, we list collinearity results for models predicting employment.

Variable	VIF	1/VIF	
simple_cob			
1	1.7	0.588991	
2	1.23	0.816188	
3	1.07	0.93723	
4	1.33	0.749537	
7	1.32	0.756217	
9	1.01	0.988751	
11	1.04	0.957415	
12	1.22	0.8222	
16	1.02	0.976807	
1.nationalỹ	5.05	0.198094	
2.gender	2.24	0.44572	
simple_mar			
2	4.87	0.205476	
3	1.79	0.557481	
4	2.29	0.436086	
age	113.91	0.008779	
duration	104.73	0.009548	
1.simple_ed	1.5	0.667683	
Mean VIF	14.55		

In order to avoid collinearity between these measures, we combined them into one index, which had the effect of greatly reducing collinearity in subsequent models, providing more reliable estimates. These are also listed below.

Variable	VIF	1/VIF	
simple_cob			
1	1.68	0.595218	
2	1.26	0.792138	
3	1.08	0.921741	
4	1.37	0.73216	
7	1.36	0.732618	
9	1.02	0.983368	
11	1.06	0.947294	
12	1.28	0.783924	
16	1.02	0.978973	
1.nationalỹ	4.17	0.240054	
2.gender	2.21	0.45281	
simple_mar			
2	4.79	0.20896	
3	1.78	0.562521	
4	2.22	0.450217	
factor_ageñ			
3	1.07	0.932674	
4	3.42	0.292036	
5	1.86	0.536491	
6	2.67	0.374428	
7	1.67	0.600323	
1.simple_ed	1.52	0.657516	
Mean VIF	1.93		

References

Arrow, K. J. (2015). The theory of discrimination. In *Discrimination in labor markets* (pp. 1–33). Princeton University Press.

Baert, S., & Vujić, S. (2016). Immigrant volunteering: a way out of labour market discrimination? *Economics Letters*, *146*, 95–98.

Barrett, A., & McCarthy, Y. (2007). The earnings of immigrants in ireland: results from the 2005 eu survey of income and living conditions. *Available at SSRN 1012371*.

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press.

Bisin, A., Patacchini, E., Verdier, T., & Zenou, Y. (2011). Ethnic identity and labour market outcomes of immigrants in europe. *Economic Policy*, *26*(65), 57–92.

Borjas, G. J. (1987). *Self-selection and the earnings of immigrants* (Tech. Rep.). National Bureau of Economic Research.

Dustmann, C., & Fabbri, F. (2003). Language proficiency and labour market performance of immigrants in the uk. *The economic journal*, *113*(489), 695–717.

Dustmann, C., Fabbri, F., Preston, I., & Wadsworth, J. (2003). Labour market performance of immigrants in the uk labour market.

Esser, H. (2006). Migration, language and integration.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, *78*(6), 1360–1380.

Heath, A., Liebig, T., & Simon, P. (2013). Discrimination against immigrants–measurement, incidence and policy instruments. *International Migration Outlook 2013*, 191–230.

Joseph, E. (2018). Whiteness and racism: Examining the racial order in ireland. *Irish Journal of Sociology*, *26*(1), 46–70.

Kravchuk, N., Bilous, O., & Synkevych, N. (2019). Minimum wage and working under the table: issues and solutions–accounting aspect. In *Business risk in changing dynamics of global village 2, 2019* (pp. 262–270). Publishing House of University of Applied Sciences in Nysa.

McGinnity, F., Enright, S., Quinn, E., Maître, B., Privalko, I., Darmody, M., ... others (2020). Monitoring report on integration 2020. *Economic and Social Research Institute (ESRI) Research Series*.

McGinnity, F., & Lunn, P. D. (2011). Measuring discrimination facing ethnic minority job applicants: an irish experiment. *Work, employment and society*, *25*(4), 693–708.

McGinnity, F., Nelson, J., Lunn, P., & Quinn, E. (2009). Discrimination in recruitment: Evidence from a field experiment.

McGinnity, F., Privalko, I., Fahey, É., Enright, S., & O'Brien, D. (2020). *Origin and integration: a study of migrants in the 2016 irish census*. Cambridge Centre for Alternative Finance.

OECD. (2018). Settling in: Indicators of immigrant integration/oecd publishing: Paris/european union, brussels.

O'Connell, P. J. (2019). Why are so few africans at work in ireland? immigration policy and labour market disadvantage. *Irish Journal of Sociology*, *27*(3), 273–295.

Portes, A., & Rumbaut, R. G. (2001). *Legacies: The story of the immigrant second generation*. Univ of California Press.

Quillian, L., Heath, A., Pager, D., Midtbøen, A. H., Fleischmann, F., & Hexel, O. (2019). Do some countries discriminate more than others? evidence from 97 field experiments of racial discrimination in hiring. *Sociological Science*, *6*, 467–496.

Sørensen, A. B. (1975). The structure of intragenerational mobility. *American Sociological Review*, 456–471.

Zschirnt, E., & Ruedin, D. (2016). Ethnic discrimination in hiring decisions: a meta-analysis of correspondence tests 1990–2015. *Journal of Ethnic and Migration Studies*, *42*(7), 1115–1134.