



Education-occupation mismatch of migrants in the Italian labour market: The effect of social networks

Van Wolleghem P.G., De Angelis M. and Scicchitano S.

INAPP (Istituto Nazionale Analisi Politiche Pubbliche)

**Società Italiana degli Economisti
Palermo - 25 October 2019**

RESEARCH QUESTIONS

- Evidence throughout Europe suggests the existence of a difference between natives and foreigners when it comes to education-occupation mismatch

Are first- and second-generation migrants more over-educated than nationals, ceteris paribus?

- Numerous are the factors leading to mismatch

What is the role of informal networks in generating mismatch? Is this different for natives and migrants?

PRESENTATION OUTLINE

- 1. Introduction: immigration, mismatch and informal networks**
- 2. Mismatch, network and other definitions**
- 3. Data and method: PLUS & Probit/PSM/IPW**
- 4. Empirical results**
- 5. Conclusion and public policy considerations**

PRESENTATION OUTLINE

- 1. Introduction: immigration, mismatch and informal networks**
- 2. Mismatch, network and other definitions**
- 3. Data and method: PLUS & PSM/IPW**
- 4. Empirical results**
- 5. Conclusion and public policy considerations**

1. Introduction: immigration, mismatch and informal networks

Why should we care ??

Immigration has become a structural phenomenon:

- Acceleration: nowadays 8.5% of the population
- Long-term (or irreversible) changes of ethnic composition
- Ageing population in the great North (west but also east)
- New push factors

Mismatch is essentially a misallocation of human resources

Migrants' over-education

Large literature on migrants' insertion in labour markets

wrt/ mismatch, different explanations:

- Information adjustment & difficult transfer of human capital
- Quality of the capital being transferred
- Mismatch in the country of origin
- Cultural proximity and language
- Attitudes toward foreigners (discrimination)
- Use of informal networks: referral hiring

The effect of networks

Literature (not as large though) has produced conclusions in shades

- Kalfa & Piracha (2017) for Australia: network increases mismatch
- Alaverdyan & Zaharieva (2019) for Germany: idem
- Chort (2016) for Senegalese community in several countries: contrary

We propose to look at the Italian case

Three-fold contribution

- We look into the Italian case
- We rely on respondents' declared use of networks (rather than proxies)
- We break down the foreign population into
 - Those who migrated
 - Those who were born foreigners in Italy or grew up in IT (second generation)

PRESENTATION OUTLINE

- 1. Introduction: immigration, mismatch and informal networks**
- 2. Mismatch, network and other definitions**
- 3. Data and method: PLUS & PSM/IPW**
- 4. Empirical results**
- 5. Conclusion and public policy considerations**

Defining education-occupation mismatch

Three main definitions

- **Normative approach:** measured using a classification elaborated ex-ante, which specifies the level of educational attainment required for each occupation. PB: need extensive data
- **Workers' self-assessment:** PB: horizontal vs. Vertical mismatch + underlying mechanisms defining perception when comparing foreigners and nationals
- **Statistical approach:** distribution of workers' education levels within occupational groups. Suitable to compare the distribution of different groups (even though there are limitations to it)
 - => Here, we'll consider the modal educational level applied to ISCO one digit

2. Mismatch, network and other definitions

International Standard Classification of Occupations (ISCO-88 (COM))

1	Legislators, senior officials and managers	(1 digit)
2	Professionals	(1 digit)
3	Technicians and associate professionals	(1 digit)
4	Clerks	(1 digit)
5	Service workers and shop and market sales workers	(1 digit)
6	Skilled agricultural and fishery workers	(1 digit)
7	Craft and related trades workers	(1 digit)
8	Plant and machine operators and assemblers	(1 digit)
9	Elementary occupations	(1 digit)
10	Armed forces	(1 digit)

2. Mismatch, network and other definitions

Informal networks

Resorting to social capital to look for and find a job:
“Friends, relatives and acquaintances”

- Intensity of use of networks (0-12)
- Current job found through informal network (0-1)

First and second generation migrants

Born with foreign citizenship who

- Prevalently grew up abroad
- Prevalently grew up in Italy (0-18 yo)

PRESENTATION OUTLINE

1. Introduction: immigration, mismatch and informal networks
2. Mismatch, network and other definitions
3. **Data and method: PLUS & PSM/IPW**
4. Empirical results
5. Conclusion and public policy considerations

3. Data and method: PLUS & PSM/IPW

Data: Participation Labour Unemployment Survey

45,000 obs; 18-75 yo; collected in October 2018 **BUT**
Focus on population available for work: 31,600 obs; 2.4%
foreigners

Controls

For all: Area of residence (x3), city size, gender, children,
work status, father's education, sector of activity, period in
which mismatch occurred

For migrants: area of origin, years since arrival

For counterfactual: education

3. Data and method: PLUS & PSM/IPW

Method: two-fold

1. Probit regressions

2. Use of counterfactual impact evaluation method

- Propensity Score Matching: logistic model and matching methods

Treatment = being foreigner

- Inverse Probability Weighting: multinomial logistic model for treatment and logistic for impact

Treatment = 1:migrated

2:grew up in IT

PRESENTATION OUTLINE

- 1. Introduction: immigration, mismatch and informal networks**
- 2. Mismatch, network and other definitions**
- 3. Data and method: PLUS & PSM/IPW**
- 4. Empirical results**
- 5. Conclusion and public policy considerations**

4. Empirical results

Tab. 4. Probit regressions, average marginal effects, Models 5 to 10.

	Model 5		Model 6		Model 7		Model 8		Model 9		Model 10	
Foreign citizen	-0.0121				-0.0166							
	(0.011)				(0.014)							
Migrated			-0.0005				-0.0038					
			(0.014)				(0.017)					
Grew up in IT			-0.0381	**			-0.0503	*				
			(0.016)				(0.028)					
Network-looking	-0.0041	***	-0.0041	***					-0.0037			
	(0.000)		(0.000)						(0.003)			
Age	0.0003		0.0003		0.0005	**	0.0005	**	0.0052	***	0.0043	**
	(0.000)		(0.000)		(0.000)		(0.000)		(0.002)		(0.002)	
Gender	-0.0556	***	-0.0553	***	-0.0543	***	-0.0541	***	-0.0664	**	-0.0909	**
	(0.004)		(0.004)		(0.004)		(0.004)		(0.028)		(0.040)	
Child(ren)	-0.025	***	-0.0251	***	-0.0233	***	-0.0234	***	-0.0423		-0.0653	*
	(0.004)		(0.004)		(0.005)		(0.005)		(0.035)		(0.039)	
Area Centre	0.018	***	0.018	***	0.0163	***	0.0162	***	0.051		0.0782	**
	(0.005)		(0.005)		(0.005)		(0.005)		(0.041)		(0.038)	
Area South	0.0098	**	0.0099	**	0.0085	*	0.0086	*	-0.0525	*	-0.0418	
	(0.004)		(0.004)		(0.005)		(0.005)		(0.031)		(0.049)	
Major cities	0.0272	***	0.0273	***	0.0302	***	0.0303	***	0.068	**	0.0887	***
	(0.004)		(0.004)		(0.004)		(0.004)		(0.029)		(0.033)	
Father's education	0.1183	***	0.1183	***	0.1029	***	0.1029	***	0.1081	***	0.1023	***
	(0.005)		(0.005)		(0.004)		(0.004)		(0.032)		(0.033)	
Work status	-0.0602	***	-0.0602	***					0.0196			
	(0.004)		(0.004)						(0.043)			
Tenure	-0.0034	***	-0.0034	***	-0.0034	***	-0.0033	***	-0.0008		-0.0034	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.003)		(0.003)	
Public	-0.0445	***	-0.0446	***	-0.0429	***	-0.0429	***	-0.1047	**	-0.0589	
	(0.004)		(0.004)		(0.005)		(0.005)		(0.047)		(0.054)	
Network-finding					-0.0651	***	-0.0654	***			-0.0784	**
					(0.005)		(0.005)				(0.036)	

4. Empirical results

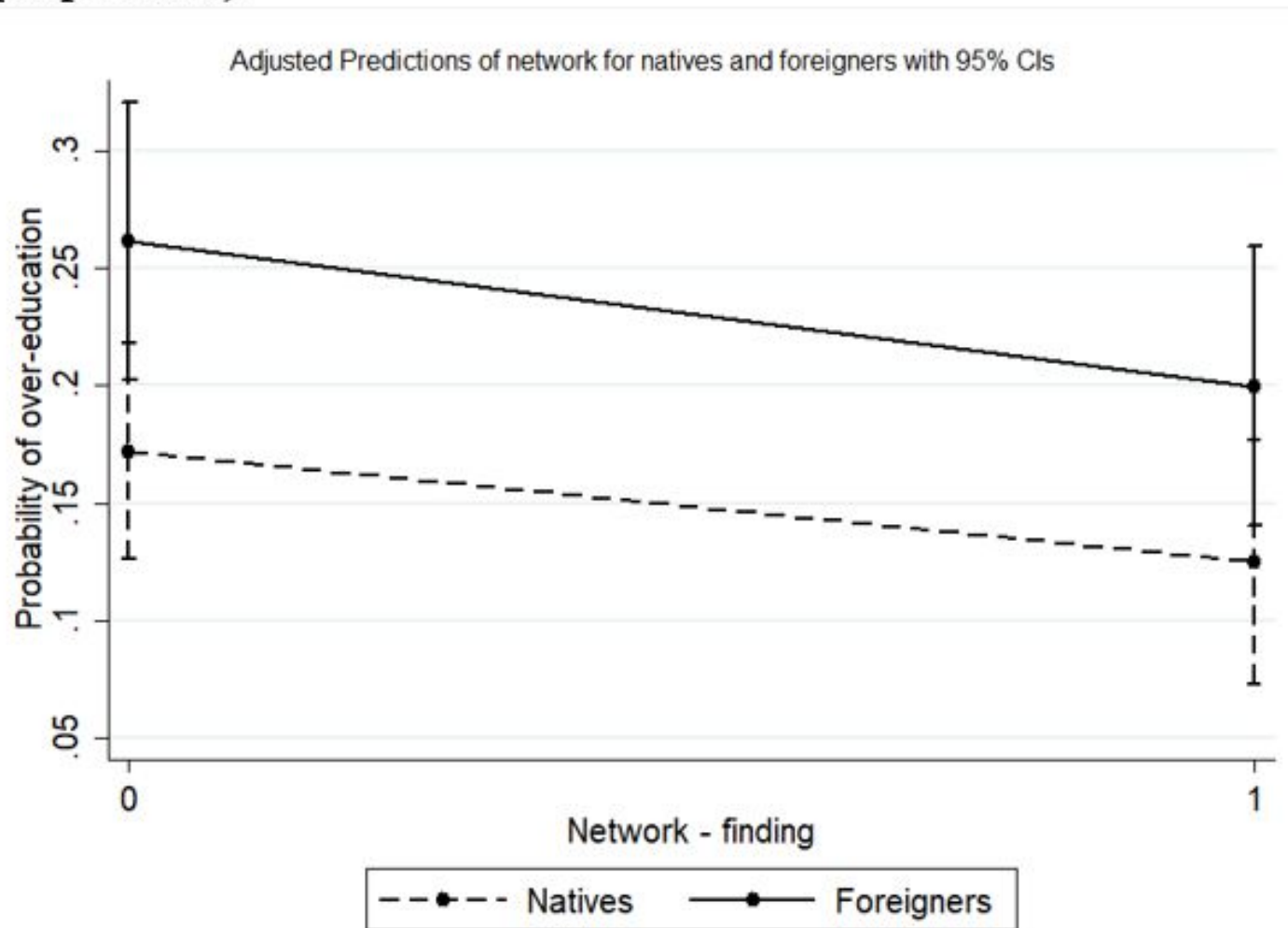
Tab. 5. Estimation of the average effect on the treated (ATT) of being a foreigner: logistic, nearest neighbour, Kernel and radius matching estimations.

ATT	Probit model	Nearest neighbour	Kernel matching ^x	Radius matching (0.1)	Probit model	Probit model
Foreign citizen	0.091 *** (0.024)	0.069 *** (0.023)	0.047 ** (0.022)	0.089 *** (0.021)	0.091 *** (0.026)	0.084 *** (0.032)
Network-looking					-0.002 (0.003)	
Network-finding						-0.054 * (0.032)

^x: bootstrap std.err.

4. Empirical results

Fig. 1. Predicted effect of networks on mismatch between natives and foreigners (proportions).



4. Empirical results

Tab. 6. Estimation of the average effect of migration and migration background: multinomial logistic estimation.

Average treatment effect on the treated	Coefficients
Migrated vs. natives	0.0655 *** (0.014)
Migration background vs. natives	0.0241 (0.047)
Migrated vs. migration background	0.155 *** (0.053)

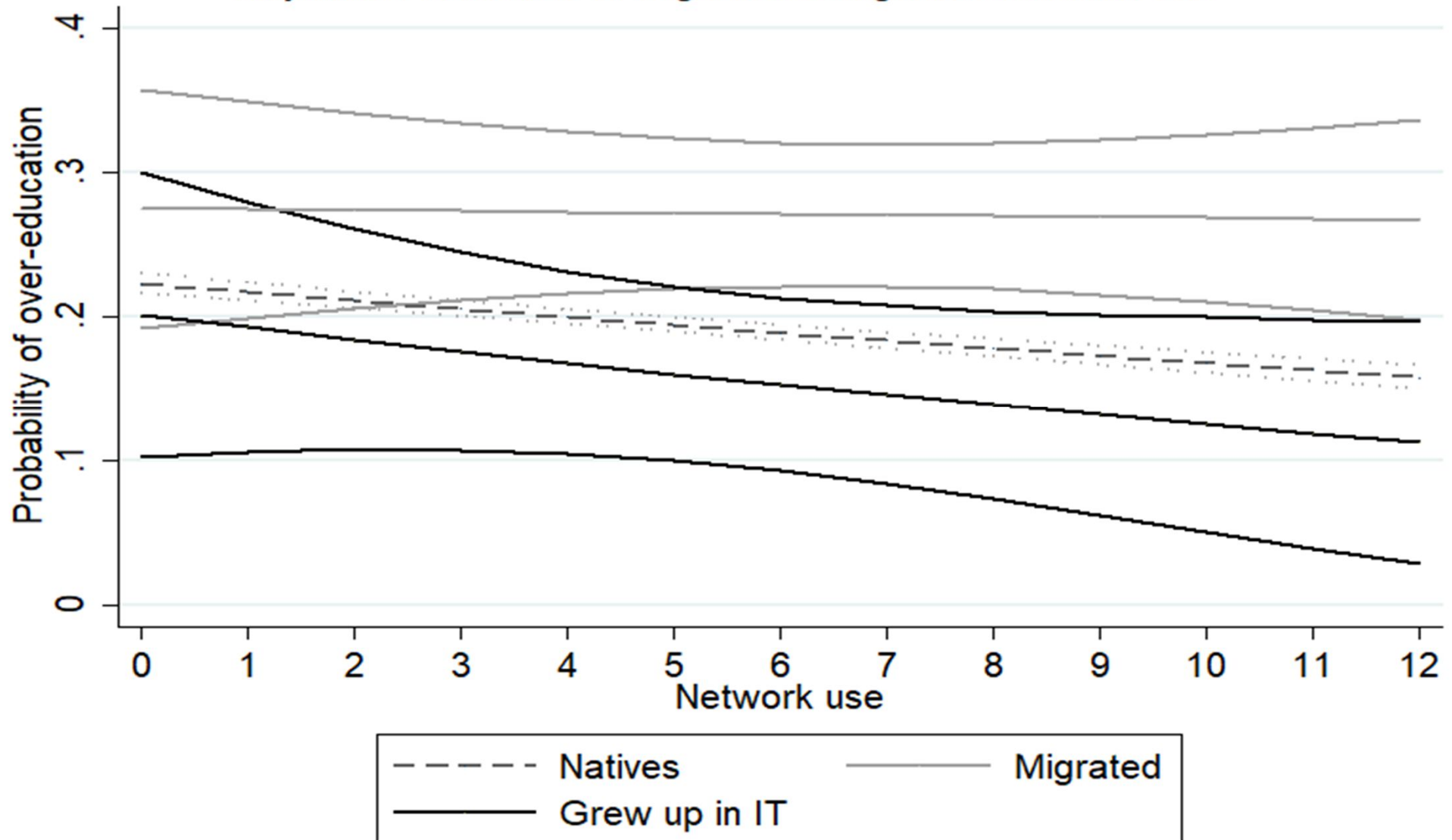
4. Empirical results

Tab. 7. Estimation of the effect of informal networks. Logistic regression with inverse probability weighting, average marginal effects.

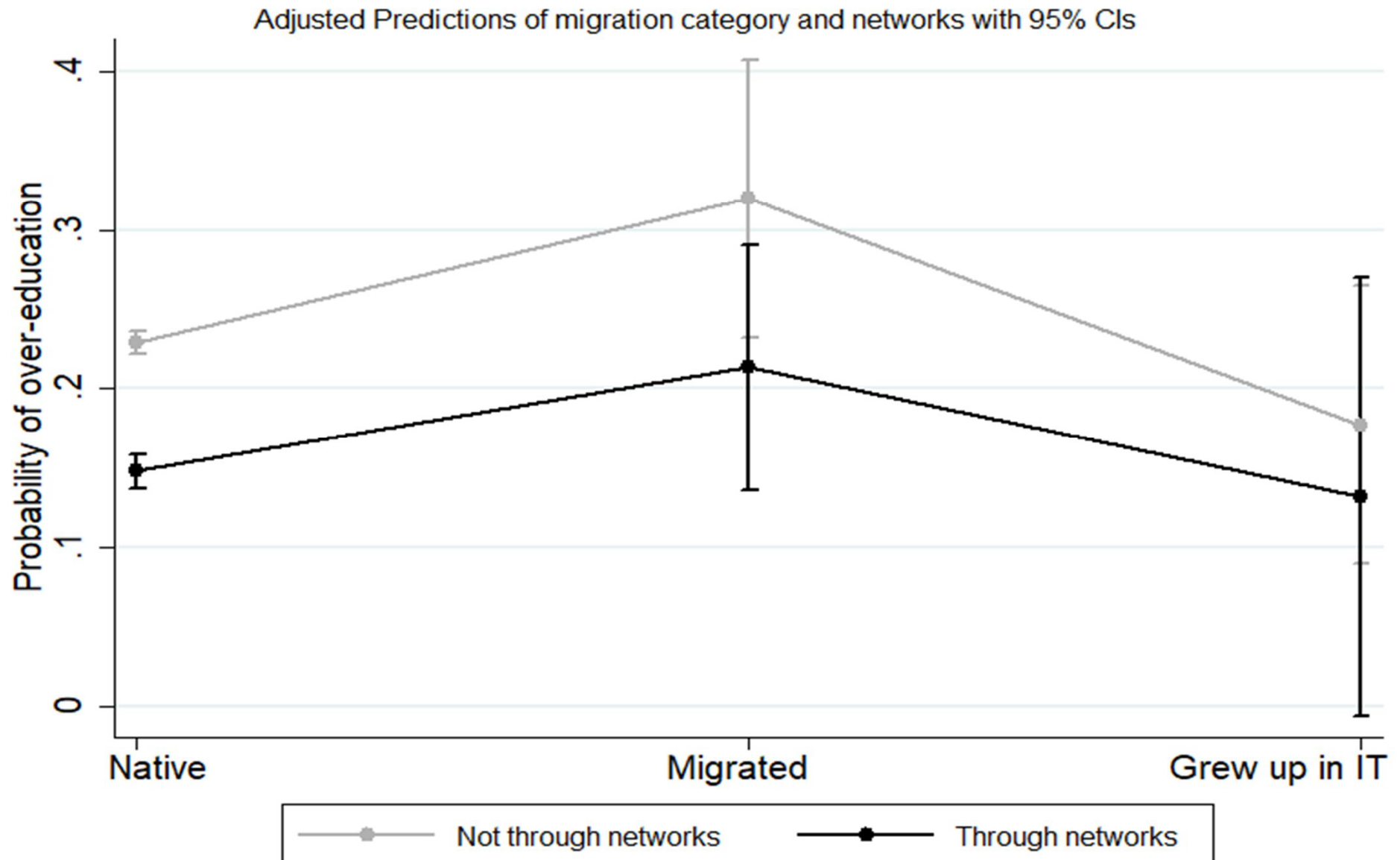
Average treatment effect on the treated	Probit model 1	Probit model 2
Migrated	0.0881 *** (0.026)	0.0827 *** (0.032)
Grew up in IT	-0.0339 (0.031)	-0.0433 (0.038)
Network-looking	-0.0055 *** (0.001)	
Network-finding		-0.0811 *** (0.006)

4. Empirical results

Adjusted Predictions of migration categories with 95% CIs



4. Empirical results



PRESENTATION OUTLINE

- 1. Introduction: immigration, mismatch and informal networks**
- 2. Mismatch, network and other definitions**
- 3. Data and method: PLUS & PSM/IPW**
- 4. Empirical results**
- 5. Conclusion and public policy considerations**

6. Conclusion and public policy considerations

Conclusions

- More research is needed!
- Migrants vs. natives & second generations
- There is an effect of networks but that does not vary much across categories

Policy hints

- What can you do about networks...
- Recognition of qualifications as the way to go? → very little research on that !!



Thank you !

Email: p.vanwolleghem.ext@inapp.org

Email 2: p.vanwoll@gmail.com

Working paper available at: <https://ideas.repec.org/p/zbw/glodps/398.html>

Visit Inapp's website at:
Inapp.org