Online Appendix “Labor Market Competition with Immigrants and Political Polarization”

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List of survey data sets

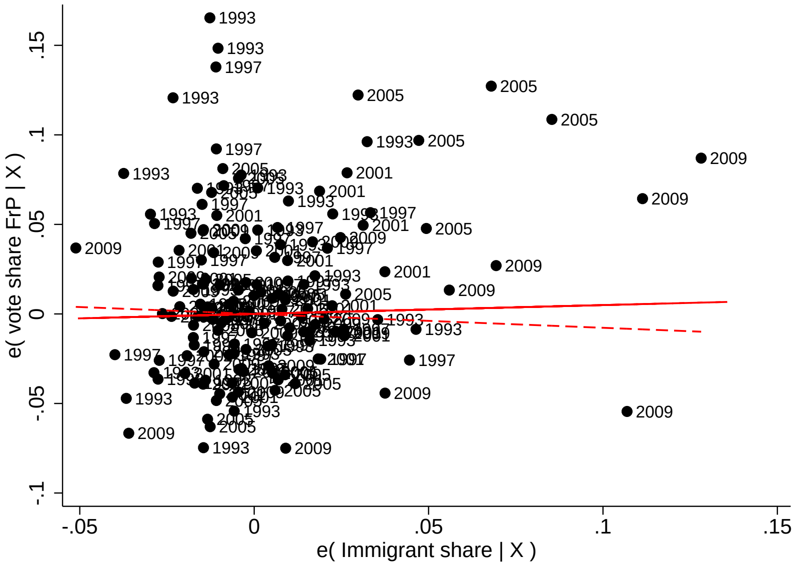
Data are gathered from a large number of data sets. A majority of the data sets are provided by the Norwegian Social Science Data Services (NSD) and publicly available (www.nsd.uib.no) for free unless noted. NSD is not responsible for the analyses/interpretation of data. All surveys are nationwide:
National Election Studies 1993, 1997, 2001, 2005, 2009
Local Election Studies 1995, 1999, 2003, 2007
The EU referendum study 1994
Standard Eurobarometer 42.0 1994
Statistics Norway's Omnibus Surveys, a total of 40 surveys in the period 1994-2004
European Social Survey 2002, 2004, 2006, 2008, 2010, 2012
International Social Survey Programme 1996, 2010, 2011, 2012
Comparative Study of Electoral Systems 1997, 2001, 2005, 2009
Generations and Gender Survey (GGS-Norway) 2007/2008
Respons Time Series of Opinion Polls 2005-2012
Medborgerundersøkelsen 2001
FAMI-survey on views on poverty 2007
NOVA-survey on views on globalization 2008/2009

Additional information on the allocation of immigrants to skill cells

We use educational attainment collected from the National Education Database. The education database is built up from records obtained directly from Norwegian educational institutions and the Norwegian State Educational Loan Fund, as well as self-reported attainment taken from census records and three surveys that were administered to all foreign residents with missing educational attainment. Still, missing education remains a problem in the immigrant labor force data. The fraction of resident immigrants in our data with missing records of educational attainment is about 20 percent. In order to compute immigrant shares by education and experience levels, it is therefore necessary to allocate immigrants with missing data across skill groups. Our allocation procedure starts with the assumption that for each observation year, birth cohort, gender, and country of origin (broadly defined in four major regions), the distribution of attainment is the same for immigrants with missing and non-missing data. The allocation procedure tend to increase counts in low education-low experience cells and leave counts in high attainment-high experience cells unchanged. The reason for the latter is that very few immigrants in the oldest birth cohorts (i.e., high experience) have missing data on education.

Partial regression plot without interactions between the fixed effects

Figure A-1: Partial regression plot without interactions between the fixed effects



Note: The full line is the regression line when the outlier in the bottom righthand corner is excluded. The dotted line is the regression line when this observation is included. The regression slopes are insignificantly different from zero.

Additional information on the IV-approach

Borjas (2003) expects his wage estimates to be downward biased from selection since immigration flows from abroad are likely to be targeted towards skill-cells with a positive wage development. One solution to this problem is to develop an instrument for inflows and estimate the effect of immigration in a 2sls approach. One promising source of exogenous variation in immigration is so-called “migration-push” factors in migration-exporting countries. Inspired by Llull (2015) we set up a regression model predicting the number of immigrants from sending countries in each skill cell from a set of push-factors. This approach is feasible since we have individual level information on the ancestry country of all immigrants in Norway from the register data. We then add a set of migration-push factors for each country of ancestry: log(GDP), log(population size), the freedom of assembly and association index (Cingranelli and Richards 2010), the political terror scale (Giavazzi et al. 2014), log of years of civil war 1800-2007, log of years of interstate wars 1800-2007, number of battle deaths, log of the employment rate, and log of distance to Oslo. Next we regress these variables on the number of immigrants from each ancestry country in a series of skill-cell-specific regressions. From these regressions we predict the number of immigrants in each skill cell, and construct a predicted share of immigrants in each skill cell for each year. Finally, we use the predicted share of immigrants as an instrument for the actual immigrant share in a 2sls-set up.

Additional specifications

Table A-1: Regression results. The dependent variable is FrP vote share. N=160.

1. Log native labor force	0.38
	(0.13)
2. Immigrant share $t-1$	0.46
	(0.11)
3. $\text{Log}(\frac{FrP}{1-Frp})$	2.62
	(1.42)

Note: Robust standard errors adjusted for clustering on skillcell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1). All regressions are weighted by the number of observations behind the aggregated vote share.

Table A-2: Regression results. The dependent variable is party vote share. N=160.

	βI_{ijt}
1. V (Venstre, Liberal Party)	-0.05
	(0.06)
2. KrF (Kristelig Folkeparti, Christian People's Party)	-0.16
	(0.11)
3. Sp (Senterpartiet, Center Party)	-0.01
	(0.10)
4. Incumbent parties	-0.24
	(0.21)
5. Turnout	-0.10
	(0.11)

Note: Robust standard errors adjusted for clustering on skillcell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1). All regressions are weighted by the number of observations behind the aggregated vote share.

Individual level estimates

Table A-3: Regression results. The dependent variable is probability of voting FrP. Linear Probability Models.

1. Immigrant share	0.28
	(0.05)
N=118,709	
2. Controls: Gender and age	0.30
	(0.06)
N=117,440	
3. Male	0.35
	(0.11)
N=59,398	
4. Female	0.26
	(0.08)
N=58,042	

Note: Robust standard errors adjusted for clustering on skillcell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1).

Table A-4: Regression results. The dependent variable is probability of voting SV. Linear Probability Models.

1. Immigrant share	0.41
	(0.11)
N=118,709	
2. Controls: Gender and age	0.42
	(0.10)
N=117,440	
3. Male	0.21
	(0.05)
N=59,398	
4. Female	0.66
	(0.16)
N=58,042	

Note: Robust standard errors adjusted for clustering on skillcell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1).

Table A-5: Regression results. The dependent variable is probability of voting FrP (column 1) and SV (column 2). Linear Probability Models.

	DV: FrP βI_{ijt}	DV: SV βI_{ijt}
1. Voted Ap in the previous election	1.76	-1.56
	(1.68)	(1.24)
N=700		
2. Voted H in the previous election	4.06	-1.33
	(1.86)	(0.79)
N=488		
3. Did not vote in the previous election	-3.14	6.59
	(2.08)	(2.83)
N=250		

Note: Robust standard errors adjusted for clustering on skillcell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1).

Excluding election years

Table A-6: Regression results. Vote share FrP. N=128.

	Excl 1993	Excl 1997	Excl 2001	Excl 2005	Excl 2009
Immigrant share	0.41	0.40	0.50	0.45	0.72
	(0.11)	(0.13)	(0.13)	(0.11)	(0.30)
Control unemployment	0.38	0.40	0.51	0.46	0.67
	(0.09)	(0.13)	(0.13)	(0.12)	(0.30)

Note: Robust standard errors adjusted for clustering on skill cell in parentheses. All regressions include education group FE, experience group FE, year FE, and interactions between these FE, see eq. (1). All regressions are weighted by the number of observations behind the aggregated vote share.

The wage effect of immigration - a theoretical framework

Here we present a simple version of the structural economic model that motivates Borjas (2003) empirical approach to analyse the wage effects of immigration. After the introduction of this model to the study of labor market impacts of immigration it has become common to interpret reduced form regression coefficients within this theoretical framework. The point of departure is a Cobb-Douglas production function of the national economy, where physical capital (K) and labor (L_t) produce aggregated output (Q_t):

(1a) $Q_t = A_t L_t^{\alpha} K^{(1-\alpha)}$

A_t is a technology parameter that reflects total factor productivity at year t, while $\alpha\varepsilon(0,1)$ is the income share of labor. Total labor supply consists of workers belonging to different groups, according to their level of education, aggregated by a constant elasticity of substitution (CES) technology:

(2a) $L_t = [\sum_{e=1}^{E} a_{et} L_{et}^{\rho}]^{\frac{1}{\rho}}$

L_{et} is the number of individuals with e level of education and a_{et} reflects the relative efficiency of these workers in the production process. $\rho = 1 - \sigma_E^{(-1)}$, where $\sigma_E\varepsilon(0,\infty)$ is the constant elasticity of substitution between workers with different levels of education. The higher the value of σ_E, the more exchangeable are the workers with different levels of education in the production process, thus the more they are competitors in the labor market. When $\sigma_E^{(-1)} = 0$, workers with different levels of education are perfect substitutes and, thus, the same kind of labor (apart from their relative efficiency). Correspondingly, the labor supply from each educational group is a CES aggregate of workers defined by the length of their labor market experience:

(3a) $L_{et} = [\sum_{a=1}^{E} b_{eat} L_{eat}^{\gamma}]^{\frac{1}{\gamma}}$

L_{eat} is the number of workers with e level of education that belongs to experience group a. b_{eat} is the relative efficiency of individuals in group a compared to workers in other experience groups within the same level of education, e. $\gamma = 1 - \sigma_A^{(-1)}$, where σ_A is the elasticity of substitution between workers in different experience groups. Finally the skill groups defined by level of education and length of experience may be divided by origin:

(4a) $L_{eat} = [N_{eat}^{\tau} + c_{eat} M_{eat}^{\tau}]^{\frac{1}{\tau}}$

where N_{eat} is the number of native workers in skill group (e,a) and M_{eat} is the number of immigrants. c_{eat} is the technology parameter reflecting the relative productivity of immigrants compared to natives. $\tau = 1 - \sigma_M^{(-1)}$, where σ_M is the elasticity of substitution between immigrant and native workers within skill group (e,a).

In a competitive labor market the marginal productivity condition will be fulfilled, implying that the wage of native workers in skill group (e,a) in year t may be expressed as:

(5a) $ln(w_{ejt}^{N}) = I_t + I_{et} + I_{eat} + (\gamma - \tau) lnL_{eat} + (\tau - 1) lnN_{eat}$

where $I_t = ln(\alpha A_t K_t^{(1-\alpha)} + (\alpha - \rho) lnL_t$, $I_{et} = ln(a_{et}) + (\rho - \gamma) lnL_{et}$ and $I_{eat} = ln(b_{eat})$. The model ignores capital adjustments, which means that we focus on the short term effects of immigration.[1] Equation (5a) illustrates that in addition to the increase in the supply of this particular type of labor, the wage effect of immigration to skill group (e,a) works through total labor supply and the aggregated supply within the e-level of education.

Borjas (2003) regresses the wage of natives, $ln(w_{ejt}^{N})$, on the skill specific immigrant shock in labor supply. The immigrant shock in labor supply is represented by the immigrant share within the (e,a) skill cell in year t. He controls for year fixed effects, which absorb the time varying factors that commonly affect the wage development of all skill groups through the elements reflected in I_t. Correspondingly, his inclusion of education by year fixed effects (captured in I_{et}) ensures that all factors which simultaneously affect the wage growth of workers within the same level of education are accounted for. Finally, fixed effects are included for experience by year, and experience by education, to absorb the variation between groups and over time in the technology parameter of the term I_{eat}.[2] Thus, substituting the vote share for the log of wage, equation (1) in the main text of our article estimates the immigration effect using Borjas' (2003) approach.

[1] In the economic literature short run is defined by the time period for which it is reasonable to assume that the capital stock is fixed. A constant supply of native workers is also assumed. For a discussion of how capital adjust to immigration in the long run, see Ottaviano and Peri (2012).

[2] To be able to control for this term by these fixed effect we must assume that $ln(b_{eat})$ may be expressed as a function of $a_t + c_t + g$.

According to the framework outlined above, this procedure identifies the direct partial wage effect of immigration (Ottaviano and Peri, 2012), which may be expressed by the elasticity: $\frac{dln(w^N_{eat}}{dln(M_{eat}}|L_t, L_{et} = (\sigma_M^{-1} - \sigma_A^{-1})WS_{Meat}$, i.e., the percent change in wage following a one percent increase in immigration, given constant levels of L_t and L_{et}, where WS_{Meat} is the relative wage share of immigrants in skill group (e,a) in year t. The wage effect is negative if $\sigma_M > \sigma_A$ i.e., if the within group substitution dominates the across group substitution. It is important to keep in mind, however, that although this approach captures a short-run, systematic variation in the wage effect of immigration, it is not an expression of the long-run, total wage effect of immigration.