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

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Outline

- Research question and motivation
- Data and descriptive evidence
- Control and treatment group
- The model
- Monte Carlo Simulation study
- Identification
- Main results
- Conclusions

Research question

In this paper, we study the impact of English deficiency, as measured by English as Additional Language (EAL), on female immigrants' labour market outcomes in the UK.

Motivation

- Lliterature that attempts to uncover the causal effect of host country language proficiency on immigrants' labour 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).
- 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.
- Here we build on Miranda and Zhu (2013), who have shown that English as Additional Language (EAL) has a strong negative causal effect on the wages for male immigrants in the UK.

Contribution

Focus on the real gross hourly wage gap of first- and second-generation female immigrants aged 19-59 who work as employees.

- **Treatment group** are first-generation female immigrants are defined as women who were born abroad to two foreign-born parents.
- **Control group** are women born in the UK but with at least one foreign-born parent.

The wage differential between first- and second-generation immigrants is arguably the best measure of the immigrant-native gap.

Contribution II

- We suggest a 3-step procedure to control for the endogeneity of EAL and correct for bias arising from selectivity into employment.
  - Endogenous treatment plus sample selection in a model for a continuous response, with treatment dummy entering the selection rule and correlated with the error term there as well (i.e. treatment is also endogenous in the selection equation).
  - Selection on unobservables (i.e. Data are NMAR (not missing at random)).
- Find very evidence of negative self-selection of EAL into employment.
- Find a large causal effect of EAL on wages of nearly 30%.

Data

Wave 1 of the UK Household Longitudinal Survey, aka. Understanding Society. This is a unique dataset:

- Contains wages and other labour market outcomes
- Direct measures of English proficiency (1st language, difficulty with speaking day-to-day English, speaking on the phone, reading and completing forms).
- Own & parents' country of birth, ethnicity etc.
- Relative large: 30k HHs (19k women), including 4k from the ethnic minority booster.

Data II

- 73% of all female 1st generation immigrants declare speaking English as Additional Language (EAL), while only 11% of 2nd generation migrants (which we refer from now as natives) declare to be EAL.
- Immigrants' education distribution is bimodal, compared to that of natives.
- Female immigrants in the UK are on average younger, and live disproportionately in London compared to white natives.
- Among migrants 55% are classified as Asians, 13% as blacks, and 22% as whites. For natives 29% are Asians, 15% blacks, and 42% are whites.

Descriptive evidence

Table 4: Log-wage equations, Wage Sample (N=2370)

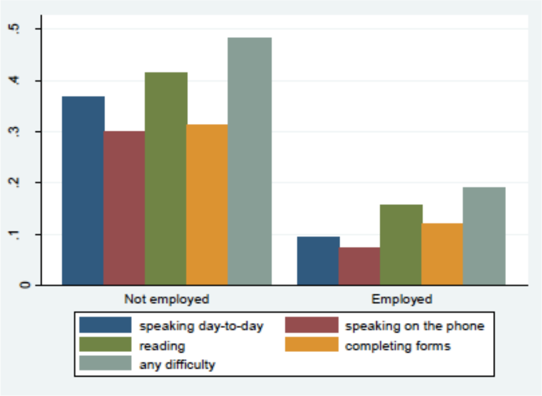
	(1)	(2)	(3)	(4)	(5)
Immigrant	-0.127	-0.085	-0.066	0.001	-0.007
	(0.024)**	(0.025)**	(0.026)**	(0.027)	(0.041)
EAL				-0.151	-0.151
				(0.030)**	(0.030)**
Age-at-arrival 10-15					0.028
					(0.058)
Age-at-arrival 16-29					0.026
					(0.048)
Age-at-arrival 30+					-0.069
					(0.062)
Highest qualification 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.

- Controlling for age and region of residence the native-immigrant wage gap in the UK is 12.7%
- Additionally controlling for the highest qualification makes little difference
- Further conditioning on ethnicity reduces the native-immigrant wage gap for females to 8.5%
- The composition-adjusted wag gap virtually disappears after controlling for EAL

Descriptive evidence

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



- 46% of female immigrants are in employment, compared to 64% of their native counterparts.

Key issues

- EAL is potentially an endogenous binary treatment.
  - Those who are good at learning English may also be good at learning other skills that makes them more productive.
- We only observe wage for those who participate in the labour market.
  - Potential sample selection on unobservable characteristics.
  - Selection may be a function of EAL and EAL may be correlated with unobservable characteristics that affect selection.

The model

The system is composed by five equations

$$\begin{aligned} EAL_i^* &= \mathbf{x}_{i,EAL}\boldsymbol{\beta}_{EAL} + u_{i,EAL} && (1) \\ s_i^* &= \mathbf{x}_{i,s}\boldsymbol{\beta}_s + \theta_s EAL_i + u_{i,s} && (2) \\ logw_i &= \mathbf{x}_{i,logw}\boldsymbol{\beta}_{logw} + \theta_{logw} EAL_i + u_{i,logw} && (3) \end{aligned}$$

with,

$$\begin{aligned} EAL_i &= 1\left(EAL_i^* > 0\right) && (4) \\ s_i &= 1\left(s_i^* > 0\right). && (5) \end{aligned}$$

The model II

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

It is assumed that explanatory variables are exogenous so that conditions

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

hold.

Dealing with endogeneity plus sample selection in the linear model

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.

- Fit the second step by 2SLS (Wooldridge 2002, p567).
- This is effectively a control function approach that delivers consistent estimators of the parameters of interest.

The challenge

In the present paper we have a similar problem, with the complication that EAL is a binary treatment and that the endogenous treatment enters the sample selection model.

- **Naïve two-stage approach**. fit a probit for EAL in a first stage and then, estimate Heckman selection model including fitted EAL from 1st stage.This delivers inconsistent estimators because it suffers from the problem of the *'forbidden regression'*.

- **How we solve the problem**. Fit the 2nd stage of Heckman by 2SLS instrumenting EAL with the fitted EAL probability from a LPM 1st stage of EAL on controls.
  - BUT. . . EAL enters also S and it is an endogenous treatment there as well.
  - Need 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.

3-step estimation procedure

Step 1 Fit the EAL model by Linear Probability Model (LPM)

Step 2 Fit a bivarate probit model for selection (into employment) and EAL.

Step 3 Fit the (log) wage equation on the selected sample by 2SLS with EAL and IMR in the list of explanatory variables and all exogenous variables in the system, the predicted EAL probability from step 1 and the IMR as instruments.

This is effectively a control function approach that delivers consistent estimators. The method delivers a LATE that is interpreted as the **effect of treatment on the treated** and that is analogous to a DiD estimator that calculates language wage effects net of age-at-arrival wage effects, scaled by the DiD difference in probability of EAL between treatment and control groups. Hence, we are able to disentangle language and age-at-arrival wage effects.

Standard errors

- The robust estimator of the covariance matrix on the 3rd stage 2SLS take into account the covariance matrix of $\hat{P}(\text{EAL}=1)$, $\widehat{\text{IMR}}$, and all instruments.

$$\hat{V}\left[\hat{\beta}_{2SLS}\right] = \left(\hat{\mathbf{X}}'\hat{\mathbf{X}}\right)^{-1}\left(\sum_{i=1}^{N}\hat{u}_i^2\hat{\mathbf{x}}_i'\hat{\mathbf{x}}_i\right)\left(\hat{\mathbf{X}}'\hat{\mathbf{X}}\right)^{-1}$$
$$= N\left[\mathbf{X}\mathbf{P}_Z\mathbf{X}\right]^{-1}\left[\mathbf{X}'\mathbf{Z}\left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\hat{\mathbf{S}}\left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\mathbf{Z}'\mathbf{X}\right]\left[\mathbf{X}\mathbf{P}_Z\mathbf{X}\right]^{-1}$$

  with $\mathbf{P}_Z = \mathbf{Z}\left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\mathbf{Z}'$, $\hat{\mathbf{S}} = (N-K)^{-1}\sum_i \hat{u}_i^2\mathbf{z}_i'\mathbf{z}_i$ and $\hat{u}_i = y_i - \mathbf{x}_i\hat{\beta}_{2SLS}$.

- Can further take into account uncertainty on $\hat{P}(\text{EAL}=1)$ and $\widehat{\text{IMR}}$ by bootstrapping SEs.

Stata code

```
capture program drop tsls_estimator
program define tsls_estimator, eclass
 version 12.1
 #delimit ;
 syntax varlist [if] [in], selvar(varname) ealvar(varname) selzvars(varlist)
  ealzvars(varlist);
#delimit cr
 gettoken y xvars:varlist, parse("")
 marksample touse
 markout `touse' `xvars' `selvar' `ealvar' `selzvars' `ealzvars'
 tempvar emppred ealpredtemp convg
 /* sum vars */
 sum `y' `selvar' `ealvar'
 * clean IMR and ealpred vars
 replace IMR = .
 replace ealpred = .
 * step 1: EAL equation
 reg `ealvar' `xvars' `ealzvars', robust
 predict `ealpredtemp', xb
 replace ealpred = `ealpredtemp'
 * step 2: (seemingly unrelated) biprobit of EAL and Selection
#delimit ;
 biprobit (`selvar' = `ealvar' `xvars' `selzvars') (`ealvar' = `xvars' `ealzvars'),
  iterate(30) robust;
#delimit cr
 predict `emppred', xb1
 replace IMR = normalden(`emppred')/normprob(`emppred')
 scalar `convg' = e(converged)
 * step 3: wage equation
 ivregress 2sls `y' `xvars' (`ealvar'= ealpred) IMR if `y'<., robust
```

```
 /* return estimated paramters */
 mat b = e(b)
 mat V = e(V)
 ereturn post b V
 ereturn scalar converged = ‘convg’
end

/* INITIALISE STATA */
clear
set logtype text
set more off

/* BEGIN LOG */

log using "$locallogpath/bs_smpmigw1.txt", replace

/* GLOBALS */

global qual "belowGCSE GCSE  Alevel HEdiploma Degree  Posgrad"
global aaagrp "aaagrp10 aaagrp16 aaagrp30"
global aaagrp_noadultmig "aaagrp10 aaagrp16"
global poor ""
global yvar "logwage"
#delimit ;
global xvars "immigrant $poor $aaagrp $qual qfnonuk age agesq
 mixed asian black othminor london se wales scot ni";
global xvars_migrant "$poor $aaagrp $qual qfnonuk age agesq
 mixed asian black othminor london se wales scot ni";
global xvars_noadultmig "immigrant $poor $aaagrp_noadultmig $qual qfnonuk age
 agesq mixed asian black othminor london se wales scot ni";
global select_zvars "lfpratio09 eduratio10"
global eal_zvars "ealcob_late10"
global clusterid "pidp"
global rep = 1000
global seed = 123456
```

```
/* load data */
use "$localdtapath/bs_smpmigw1", clear
* keep Immigrant subsample only
keep if immigrant==1
/* generate IMR and ealpred variables */
gen double IMR = .
gen double ealpred = .
/* set sample */
marksample touse
markout `touse' $xvars $selvar $aelvar $selzvars $ealzvars $clusterid
keep if `touse'
/* bootrap SEs */
di "$xvars_migrant"
#delimit ;
bootstrap _b, reps($rep) seed($seed)
 nowarn reject(e(converged)!=1) nodrop: tsls_estimator logwage
 $xvars_migrant,  selvar(select) ealvar(eal)
 selzvars("$select_zvars") ealzvars("$eal_zvars");
#delimit cr
```

Potential drawbacks

We require joint normality in the 2nd stage and suppose that the expected value of the residual in the 3rd stage is a linear function of the residual in the selection equation of the second stage (see Vella 1998). It is possible to relax these assumptions.

- Fit 1st and 2nd stage using semi-nonparametric index models (Gallant and Nychka 1987), and add powers of the EAL and selection indexes as instruments in the 2SLS fitted in our 3rd stage.
- Need at least two continuous variables to serve as instruments to secure identification of a double-index model (see De Luca 2008, p198).
- We do not have that luxury. So, we do not pursue the semi-non-parametric avenue here.

Does it work? Monte Carlo simulation

- Generated $r = 1, \ldots, 10000$ simulated data sets with sample size of 1,000.
- 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.
- Three independent standard normal variables *zyvar*, *ztreat*, and *zsel* play the role of instruments.
- For $r = 1, \ldots, 10000$, three error terms $u_y^r, u_{treat}^r, u_s^r$ were drawn from a multivariate normal distribution with $sd(u_y) = 0.7$, $sd(u_{treat}) = sd(u_s) = 1$ and correlations $Cor(u_{treat}, u_s) = Cor(u_y, u_{treat}) = -0.2$ and $Cor(u_y, u_s) = 0.8$.

Does it work? Monte Carlo simulation

- OLS, 2SLS, and TSE were fitted at each Monter Carlo iteration. Standard errors for the TSE were bootstrapped 50 times in each replication.
- We consider three different experiments.
  - Experiment 1 we have an average probability of selection of 0.75.
  - Experiment 2 we have an average probability of selection of 0.5,
  - 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 to be important, parameters in the selection equation are set such that the noise/signal ratio is 0.3.

Does it work? Monte Carlo simulation II

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.

Does it work? Monte Carlo simulation III

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 Squares						
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.

Main results

Sample, control and treatment group

Women aged 19-59 who work as employees, excluding self-employed

- Control group
  - Women born in the UK with at least one foreign-born parent.
- Treatment group
  - First-generation female immigrants born abroad to two foreign-born parents.

Identification I

- Critical period for second language acquisition (Bleakley and Chin 2004, 2010), (Van Ours and Veenman 2006).
- EAL instrumented by the language of the origin country interacted with age-at-arrival (AAA) for the subpopulation of immigrants (Bleakley & Chin (2004 REStat, 2010 AEJAE)).
  - Effectively compares older and younger arrivals from non-English-speaking countries, after controlling for an AAA effect which is the same for all immigrants regardless of their native language.
  - $F = 1142.44$ for exclusion of the interaction term.

Note that instrument equals zero for all second-generation immigrations who were born in the UK by definition.

Identifying assumption I

After netting out educational attainment and other background variables, including age-at-arrival, differences in English proficiency between immigrants from English-speaking and non-English-speaking countries before and after the critical age are uncorrelated with current wage.

Identification II

- Women's labour market participation instrumented by female-male ratio of labour force participation (Blau et el. 2011 REStat), and secondary education attainment of country of birth (UNDP).
  - $F = 33.22$ for exclusion of female-male ratio of labour force participation.
  - $F = 3.40$ for exclusion of secondary education attainment of country of birth.

Identifying assumption II

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.

Main Results: 1st stage

Table 5: Linear Probability Model (LPM) of EAL, only migrants (N=2013)

	EAL
Age-at-arrival 10-15	-0.357 (0.038)**
Age-at-arrival 16-29	-0.321 (0.034)**
Age-at-arrival 30+	-0.289 (0.038)**
Born in non-English-speaking country * (age-at-arrival>9)	0.694 (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.

Main Results: 2nd stage

Table 6: Biprobit of EAL and Selection into Employment Estimates, only migrants (N=2013)

	EAL	Employment
EAL		0.166 (0.160)
Age-at-arrival 10-15	-1.601 (0.216)**	-0.005 (0.135)
Age-at-arrival 16-29	-1.234 (0.191)**	-0.068 (0.109)
Age-at-arrival 30+	-1.072 (0.214)**	0.062 (0.136)
Exclusion restrictions:		
Born in non-English-speaking country * (age-at-arrival>9)	2.623 (0.164)**	
Labour Force Participation Rate Female-Male Ratio		0.744 (0.213)**
Secondary Education Attainment Female-Male Ratio		-0.415 (0.213)*
ρ (p-value)	-0.272 (0.093)**	

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.

Main Results: 3rd stage

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
	(0.143)**	(0.039)**	(0.070)**
Age-at-arrival 10-15	0.057	0.042	0.056
	(0.075)	(0.062)	(0.062)
Age-at-arrival 16-29	0.054	0.012	0.042
	(0.074)	(0.050)	(0.052)
Age-at-arrival 30+	-0.053	-0.099	-0.065
	(0.093)	(0.067)	(0.070)
Inverse Mills Ratio (IMR)	-0.165	-	-
	(0.401)		

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.

From 2SLS to 3-step the effect of EAL goes up by 0.43 SDs.

Conclusions

- Find evidence of negative selection of EAL into employment.
- 3-step estimate of the causal effect of EAL of -30% on wages for female immigrants, significant at 5%.
- Instrumenting EAL by interacting being born in non-English-speaking country and AAA>9 to identify a LATE that is straightforward to interpret for the subpopulation of first-generation immigrants.
- Failure to account for endogeneity of EAL and self-selection into employment results in underestimation of the impact of EAL on wages.
- Failure to account for self-selection into employment results in overestimation of the effect of EAL by 0.4 SD.
- Estimate could be a lower bound, as it conditions on the highest educational qualification.

The End, thanks!

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