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The Causal Effect of Deficiency at English on Female Immigrants' Labor Market Outcomes in the UK

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ABSTRACT

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We investigate the extent to which deficiency at English as measured by English as Additional Language (EAL), contribute to the immigrant-native wage gap for female employees in the UK, controlling for covariates. To deal with the endogeneity of EAL and a substantial problem of self-selection into employment we suggest a 3-step estimator (TSE). The properties of this estimator are investigated in a Monte Carlo simulation study and we show evidence that TSE delivers a consistent and asymptotically normal estimator. We find a large and statistically significant causal effect of EAL on the immigrant-native wage gap for women.

NON-TECHNICAL SUMMARY

Using the first wave of the UK Household Longitudinal Survey, we investigate the extent to which deficiency at English as measured by English as Additional Language (EAL), contribute to the immigrant-native wage gap for female employees in the UK, after controlling for age, region of residence, educational attainment and ethnicity. To deal with the potential endogeneity of EAL and a substantial problem of self-selection into employment we suggest an easy to implement 3-step estimation (TSE) procedure. The properties of the TSE estimator are investigated in a Monte Carlo simulation study and we show evidence that our procedure delivers a consistent and asymptotically normal estimator. We find that English as Additional Language (EAL) has a causal effect of -25% on wages for UK female immigrants and that the adjusted immigrant-native wage gap is fully accounted by EAL.

JEL Classification: J15, J31, J61, C21

Keywords: English as Additional Language (EAL), immigrant-native wage gap, endogenous treatment, sample selection

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1 Introduction

The persistence of the ethnic minority employment and wage gap, and more generally the persistence of racial inequality, has become a major public policy issue in the UK. In 2005, the Business Commission on Race Equality in the Workplace was set up at the request of Gordon Brown (Chancellor of the Exchequer at the time). In 2007, the Commission published a report entitled ‘60/76’, highlighting the proportion of ethnic minorities and whites in the working age group who are in employment respectively (National Employment Panel 2007).

In this paper we investigate the extent to which deficiency at English contribute to the immigrant-native wage gap for female employees in the UK, after controlling for age, region of residence, educational attainment and ethnicity. The literature that attempts to uncover the causal effect of host country language proficiency on immigrants’ labor market outcomes is rather limited and often plagued by small sample sizes and identification issues (see e.g. Chiswick 1991, Chiswick and Miller 1999, Dustmann 1994, Leslie and Lindley 2001, and Lindley 2002). One additional challenge with the study of female immigrants is the need to account for the strong selectivity into employment, potentially varying according to the immigrant status, which is usually found to be insignificant (or assumed to be absent) for studies of prime age male immigrants.

The main novelty of this paper is the use of a three-step estimation procedure, which allows for endogeneity of EAL and corrects for bias arising from self-selection into employment. Our Monte Carlo simulations show that this estimator is consistent where a naïve two stage least squares (2SLS) estimator would be not. Moreover, we report robust standard errors taking into account the variation of parameters in the first and second step using bootstrapping. To the best of our knowledge, no previous study has attempted to address both econometric issues at the same time. For example, whereas Leslie and Lindley (2001) use a simultaneous equation approach to enable language proficiency and employment to be jointly determined, they estimate the immigrant-native wage gap using a decomposition approach, hence treating language proficiency as exogenous. In contrast, Lindley (2002) adopts two alternative approaches, one relying a two stage least squares (2SLS) approach which combines an earnings equation and a probit equation for English language proficiency, while the other using a language fluency selection model approach. However, neither approach allows for self-selection into employment, which might in turn depend on language proficiency itself.

Our choice of measure for deficiency at English is a binary variable known as English as Additional Language (EAL), which is based on the response to a subjective question enquiring whether or not an individual considers that she/he speaks English as a native speaker.[1] Compared to more subjective self-assessed English proficiency normally used in the literature, this measure is less prone to measurement errors and hence allows for more precise estimates of the causal effect of language.[2]

Recently Miranda and Zhu (2013) have shown that EAL has a strong negative causal effect of -23% on the wages for male immigrants in the UK, by using the interaction of language of country of birth and a late age-at-arrival indicator as instrument. The identification strategy was inspired by the theory of the critical period for second

[1] In particular, the question is: 'Is English your first language?'

[2] Using German panel data, Dustmann and van Soest (2002) show that measurement errors in self-reported language proficiency could lead to severe underestimate of the effect of language on earnings.

language acquisition in psychology and has been used in US studies by Bleakley and Chin (2004, 2010), and in a Dutch study by van Ours and Veenman (2006).

Here we extend the model to the study of female immigrants in the UK, who apparently suffer from a much more pronounced employment-gap rather than a wage-gap at the mean when compared to their native counterparts. This pattern is in sharp contrast to that for men. While we identify the effect of EAL using the same strategy as in Miranda and Zhu (2013), we account for the endogenous selection into employment by exploiting variations in the female-to-male ratios of labor force participation and educational attainment by country of birth. The idea is that these variables proxy gender-based social norms of work orientation, but do not affect wages directly. Empirically, both measures turn out to be strong predictors of employment for our sample members.

We use the first wave of the UK Household Longitudinal Survey (also known as Understanding Society), a very rich dataset containing various measures of deficiency at English, migration history and parental backgrounds. For women aged 19-59 in our sample, there is a statistically insignificant immigrant-native wage gap of 1.2 percentage points, which is dwarfed by a staggering 24 percentage points employment gap, both in favor of native women.

We find evidence of negative selection of EAL into employment on unobservables, i.e. female immigrants with unobservable attributes that make them more prone to EAL are less likely to be in employment. Moreover, we also present evidence of self-selection bias on the wage equation, which if uncorrected, would result in biased estimates of the causal effect of EAL on the immigrant-native wage gap for women. Our findings are robust to various model specifications and the exclusion of adulthood immigrants.

Our research thus highlights the importance of both allowing for endogeneity of host country language deficiency and accounting for selection into employment in the analysis of female immigrants' labor market outcomes.

The remainder of the paper is organized as follows. Section 2 introduces the data and sets up the analysis. The methodological approach and a Monte Carlo simulation study are presented in section 3. Next, empirical results are presented and discussed in Section 4. Finally, Section 5 concludes.

2 Data and set-up of the analysis

We use the first wave of the UK Household Longitudinal Survey (UKHLS), also known as Understanding Society, which is an ideal data to study the impact of host country language deficiency of immigrants on their labor market outcomes.[3] UKHLS is a longitudinal survey of just over 30,000 households and 18,722 women aged 19-59 in the UK undertaken over the period 2009-2011, including the ethnic minority boost sample. The survey contains not only information on ethnicity and country of birth of the immigrant and both parents, but crucially also measures of English proficiency including an indicator of whether English is their first language.

[3] Our results are robust to the use of the pooled sample that combines Wave 1 and Wave 2. However, there is strong evidence of differential sample attrition rates between natives and immigrants. As the current release of the data does not contain sampling weights, we only present the results using the first wave in the interest of transparency.

In this paper, we focus on the immigrant-native real gross hourly wage gap of female employees aged 19-59.[4] Natives are defined as ethnic whites who speak English as first language and were born in the UK to both UK-born parents. Conversely, immigrants are defined as people who were born abroad to two non-native parents. We only include non UK-born immigrants in the treatment group, in order to exploit the variation in deficiency at English induced by the variation in the age-at-arrival of immigrants from non-English-speaking versus English-speaking countries. Self-employed women are excluded from our sample, as no earnings information is available.[5] After listwise deletion of observations with missing values in key variables,[6] we end up with a sample of 13,296 females, of which 8,854 are salaried employees with non-missing wages.[7] We refer to the former as the full sample, and the latter as the wage sample.

Table 1A and 1B report summary statistics by immigrant status, for the full and wage sample respectively. Indeed, these two samples have very different characteristics.

Table 1A shows that only 46% of female immigrants are in employment, compared to 70% of their native counterparts. The 24 percentage point employment gap represents

[4] Real gross hourly wages are derived from gross earnings over the past 12 months and reported working hours. The upper age limit is set at 59 because women at 60 or above in the UK are entitled to receive state pension.

[5] Only 5% of natives and 4% of immigrants are self-employed, respectively.

[6] The overall non-response rate is approximately 10%.

[7] Women with missing wages but declare being in employment or on maternity leave are excluded from the non-participation group. Together they account for just over 3% of women with missing wages.

over half of the immigrant women's labor force participation rate, and must be borne in mind when studying the female wage-gap between immigrants and natives.[8]

While all natives are native English speakers by construction, 73% of all female immigrants declare speaking English as Additional Language (EAL). Immigrants' education distribution is bimodal, compared to that of natives. For instance, whereas immigrants are over 11 percentage points more likely to hold no qualifications, they are also 8 percentage points more likely to hold a higher (post-graduate) degree. Female immigrants in the UK are on average younger, and live disproportionately in London compared to white natives. Whereas all natives are white by construction, there is significant heterogeneity in the ethnic composition of female immigrants, with 55% classified as Asians, 13% as blacks, and 22% as whites.

Table 1B shows that conditional on being in salaried employment, the raw immigrant-native wage gap for women is a statistically insignificant 0.012 log points (or 1.2 percentage point)[9] in favor of natives. About 63% of female immigrants in work declare EAL. The 10 percentage point reduction in the EAL incidence among immigrants in the wage sample relative to the full sample indicates a role of English proficiency in selection into work.[10] Compared to the full sample, the education distribution of immigrants in the

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[8] The corresponding employment gap for males is 8.5 percentage points, representing 12.7% of male immigrants' labour force participation rate.

[9] A gap of β log points can be transformed into a $100*(\exp(\beta)-1)$ percentage difference. For small values of β (say less than 0.20), $100*\beta$ gives a reasonable approximation of the actual percentage change.

[10] There is also strong indication that English proficiency might be a key determinant of occupation, even conditional on educational qualifications. Table A1 in the Appendix compares the top 10 occupations (3-digit SOC) of natives and immigrant women without higher education qualifications. It is obvious that immigrant women are

wage sample shows a significant shift to the higher end, with the negative gap in the no qualification category diminished by 80%. This strongly suggests a positive selection into employment in terms of educational attainment amongst immigrant women. On average, female immigrants in employment are also younger, and more likely to live in London (but slightly more dispersed geographically compared to the full sample), compared to their native counterparts.

In Figure A1, we further explore alternative measures of deficiency at English. In our survey, if a person declares EAL, questions are then asked about whether she has difficulty in: (1) speaking day-to-day English, (2) speaking on the phone, (3) reading English, and (4) completing forms in English. For each of those four aspects of English difficulties, the degree of difficulty is also asked, with possible answers of a little difficult, fairly difficult, very difficult and cannot speak (read) at all.

Among all first-generation female immigrants who declare EAL and are not in employment, 48% report having some difficulty in English, with the highest incidence in reading (41%) and the lowest incidence in speaking on the phone (30%). For immigrants with EAL and in employment, only 19% report having some difficulty in English, again with the highest incidence in reading (16%) and the lowest incidence in speaking on the phone (7%). When we convert the degree of difficulty into scores with 1 for a little difficult and 4 for cannot speak (read) at all, the total mean score is 6.7 for the non-employed and 4.0 for the employed for immigrants who report having some difficulty. This implies that even for those who report having difficulties with English, the mean

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disproportionately working in occupations such as cleaning, elementary personal services, and manufacturing, all of which require low English proficiency.

level of deficiency at English is not much more than finding it a little difficult in each aspect of the language among those in work, but closer to fairly difficult among those not in work. However, there might be considerable measurement errors in this highly subjective measure of language deficiency, compared to EAL.

3 A three-step estimation procedure to deal with sample selection and endogenous treatment in a regression for continuous response.

As discussed in the previous section, investigation of the role of English deficiency (as measure by EAL) on the immigrant-native wage gap for female employees in the UK is essentially complicated by the fact that women self-select into employment and work status is likely to be correlated with both EAL and log-wage. Here we present an easy to implement procedure to deal with the endogeneity of EAL on the log-wage and selection equation, plus the sample selection into employment.

Denote by $logw_i$ the main continuous response variable, by EAL_i the endogenous binary treatment, and by s_i the selection variable, with $i = 1, \dots, N$. We say that if $EAL_i = 1$ an individual is treated, whereas if $EAL_i = 0$ the individual is not treated. The main response is only observed if $s_i = 1$ and missing when $s_i = 0$. Treatment and selection conditions are always observed. The system is composed by five equations

$$EAL_i^* = \boldsymbol{x}_{i,EAL}\boldsymbol{\beta}_{EAL} + u_{i,EAL} \qquad (1)$$

$$s_i^* = \boldsymbol{x}_{i,s}\boldsymbol{\beta}_s + \theta_s EAL_i + u_{i,s} \qquad (2)$$

$$logw_i = \boldsymbol{x}_{i,logw}\boldsymbol{\beta}_{logw} + \theta_{logw} EAL_i + u_{i,logw}, \qquad (3)$$

with,

$$EAL_i = 1(EAL_i^* > 0) \quad (4)$$

$$s_i = 1(s_i^* > 0). \quad (5)$$

Vectors of control variables have dimensions (including the constant) $1{\times}K_{EAL}$, $1{\times}K_s$, $1{\times}K_{logw}$ and $\boldsymbol{\beta}_{EAL}$, $\boldsymbol{\beta}_s$, and $\boldsymbol{\beta}_{ylogw}$ are conformable vectors of parameters. There is available at least one instrument for selection in the sense that there is at least one explanatory variable that enters $\boldsymbol{x}_{i,s}$ but not $\boldsymbol{x}_{i,EAL}$ or $\boldsymbol{x}_{i,logw}$. Similarly, there is an instrument for the treatment so that at least one element of $\boldsymbol{x}_{i,EAL}$ does not enter $\boldsymbol{x}_{i,s}$ or $\boldsymbol{x}_{i,logw}$. The error terms follow a multivariate distribution with mean vector $\mathbf{0}$ and covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_{EAL,EAL} & \sigma_{EAL,s} & \sigma_{EAL,logw} \\ \sigma_{s,EAL} & \sigma_{s,s} & \sigma_{s,logw} \\ \sigma_{logw,EAL} & \sigma_{logw,s} & \sigma_{logw,logw} \end{bmatrix}.$$

It is assumed that explanatory variables are strictly exogenous so that conditions

$$\mathrm{E}(u_{i,EAL} \mid \boldsymbol{x}_i) = \mathrm{E}(u_{i,s} \mid \boldsymbol{x}_i) = \mathrm{E}(u_{i,logw} \mid \boldsymbol{x}_i) = 0$$

hold. The equation of main interest is (3) and this equation can only be estimated when $s_i = 1$. Direct estimation of (3) by ordinary least squares (OLS) is complicated by the fact that the treatment is endogenous in both main response $\mathrm{E}(u_{i,logw} \mid EAL_i) \neq 0$ and selection $\mathrm{E}(u_{i,s} \mid EAL_i) \neq 0$ equations, plus there is a problem of sample selection in unobservables because $\mathrm{E}(u_{i,s} \mid u_{i,logw}) \neq 0$.

Our three-step estimation approach follows a similar strategy of that taken by Wooldridge (2002) to estimate a model for a continuous response with an endogenous explanatory variable and sample selection. Basically, Wooldridge recommends using a two-step Heckman sample selection approach to correct for the selection bias, while explicitly addressing the problems caused by the endogenous explanatory variable in the second step. To do this, he recommends fitting the second step of the Heckman model by two-stage least squares (2SLS) (see Wooldridge 2002, p567). This is effectively a control function approach that delivers consistent estimators of the parameters of interest. In the present paper we have a similar problem to the one discussed by Wooldridge, with the only complication that the endogenous variable is a binary treatment indicator and that the endogenous treatment enters the sample selection model.

A naïve two-stage approach would fit a probit model for EAL in a first stage and then, in a second stage, estimate the Heckman sample selection model including the fitted EAL probability from the first stage in the list of control variables. This approach seems intuitive. However, it turns out that it suffers from the problem of the 'forbidden regression' and delivers inconsistent estimators (see Wooldridge 2002, p236 and p478). Basically, the forbidden regression problem arises because EAL is a binary variable that, by its dichotomous nature, has a conditional expectation which is a nonlinear function of the exogenous variables. Because of this nonlinearity, the fitted EAL probability from the first stage probit is, in general, correlated with the residuals in the selection and wage equations of the Heckman model.

To avoid this problem, and following Wooldridge's suggestion, one could think of fitting the second stage of the Heckman model by 2SLS instrumenting EAL with the fitted EAL probability from a first stage OLS regression. That will deal with the endogeneity of EAL in the second stage of the Heckman model. We must still deal, however, with the further complication that EAL enters also the selection equation and it is an endogenous treatment there as well. As a consequence, we need to find a way of obtaining a consistent estimator of the parameters in the selection equation so that it is possible to calculate the correct inverse Mills ratio (IMR) to add as a control in Heckman's second stage. We propose fitting a bivariate probit for EAL and selection to achieve this objective. This leads us to the following 3-stage approach:

1) Fit the EAL (treatment) model by OLS (Linear Probability Model) with the postulated instrument and all other exogenous variables in the system. Get the predicted probabilities from this model.

2) Fit a bivariate probit model for selection (into employment) and treatment (EAL) with each equation having its postulated instrument plus all other exogenous variables in the system. Calculate the IMR using the linear predictor from the selection equation.

3) Fit the (log) wage (main response) equation on the selected sample by 2SLS with EAL as endogenous variable and using predicted EAL probability from step 1, IMR from step 2, and all exogenous variables in the system as instruments.

We call this the Three-step Estimator (TSE). This control function procedure delivers consistent estimators in the (log) wage equation and explicitly addresses the potential sample selection into employment and the potential endogeneity of the EAL treatment variable. The TSE estimator is analogous to a difference-in-differences estimator that calculates language wage effects net of age-at-arrival wage effects, scaled by the difference-in-differences effect of the instrument on the probability of EAL. Importantly, the TSE estimator has an intuitive interpretation as it delivers an estimator of the average treatment effect on the treated (ATT).[11] Notice that the standard errors of the 2SLS in the third step are not correct because it do not take into account the variation of the parameters of the first and second steps. In order to correct for such parameter variation, we suggest bootstraping the standard errors.

An important drawback of the TSE method is that we require joint normality in the second stage and require the error terms in the treatment and selection equations (1)-(2) to be homoscedastic. Moreover, the expected value of the residual in the third stage is supposed to be a linear function of the residual in the selection equation in the second stage (see Vella 1998). These assumptions can be relaxed by fitting the first and second stage using the semi-nonparametric index models described by Gallant and Nychka (1987), and then add powers of the EAL and selection indexes as instruments in the 2SLS fitted in our third stage to implement a flexible control function.[12] Nonparametric identification of a double-index model, however, requires having at hand at least two continuous variables for imposing exclusion restrictions; one for each index (see De Luca 2008, p198). Unfortunately, in the present application we do not have available

[11] Basically there are four groups: (a) immigrants from English-speaking countries arrived to the UK before age 10-14, (b) immigrants from English-speaking countries arrived to the UK after age 10-14, (c) immigrants from non-English-speaking countries arrived to the UK before age 10-14, and (d) immigrants from English-speaking countries arrived to the UK after age 10-14. The language wage effect, net of age-of-arrival wage effects, is the wage DiD between groups ((d)-(c))-((b)-(a)). And the IV estimator is this DiD wage effect divided by the DiD difference in probability of EAL between groups ((d)-(c))-((b)-(a)). This gives a Local Average Treatment Effect (LATE) that is interpreted as the average treatment effect on the treated (ATT).

[12] This would follow suggestions by Newey (2009) in the context of a sample selection model with no endogenous treatment.

continuous variables that could be used to impose such exclusion restrictions and hence we will not pursue the semi-non-parametric avenue here.

3.1 Monte Carlo simulation study

To investigate the properties of the TSE we generated $r = 1, \dots, 10000$ simulated data sets with sample size of 1,000. Throughout the simulation study we denote by y the main continuous response, by $treat$ the endogenous treatment, and by s the sample selection dummy. At each replication two independent standard normal variables (x_1 and x_2) and two Bernoulli variates (d_1 and d_2) with $p = 0.5$ were simulated to play the role of explanatory variables. Variables x_1, x_2, d_1, d_2 enter all treatment, selection, and main response equations. To secure identification three independent standard normal variables $zyvar$, $ztreat$, and $zsel$ were generated at each replication to play the role of instruments. $zyvar$ enters only the main response equation, $ztreat$ enters only the treatment equation, and $zsel$ enters only the selection equation. Finally, for $r = 1, \dots, 10000$, three error terms u_y^r, u_{treat}^r, u_s^r were drawn from a multivariate normal distribution with $sd(u_y) = 0.7$, $sd(u_{treat}) = \mathrm{sd}(u_s) = 1$ and correlations $Cor(u_{treat}, u_s) = Cor(u_y, u_{treat}) = -0.2$ and $Cor(u_y, u_s) = 0.8$. Equations (1)-(5) – with the required change of variable names – together with controls and instruments were used to generate y_i^r, $treat_i^r$, s_i^r for $r = 1, \dots, 10000$ and $i = 1, \dots, 1000$. At each Monte Carlo replication we fitted equation (3) by OLS, 2SLS, and TSE. Standard errors for the TSE were bootstrapped 50 times in each replication.

We aim to show that TSE performs better than OLS and 2SLS when there is non-negligible sample selection on unobservable heterogeneity and the treatment is (moderately) endogenous for selection and main response.

We consider three different experiments. In experiment 1 we have an average probability of selection of 0.75, in experiment 2 we have an average probability of selection of 0.5, and in experiment 3 we have an average probability of selection of 0.25. In all cases the average probability of treatment is 0.5. All other parameters are chosen so that the noise/signal ratio is 0.25 in both main response and treatment. Because we would like selection in unobservables to be important, parameters in the selection equation are set such that the noise/signal ratio is 0.3. Details on the value of the true parameters are written on the footnote of Table 2.

Results are presented in Tables 2 and 3. Unsurprisingly, in all three experiments OLS performs the worst and delivers a bias for the treatment of almost 20%, which is consistent with the fact that the treatment is endogenous and there is a substantial problem of sample selection on unobservable heterogeneity. Once the endogeneity of the treatment is taken into account using the naïve 2SLS estimator, the bias for the treatment falls to around 8% to 12%. Finally, results show the bias for the treatment for the TSE estimator is below 2% in all cases.

We also find that the mean standard error of the TSE approximates well the Monte Carlo standard deviation. Regarding the coverage of the 95% confidence interval, results in

Table 3 show that the TSE achieves a nominal coverage that is near the advertised level.[13] Nominal coverage for OLS and 2SLS are clearly well below 95%.

4 Results and discussions

In this section we explore the extent to which the immigrant-native wage gap depends on the inclusion of various controls, and in particular, on how EAL helps to explain the composition-adjusted gap.

4.1 Least Squares wage equations

In a wage equation, a negative coefficient on an immigrant dummy indicates a regression-adjusted native-immigrant wage gap in favor of natives. The raw immigrant-native wage gap of 0.012 from Table 1B would thus be captured by a coefficient of -0.012 in a regression of log wage on the immigrant dummy only.

In Table 4 we successively introduce sets of control variables. In column 1, after accounting for differences in age profiles and region of residence, the immigrant-native wage-gap increases by 0.11 log points and becomes highly statistically significant. Interestingly, adding the highest qualifications as well as a dummy indicator for highest qualification obtained abroad in column 2 hardly makes any difference.[14] Additionally

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[13] The nominal coverage is significantly different from 0.95 in 0 out of 18 occasions using an exact binomial test.

[14] The interaction terms of the highest qualifications dummies with the foreign dummy are jointly insignificant at any conventional level.

controlling for ethnicity in column 3 reduces the female immigrant-native gap by 90% and makes it statistically insignificant.

We then explore the extent to which deficiency at English explains this remaining wage gap in the next two columns. When EAL is added in column 4, the gap becomes a statistically significant 0.09 log points in favor of immigrants. This implies that all remaining wage gap is explained by deficiency at English. When we further include dummies for age-at-arrival in the UK for immigrants (column 5), the immigrant coefficient remains positive but statistically insignificant while the EAL effect remains significant and is of the same magnitude as before. We include age-at-arrival in bands of 0-9, 10-15, 16-29 and 30+ to disentangle effects of language (note that there is perfect multicollinearity between age, age-at-arrival and years living in the UK) and the effect of assimilation.[15]

To sum up, while the raw immigrant-native wage gap for women is statistically insignificant, we find a large and statistically significant immigrant-native wage gap, after accounting for effect of age profile, region of residence and highest qualifications. Further controlling for ethnicity reduces the gap by about 90%, and renders the gap insignificant statistically. Moreover, deficiency at English as measured by EAL is

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[15] However, our identification of EAL only relies on the ***interaction*** between born in a non-English speaking country and age-at-arrival greater than 9 (following e.g. Bleakley and Chin (2004, 2010)).

capable of explaining the entire remaining regression-adjusted native-immigrant wage gap.[16]

It will be of considerable interest to compare the effect of EAL for female immigrants to their male counterparts at this stage. To save space, we only present the final specification using the corresponding male sample in Table A2 (under OLS). The size of the effect of EAL for men is -0.156, only slightly smaller than the estimate of -0.191 found for women.

4.2 Three step estimation

4.2.1: Step 1 - Linear Probability Model (LPM) of EAL

Table 5 reports the Linear Probability Model (LPM) of EAL, which would form the first stage of a Two Stage Least Square model in the absence of selectivity into employment.

We instrument EAL using born in a non-English-speaking country interacted with a dummy for age-at-arrival greater than 9.[17] Figure 1 shows the regression-adjusted mean probability of EAL, with 95% confidence intervals, by age-at-arrival and language of home country.[18] Female immigrants from non-English-speaking countries who arrived

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[16] Dropping ethnicity controls from the preferred specification increases the EAL effect from -0.191 to -0.202 while dropping qualifications (but keeping ethnicities) increases it to -0.254.

[17] Non-English-speaking home countries in our sample are countries other than Australia, Canada, Jamaica, New Zealand, Republic of Ireland and USA.

[18] These are effectively predicted probabilities based on a linear probability model of EAL on age-at-arrival dummies interacted with a born in non-English-speaking country dummy and controls for age, age squared, region of residence, highest qualification and ethnicity. The patterns are robust to the exclusion of controls.

before the age of 5-9 are, statistically, as likely to be EAL as immigrants from English-speaking countries. In contrast, if immigration occurred after age 5-9, and certainly after age 10-14, the two groups are statistically different. These finding are consistent with Bleakley and Chin (2010) who use an age-at-arrival cut-off at 10 in their preferred specification of English proficiency. Therefore, in line with previous work which focuses on male immigrants, we use age 10 as the critical cut-off point to implement the IV estimator.[19,20]

According to the theory of the critical period for second language acquisition, children are much more able to achieve native-like perfection in a second language than adults. Bleakley and Chin (2004, 2010) show that, after netting out educational attainment and other background variables, differences in English proficiency between immigrants from English-speaking and non-English-speaking countries before and after the critical age are uncorrelated with current wages because any non-language age-at-arrival wage effects are the same for all immigrants in the US regardless of their home country language. If this hypothesis is correct, as it is our view, the interaction term between language of country of origin and age-at-arrival is a valid instrument for EAL in the wage equations because it is correlated with current wages only through the channel of deficiency at English as measured by the EAL status.

[19] Figure A2 shows the corresponding regression-adjusted mean probability of any difficulty in English by age-at-arrival and language of home country respectively, for women in employment. While the overall pattern is the same as for EAL, there is a lack of precision, due to the greater noise with this self-reported measure. Ultimately this would imply a weaker instrument for deficiency at English. Therefore we only report results using EAL as the measure of deficiency at English in this paper.

[20] We undertake sensitivity analysis using the age 5 cut-off, and find very similar results.

Table 5 shows that the instrument is a very strong predictor of EAL status (t-ratio of 30.7). Arriving in the UK after age 9 from a non-English-speaking country (i.e. the interaction term), increases the probability of EAL by 71 percentage points.

4.2.2: Step 2 – bivariate probit model of EAL and selection into employment

Table 6 reports the estimates of the bivariate probit model of EAL and selection into employment, which allows non-zero correlation between the equations' disturbances. Note that we have also allowed EAL to affect selection into employment directly, but not vice versa. This is plausible, given that employment is observed for women aged 19 and above, by which age their EAL (or first language status) should have been well determined.

Since Table 6 reports coefficients rather than marginal effects, we will focus on the statistical significance of the exclusion restrictions and the cross-equation correlation coefficient ρ and their implications for the wage equations in the final stage.

Similar to the LPM specification in Step 1, the interaction between non-English speaking country of birth and arriving in the UK after age 9 strongly predicts EAL in a probit model, with a z-score of 16.1. In the employment selection equation, higher female to male ratios of labor force participation rates or higher female educational attainment as measured by percentage of age 25 or above with at least secondary education of women relative to men in the country of birth are also strong predictors of female immigrants' labor market participation in the host country.[21] Hence both exclusion restrictions work very well. Table 6 also reports a cross-equation correlation coefficient between the disturbances of -0.200, which is significant at the 10% level. We interpret this as evidence of a negative selection of EAL into employment, i.e. that female immigrants with unobservable attributes that make them more prone to EAL are less likely to be in employment, despite an insignificant (and positive) direct effect of EAL on employment.[22]

4.2.3: Step 3 –2SLS incorporating the first two stages

Finally, Table 7 reports 2SLS estimates, with EAL instrumented using predicted EAL from Step 1, IMR calculated from Step 2, and all exogenous control variables in the system. This procedure explicitly accounts for truncation of missing wages for non-labour market participants as well as dealing with the endogeneity of EAL. Importantly, the TSE estimator is able to disentangle language and age-at-arrival wage effects. Robust standard errors for the TSE estimator are bootstrapped with 1000 repetitions.[23]

[21] Both proxies for gender-based social norms of work orientation are downloaded from the latest International Human Development Indicators (UNDP 2012). Blau *et al.* (2011) show that immigrant women from countries with high female labour force participation persistently work more than those from low female labour participation countries, using US census data.

[22] Indeed, by assuming independence of the disturbances (i.e. imposing ρ=0), we would have found a negative and statistically significant direct effect of EAL on employment.

[23] At each bootstrap replication Huber-White-Eicker robust standard errors are calculated. At the end, the bootstrap standard errors are calculated on the basis of these 1,000 replicates.

In order to assess the impact of allowing for endogeneity of EAL and selectivity, we also report the corresponding OLS wage estimates and a naïve 2SLS specification which allows for endogeneity of EAL but ignores selectivity.

Table 7 shows that allowing for endogeneity of EAL increases the size of its effect by 0.085 log points, from -0.191 in the OLS to -0.276 in the 2SLS. Additionally accounting for selection into employment reduces the effect by 0.03 log points, to -0.246. This is not surprising, given the rather large positive coefficient on IMR which is unfortunately not very precisely determined. Our results thus show that while failure to account for the endogeneity of EAL and the self-selection into employment will lead to a seriously downward biased estimate of EAL for women by as much as one fifth, ignoring the self-selection into employment has the potential to bias the estimate in the opposite direction.[24]

In the interest of completeness, we also present the corresponding 3-step and 2SLS results for men in Table A2. It is reassuring to see that not accounting for selectivity into employment, as was the case in e.g. Miranda and Zhu (2013), does not lead to significant bias in the causal effect of EAL for men.[25] The fact that the IMR is small and insignificantly different from zero supports the notion that selectivity is relatively unimportant as far as prime-aged males are concerned.

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[24] GMM and LIML estimates (available upon request) also come out very similar, giving further support to the robustness of our IV results.

[25] We find that the female-male ratios of labour market participation rate and secondary education attainment fail to explain the selection into employment for male immigrants. This is consistent with Blau *et al.* (2011) who find that the labour supply of immigrant men in the US is unaffected by source country female participation.

4.3 Robustness checks

Table 8 replicates Table 7, but on a modified sample. We exclude early retirees (who are under the state retirement age), full-time students under 30 (accounting for 85% of all full-time students) from the non-participant group and anyone whose current economic status is other than being an employee from the participant group. This change reduces the wage sample by 5% and the non-employment sample by 11%. The estimates remain largely the same.

One potential threat to the identification of the EAL effect is the potential endogeneity of immigration and return migration. We get around the problem by replicating Table 8 using only natives and immigrants who arrived in the UK by the age of 18 (usually as dependants of their parents). Table 9 shows that the 3-step and the 2SLS estimates of EAL are -0.399 and -0.279 respectively and become statistically insignificant, due to the loss of about 70% of the immigrant sample by only using childhood immigrants. However, the fact that the size of the effect is larger suggests that our findings are not driven by selective (return) migration.

Finally, we replicate Table 8 using only the subsample of immigrants. The EAL effect in Table 10 is now -0.303 instead of -0.218 from Table 8, and remains statistically significant at the 5% despite the much smaller sample used. Moreover, the gap between the 3-step estimate and the 2SLS estimate ignoring selectivity into employment widens to 11 percentage points. This implies that the EAL effect is not driven by systematic differences in characteristics between natives and immigrants (the composition effect). This finding fits well with our story that the causal effect of EAL is identified by variation ***within*** the sub-population of immigrants in deficiency at English induced by age-at-arrival between immigrants from English-speaking and non-English-speaking countries.

5 Conclusions

Although the immigrant-native wage gap for women in the raw data is statistically insignificant, controlling for differences in age profile and region of residence increases the gap by 11 percentage points, making it statistically significant at any conventional level. Interestingly, further controlling for the highest qualification makes little difference to the wage gap.

In order to focus on the effect of language deficiency, we further condition on ethnicity. We find a composition-adjusted immigrant-native wage gap for female employees in the UK of only 1.2%, which is the same size as the raw wage gap and insignificant. However, the gap reverses sign and becomes statistically significant after controlling for the EAL indicator.

We address the potential endogeneity of EAL and selection into employment using a flexible 3-step estimation procedure. EAL is effectively identified by an IV strategy using non-English-speaking country of birth interacted with a late age-at-arrival indicator as instrument. This gives us a Local Average Treatment Effect (LATE) that is straightforward to interpret for the subpopulation of first-generation immigrants affected by the instrument and offers a meaningful control group. Moreover, we allow for interdependence between selection into employment and EAL using a bivariate probit model where selection is identified using proxies for gender-based social norms of work orientation which vary by country of birth. Our final 2SLS estimate with correction for selection suggests that EAL has a causal effect of -25% on wages for female immigrants, which is significant at 1%, compared to an OLS estimate of -19% and a 2SLS estimate without selection correction of -28%. The causal effect of EAL on the immigrant-native wage gap remains robust when we account for potential misclassification of employment status or restrict our sample to non-UK born immigrants only. Our research thus highlights the importance of both allowing for endogeneity of host country language deficiency and accounting for selection into employment in the analysis of female immigrants' labor market outcomes.

The size of the effect of deficiency at English we find in our more recent data is comparable to studies based on surveys conducted in the early 1990s, e.g. Dustmann and Fabbri (2003). This implies that the large inflow of immigrants following the EU expansion in 2004 has not significantly affected the returns to English proficiency in the UK labor market.

It is worth noting that the estimated effect of deficiency at English is conditional on the highest educational qualification, which is often attained by the immigrant after arriving in the UK. Lindley *et al.* (2006) suggested that qualifications have become an increasingly important determinant of employment of women across ethnic groups in the UK. Recently Dustmann *et al.* (2010) singled out improved English proficiency as the most important factor why ethnic minority pupils improve relative to White British pupils in the compulsory education stage which ends at age 16, using the National Pupil Database (NPD) and the Millennium Cohort Studies (MCS). To the extent that late arrival from a non-English-speaking country (i.e. our IV) will have an adverse effect on educational attainment, our IV estimate can be regarded as a lower bound (i.e. biased towards zero) of the gross effect of language deficiency. Further research is needed before we can have a better understanding of all the channels through which language deficiency impacts labor market outcomes.

Our results suggest that EAL has no bearing on women's labor market participation decisions, conditional on other controls and once the endogeneity of EAL is explicitly controlled for. Moreover, English language proficiency turns out to be the main factor that explains wage differentials between native and immigrant workers. This means that if policy makers want to increase the labor market participation of immigrant women, they will need to look beyond EAL to address the problem. Our findings highlight the important role that 'gender roles', possibly transmitted to women by cultural background, play on the labor market participation decisions of immigrant women. As a consequence, an exclusive policy focus on English Language proficiency might be misplaced. However, conditional on labor market participation, our results show that English language proficiency plays a primary role in determining an immigrant's pay, relative to an otherwise similar native female worker.

From the point of view of the policy maker our results suggest that, for the population of female migrants that are in work, the UK government can significantly increase the welfare of immigrant families by improving women's English proficiency. This may be financed by the increased tax revenue resulting from the rise on immigrant women's income. The second policy implication is that offering English language training alone is not enough to narrow the native-immigrant employment gap for women. Something else needs to be put in place that breaks the traditional inertia that ties women out of the labor market in childrearing activities and household production.

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Figure 1: Regression-adjusted EAL probability by age-at-arrival and home country language, Sample of females immigrants in employment, N=1038

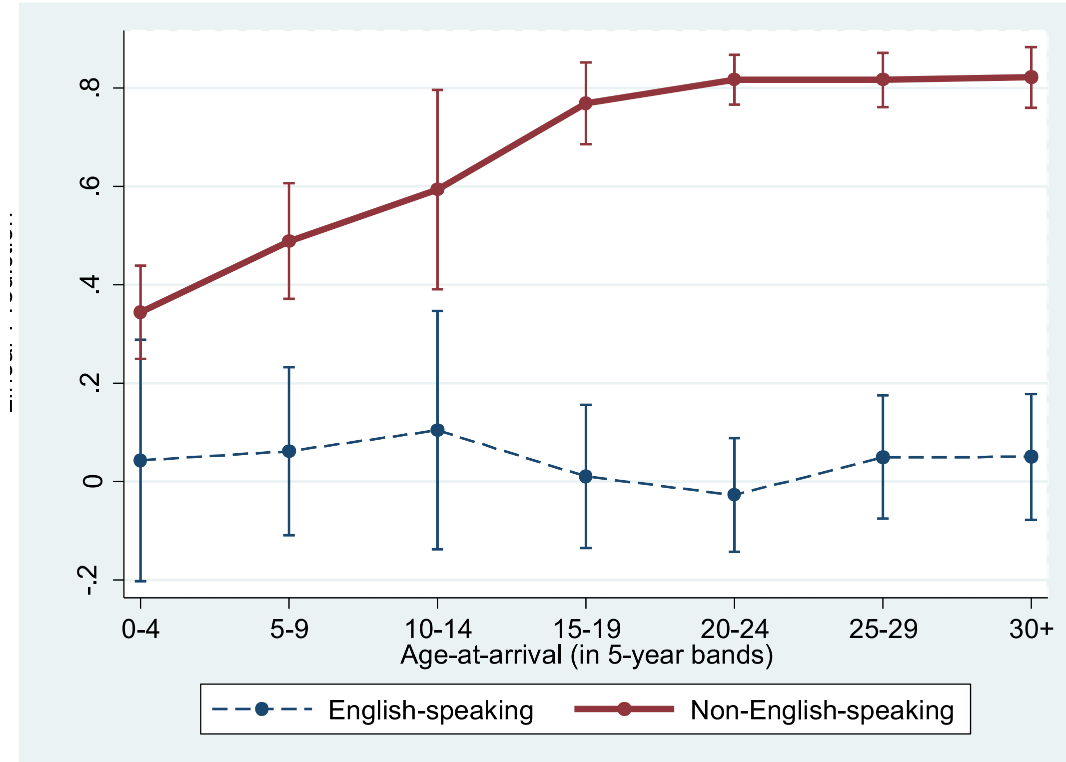

Table 1: Summary statistics, by immigrant status

1A) Full sample (N=13296)

	Immigrants (N=2013)	**Natives (N=11283)**	**Immigrant-native gap**
In employment	0.462	0.703	-0.241**
EAL	0.732	0	0.732**
No qualification	0.290	0.176	0.113**
Below GCSE/O-Level	0.082	0.090	-0.008
GCSE/O-Level	0.137	0.280	-0.143**
A-Level	0.099	0.116	-0.017**
Higher Education Diploma	0.098	0.122	-0.023**
First Degree	0.144	0.149	-0.005
Higher Degree	0.150	0.067	0.083**
Highest qualification is foreign	0.318	0.003	0.316**
Age	37.6	40.0	-2.3**
White	0.219	1.000	-0.781**
Mixed	0.015	0	0.015**
Asian	0.554	0	0.554**
Black	0.131	0	0.131**
Other Ethnicity	0.080	0	0.080**
London	0.479	0.053	0.426**
Southeast	0.080	0.126	-0.046**
Rest of England	0.389	0.615	-0.226**
Wales	0.015	0.056	-0.041**
Scotland	0.020	0.094	-0.074**
Northern Ireland	0.017	0.056	-0.039**

Note: **(*) = significant at 5% (10%) level based on Welch's t-test.

1B) Wage sample (N=8854)

	Immigrants (N=929)	Natives (N=7925)	Immigrant-native gap
Log real hourly wage	2.225	2.237	-0.012
EAL	0.631	0	0.631**
No qualification	0.145	0.121	0.024**
Below GCSE/O-Level	0.073	0.088	-0.015
GCSE/O-Level	0.118	0.273	-0.155**
A-Level	0.104	0.118	-0.014
Higher Education Diploma	0.152	0.138	0.014
First Degree	0.198	0.181	0.017
Higher Degree	0.209	0.081	0.128**
Highest qualification is foreign	0.386	0.004	0.383**
Age	38.1	40.2	-2.1**
White	0.318	1.000	-0.682**
Mixed	0.019	0	0.019**
Asian	0.398	0	0.398**
Black	0.184	0	0.184**
Other Ethnicity	0.081	0	0.081**
London	0.469	0.049	0.420**
Southeast	0.111	0.130	-0.019*
Rest of England	0.347	0.618	-0.271**
Wales	0.019	0.053	-0.034**
Scotland	0.028	0.095	-0.067**
Northern Ireland	0.026	0.055	-0.029**

Note: **(*) = significant at 5% (10%) level based on Welch's t-test.

Table 2: Monte Carlo simulation study – estimated bias and standard deviations of point estimates for coefficients in the equation for y_i

Coefficient	*True value*	*Results for 25% missing*		*Results for 50% missing*		*Results for 75% missing*	
		Bias	*Standard deviation*	*Bias*	*Standard deviation*	*Bias*	*Standard deviation*
A) Ordinary Least Square							
Treatment	1.00	-0.198	0.059	-0.228	0.073	-0.248	0.107
x_1	1.00	-0.003	0.028	0.000	0.034	0.003	0.048
x_2	-1.00	0.000	0.028	0.001	0.034	-0.002	0.048
d_1	1.00	-0.004	0.056	-0.000	0.068	0.002	0.095
d_2	-1.00	0.003	0.055	-0.002	0.067	-0.005	0.095
zyvar	1.00	0.000	0.028	0.000	0.034	-0.000	0.048
B) Naïve Two Stage Least Squares							
Treatment	1.00	-0.082	0.088	-0.113	0.110	-0.127	0.167
x_1	1.00	0.008	0.029	0.011	0.035	0.013	0.050
x_2	-1.00	-0.007	0.029	-0.010	0.035	-0.012	0.050
d_1	1.00	0.007	0.057	0.011	0.068	0.012	0.096
d_2	-1.00	-0.009	0.056	-0.012	0.068	-0.015	0.097
zyvar	1.00	0.000	0.028	0.000	0.033	-0.000	0.048
C) Three Step Estimation							
Treatment	1.00	0.005	0.091	0.010	0.113	0.018	0.164
x_1	1.00	-0.000	0.029	-0.000	0.035	-0.000	0.048
x_2	-1.00	0.002	0.030	0.002	0.035	0.002	0.048
d_1	1.00	-0.001	0.057	-0.001	0.068	-0.002	0.094
d_2	-1.00	-0.000	0.057	-0.001	0.068	-0.002	0.093
zyvar	1.00	0.001	0.027	0.000	0.032	0.000	0.045

Note. Statistics calculated over 10,000 Monte Carlo replications with sample size of 1,000. Standard errors bootstrapped 50 times in each Monte Carlo replication. Mean probability of treatment is 0.5 in all cases. Simulated error tems of equations (1)-(3) are multivariate normal with mean vector zero and $sd(u_y) = 0.79$, $sd(u_{treat}) = \mathrm{sd}(u_s) = 1$, $Cor(u_{treat}, u_s) = Cor(u_y, u_{treat}) = -0.2$ and $Cor(u_y, u_s) = 0.8$. Noise/signal ratio is 0.25 in main response and treatment equations and 0.3 in the selection equations. True parameters in the treatment equation are: x_1=-0.58, x_2=0.58, d_1=-0.58, d_2=0.58, ztreat=1.8. True parameters in the selection equation are: treat=1.2, x_1=-0.12, x_2=0.12, d_1=-0.12, d_2=0.12, zsel=-1.75.

Table 3: Monte Carlo simulation study – average standard error divided by standard deviation of estimates (ASE/SD) and coverage of estimated 95% confidence intervals

Coefficient	***Results for 25% missing***		***Results for 50% missing***		***Results for 75% missing***	
	ASE/SD	*Coverage (%)*	*ASE/SD*	*Coverage (%)*	*ASE/SD*	*Coverage (%)*
A) Ordinary Least Square						
Treatment	*1.00*	*8*	*1.00*	*12*	*0.99*	*35*
x1	*1.00*	*95*	*1.01*	*96*	*1.01*	*95*
x2	*1.00*	*95*	*1.02*	*95*	*1.01*	*95*
d1	*0.99*	*95*	*1.00*	*95*	*1.00*	*95*
d2	*1.01*	*95*	*1.00*	*95*	*1.00*	*95*
zyvar	*0.99*	*95*	*1.00*	*95*	*1.00*	*95*
B) Naïve Two Stage Least Squares						
Treatment	*1.00*	*84*	*0.99*	*82*	*0.97*	*87*
x1	*1.00*	*94*	*1.01*	*94*	*1.00*	*94*
x2	*0.99*	*94*	*1.01*	*94*	*1.00*	*94*
d1	*0.99*	*95*	*0.99*	*94*	*0.99*	*95*
d2	*1.00*	*95*	*1.00*	*95*	*0.99*	*94*
zyvar	*0.99*	*95*	*1.00*	*95*	*0.99*	*94*
C) Three Step Estimation						
Treatment	*1.01*	*95*	*1.00*	*94*	*1.00*	*94*
x1	*1.00*	*94*	*1.01*	*95*	*1.01*	*95*
x2	*1.00*	*94*	*1.01*	*94*	*1.01*	*95*
d1	*0.99*	*94*	*1.00*	*94*	*1.00*	*95*
d2	*1.00*	*95*	*1.01*	*95*	*1.01*	*95*
zyvar	*1.00*	*94*	*1.00*	*95*	*1.01*	*94*

Note. Statistics calculated over 10,000 Monte Carlo replications with sample size of 1,000. Standard errors bootstrapped 50 times in each Monte Carlo replication.

Table 4: Log-wage equations, Wage Sample (N=8832)

	(1)	(2)	(3)	(4)	(5)
Immigrant	-0.119	-0.115	-0.012	0.086	0.080
	(0.021)**	(0.023)**	(0.035)	(0.039)**	(0.050)
EAL				-0.191	-0.191
				(0.036)**	(0.037)**
Age-at-arrival 10-15					0.032
					(0.058)
Age-at-arrival 16-29					0.021
					(0.049)
Age-at-arrival 30+					-0.061
					(0.062)
Highest qualification dummies	no	yes	yes	yes	yes
Ethnicity dummies	no	no	yes	yes	yes

Note: Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared and region dummies.

Table 5: Linear Probability Model (LPM) of EAL, Full Sample (N=13296)

	EAL
Immigrant	0.453 (0.032)**
Age-at-arrival 10-15	-0.356 (0.039)**
Age-at-arrival 16-29	-0.314 (0.034)**
Age-at-arrival 30+	-0.304 (0.036)**
Born in non-English-speaking country * (age-at-arrival>9)	0.712 (0.023)**

Note: Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Table 6: Biprobit of EAL and Selection into Employment Estimates, Full Sample (N=13296)

	EAL	**Employment**
EAL		0.025 (0.163)
Immigrant	6.860 (0.150)**	-0.032 (0.116)
Age-at-arrival 10-15	-1.613 (0.216)**	0.002 (0.130)
Age-at-arrival 16-29	-1.242 (0.191)**	-0.093 (0.106)
Age-at-arrival 30+	-1.092 (0.213)**	-0.031 (0.126)
Exclusion restrictions:		
Born in non-English-speaking country * (age-at-arrival>9)	2.639 (0.164)**	
Labour Force Participation Rate Female-Male Ratio		0.841 (0.181)**
Secondary Education Attainment Female-Male Ratio		-0.527 (0.209)**
ρ (p-value)	-0.200 (0.102)*	

Note: Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Table 7: 3-step wage estimates and the corresponding OLS and 2SLS Estimates, Wage Sample (N=8854)

	3-Step	**OLS**	**2SLS**
EAL	-0.246	-0.191	-0.276
	(0.075)**	(0.037)**	(0.066)**
Immigrant	0.085	0.080	0.095
	(0.057)	(0.050)	(0.052)*
Age-at-arrival 10-15	0.040	0.032	0.048
	(0.067)	(0.058)	(0.059)
Age-at-arrival 16-29	0.027	0.021	0.056
	(0.059)	(0.049)	(0.051)
Age-at-arrival 30+	-0.042	-0.061	-0.027
	(0.069)	(0.062)	(0.065)
Inverse Mills Ratio (IMR)	0.299	-	-
	(0.216)		

Note: Standard errors for 3-step bootstrapped with 1000 repetitions. Robust standard errors for OLS and 2SLS in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Table 8: 3-step wage estimates and the corresponding OLS and 2SLS Estimates, Modified Wage Sample (N=8392)

	3-Step	**OLS**	**2SLS**
EAL	-0.218	-0.175	-0.248
	(0.078)**	(0.038)**	(0.067)**
Immigrant	0.101	0.098	0.110
	(0.058)*	(0.052)*	(0.053)**
Age-at-arrival 10-15	0.040	0.031	0.045
	(0.068)	(0.061)	(0.062)
Age-at-arrival 16-29	0.023	0.013	0.044
	(0.062)	(0.053)	(0.054)
Age-at-arrival 30+	-0.035	-0.053	-0.022
	(0.071)	(0.064)	(0.067)
Inverse Mills Ratio (IMR)	0.222	-	-
	(0.165)		

Note: Standard errors for 3-step bootstrapped with 1000 repetitions. Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Table 9: 3-step wage estimates and the corresponding OLS and 2SLS Estimates, Natives and Childhood Immigrants (N=8178)

	3-Step	**OLS**	**2SLS**
EAL	-0.399	-0.159	-0.279
	(0.427)	(0.066)**	(0.194)
Immigrant	-0.003	0.043	0.050
	(0.107)	(0.071)	(0.074)
Age-at-arrival 10-15	0.074	0.021	0.047
	(0.116)	(0.058)	(0.070)
Age-at-arrival 16-18	0.113	0.114	0.157
	(0.132)	(0.101)	(0.101)
Inverse Mills Ratio (IMR)	0.388	-	-
	(0.475)		

Note: Standard errors for 3-step bootstrapped with 1000 repetitions. Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Table 10: 3-step wage estimates and the corresponding OLS and 2SLS Estimates, Wage Sample of immigrants only (N=929)

	3-Step	**OLS**	**2SLS**
EAL	-0.303	-0.192	-0.273
	(0.182)*	(0.039)**	(0.070)**
Age-at-arrival 10-15	0.057	0.042	0.056
	(0.072)	(0.062)	(0.062)
Age-at-arrival 16-29	0.054	0.012	0.042
	(0.079)	(0.050)	(0.052)
Age-at-arrival 30+	-0.053	-0.099	-0.065
	(0.095)	(0.067)	(0.070)
Inverse Mills Ratio (IMR)	-0.165	-	-
	(0.414)		

Note: Standard errors for 3-step bootstrapped with 1000 repetitions. Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.

Appendices

Figure A1: Fractions of immigrants with difficulties in English, by employment status, EAL=1 (N=1592)

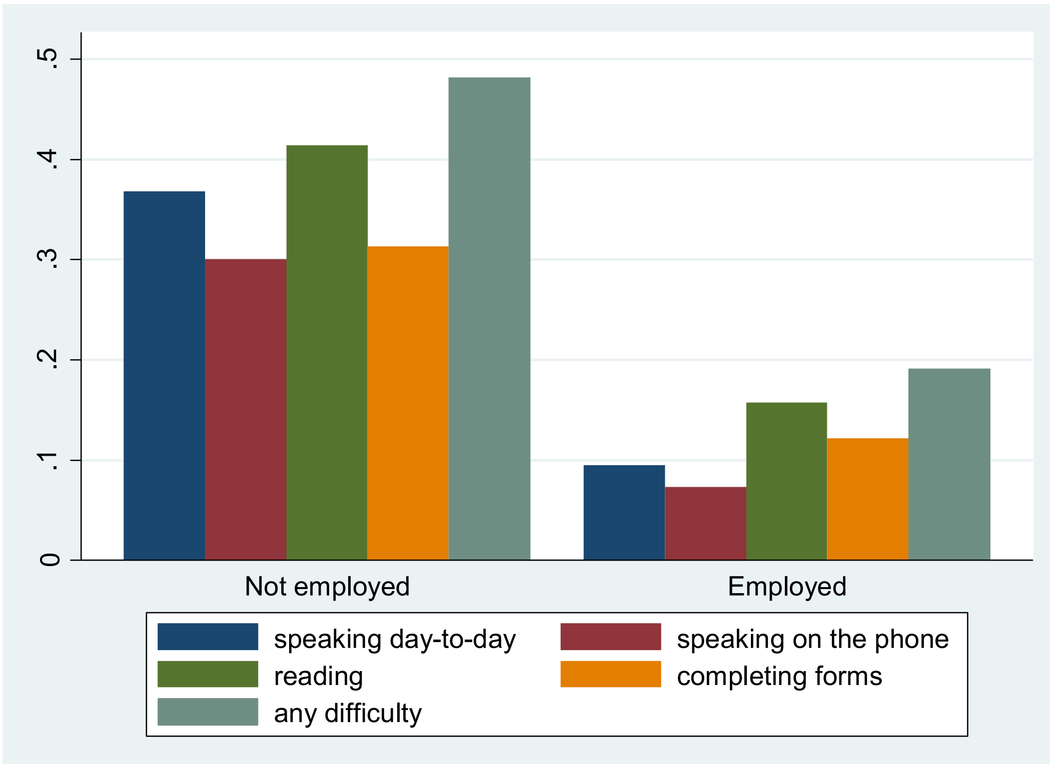

Figure A2: Regression-adjusted probability of any difficulty in English by age-at-arrival and home country language, sample of female immigrants in employment (N=1038)

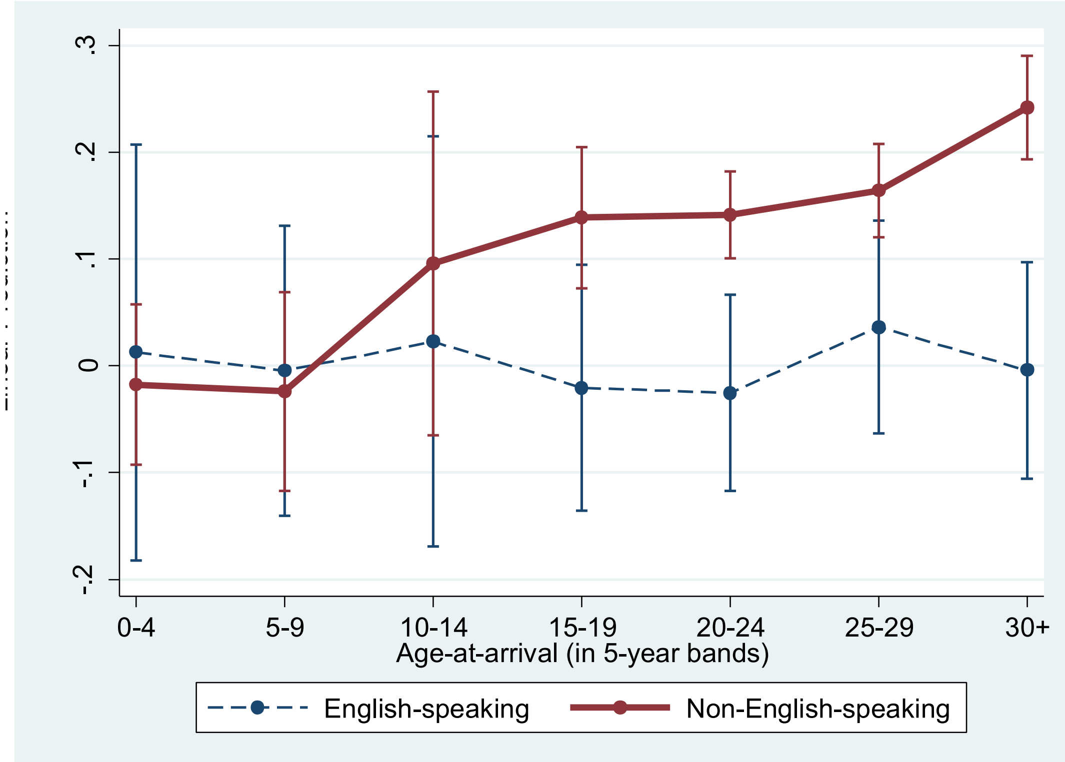

Table A1: Top 10 Occupations of Women without higher education Qualifications (in descending order of importance)

Occu-pation	Immigrants (share in %)	Natives (share in %)
1	Sales assistants and retail cashiers (13.4)	Sales assistants and retail cashiers (11.0)
2	Healthcare and related personal service (11.3)	Healthcare and related personal service (10.8)
3	Elementary cleaning occupations (8.5)	Childcare and related personal services (6.8)
4	Elementary personal services occupation (7.8)	Secretarial and related occupations (6.3)
5	Childcare and related personal services (7.4)	Administrative occupations: general (5.7)
6	Secretarial and related occupations (3.9)	Administrative occupations: finance (5.5)
7	Administrative occupations: finance (3.2)	Elementary personal services occupation (5.4)
8	Assemblers and routine operatives (3.0)	Elementary cleaning occupations (4.7)
9	Elementary process plant occupations (3.0)	Customer service occupations (3.0)
10	Administrative occupations: general (2.8)	Administrative occupations: government (2.8)
Total Share	64.3	62.0

Table A2: 3-step wage estimates and the corresponding OLS and 2SLS Estimates, Male Employment/Wage Sample (N=9338/7081)

	3-Step	**OLS**	**2SLS**
EAL	-0.305	-0.156	-0.289
	(0.182)*	(0.052)**	(0.093)**
Immigrant	0.214	0.161	0.208
	(0.100)**	(0.059)**	(0.069)
Age-at-arrival 10-15	-0.032	-0.078	-0.043
	(0.108)	(0.071)**	(0.073)
Age-at-arrival 16-29	-0.057	-0.106	-0.053
	(0.085)	(0.056)*	(0.062)
Age-at-arrival 30+	-0.123	-0.169	-0.114
	(0.085)	(0.063)**	(0.073)
Inverse Mills Ratio (IMR)	-0.129	-	-
	(0.635)		

Note: Standard errors for 3-step bootstrapped with 1000 repetitions. Robust standard errors in parentheses; **(*) = significant at 5% (10%) level. Other controls include age, age squared, region dummies, highest qualification dummies and ethnicity dummies.