“Skilled immigrants to France: The impact on innovation”

by Anna Maria Mayda, Gianluca Orefice
and Gianluca Santoni

Anna Maria Mayda
Georgetown University and CEPR

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How can immigrants help Europe? (broader research agenda I am interested in)

There are two main aspects of immigration to Europe that have received less attention in political discussions and academic research, yet they are crucial to understand how immigration can help Europe:

1) the role of (especially low-skilled, young) immigration in a context characterized by population aging: see Börsch-Supan, Leite and Rausch (2019) and my own discussion of this paper, Mayda (2019);

2) the impact of skilled migration to Europe, in particular in terms of innovation.

Today I will focus on the latter point and present some results from Mayda, Orefice and Santoni (2020).

Existing literature

- Recent contributions in the migration literature investigate the impact of skilled immigration on innovation and patenting activity in the United States.

- See for example: Hunt and Gauthier-Loiselle (2010), Kerr and Lincoln (2010), Doran et al (2014):

  - **Hunt and Gauthier-Loiselle (2010)** exploits cross-state variation for the United States and finds that a one percentage-point increase in the share of immigrant college graduates in the population leads to an increase in patents per capita of 9 to 18 percent – the main reason being that they disproportionately hold STEM (Science, Technology, Engineering and Mathematics) degrees.

  - **Kerr and Lincoln (2010)** look at whether shifts in national H1-B admissions are associated with stronger or weaker patenting activity of ethnic inventors in states/cities/firms that are very dependent on the program relative to less dependent ones. Mostly, this is a city-level analysis – the firm-level analysis is only for a small sample of companies (77 firms).

  - **Doran et al (2014)** exploit the visa lottery in fiscal years 2006 and 2007 to analyze the effects of H1B visas on patenting and overall firm employment. This paper finds no evidence of an effect on patenting and at most a moderate effect on overall employment in the firm.

Existing literature (cont.)

- Chellaraj et al. (2008) document that the presence of foreign graduate students has a positive impact on future patents in the United States.

- Burchardi (2020) estimate a strong and significant causal impact of immigration on the number of patents filed per person.

- Parrotta et al. (2014) analyze the connection between worker diversity within a firm and its patenting activity using data for Denmark. Their results suggest that ethnic diversity leads to more patenting.

- Italy: Bratti and Conti (2017) find no evidence of either positive or negative effects of migrants on innovation.

- Yet **the literature mostly focuses on the United States and for the most part uses aggregate data or very small samples of firm-level data.**

Evidence from Europe: Mayda, Orefice and Santoni (2020)

- In this paper, we investigate the impact of skilled migration on innovation (patenting activity) in a European country (France) that has received a substantial number of skilled migrants.

- **Why France?**

- France represents an interesting counterpart to the U.S. case. Indeed France, like most European countries, does not have a large program explicitly targeted at attracting skilled migrants, except for the **EU blue cards**, for which the take up rate has been low (see following map). Yet France has been able to attract skilled migrants.

- The **Macron administration** is carrying out reforms of immigration policy that are meant to both discourage asylum seekers and **encourage skilled foreign workers to apply for visas.**

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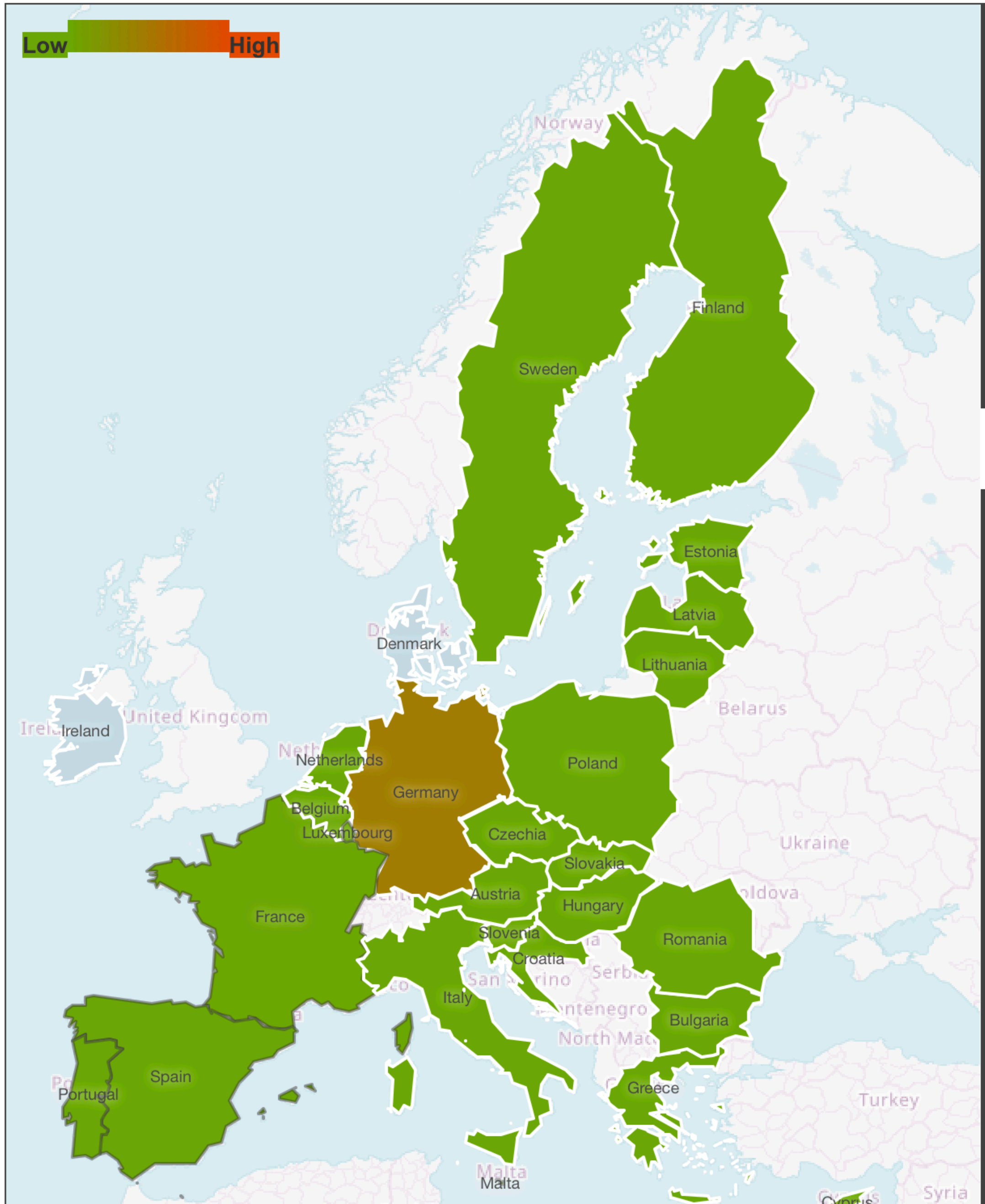
Country facts | Essential information



Countries to compare

- [x] **Select all**
- [x] Austria
- [x] Belgium
- [x] Bulgaria
- [x] Croatia
- [x] Cyprus
- [x] Czech Republic
- [x] Estonia
- [x] Finland
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- [x] Germany
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- [x] Malta
- [x] Netherlands
- [x] Poland
- [x] Portugal
- [x] Romania
- [x] Slovakia
- [x] Slovenia
- [x] Spain
- [x] Sweden

Sort by

- ( ) Fee
- ( ) Validity period
- ( ) Salary threshold
- (•) Blue Cards issued

Compare

Why France?

- Importantly, the wealth of data available for France allows us to carry out an investigation of the different channels through which skilled immigrants are likely to affect innovation and patenting. We will consider four different channels.

- We use **micro-level data on French firms** spanning the period 1995–2011.

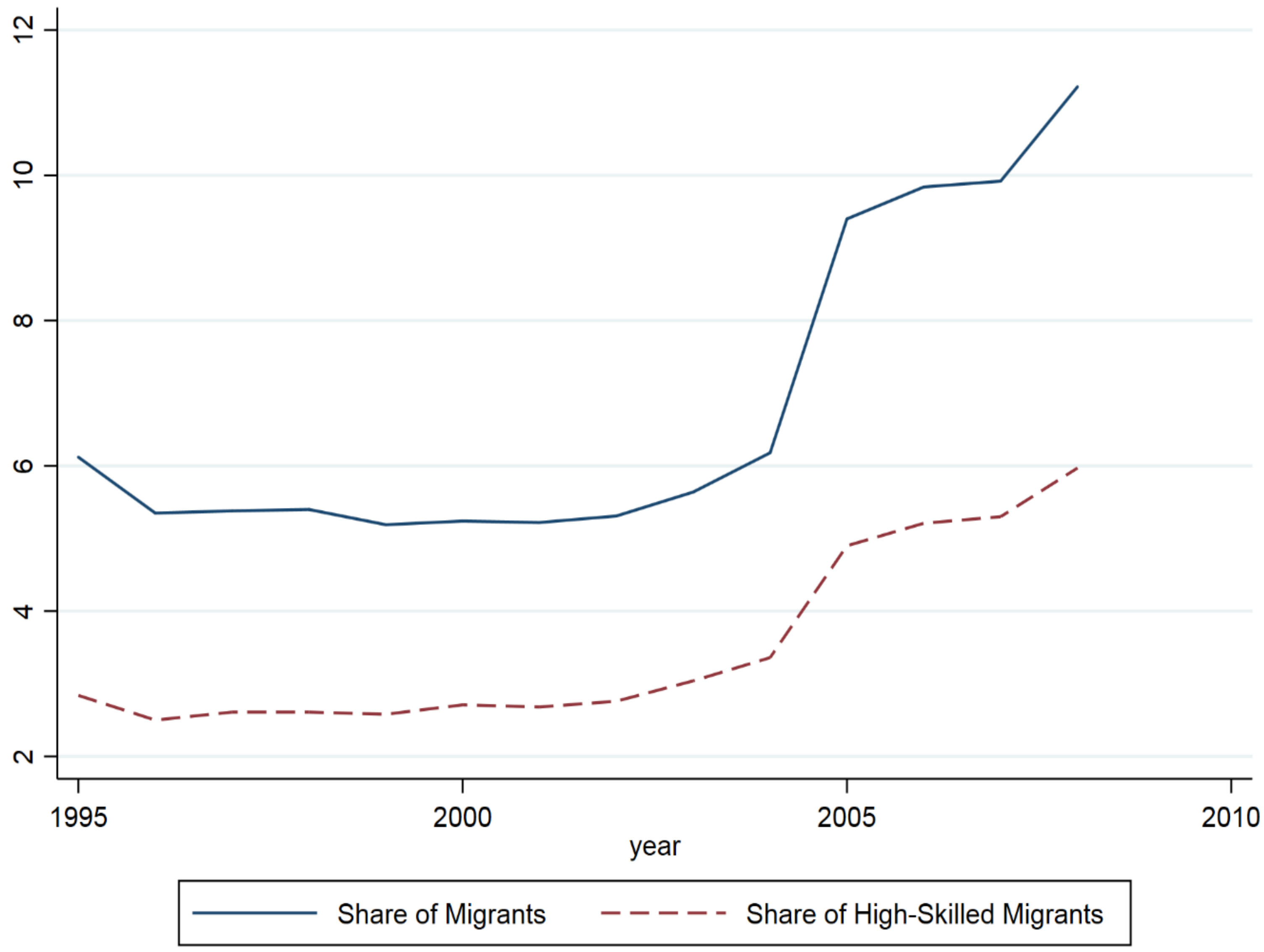
Preview of our main results

- We find evidence of a *causal* effect of skilled migration on innovation activity in France: between 1995 and 2011, an increase in the share of skilled migrants in a French district significantly raises the number of patents.
- The effect of skilled migrants is significantly higher than the effect of skilled natives.
- We instrument for the share of skilled migrants using a **modified version of the Card instrument**.
- We provide evidence for the exclusion restriction by carrying out a pre-treatment trend exercise.

Preview of our main results (cont.)

- Our results also hold at the **firm level**, controlling for firm-level characteritics.
- In addition, we explore **heterogeneity** in the impact of skilled migration with respect to firm-level characteristics as well as district level ones.
- Finally, we show that one channel through which the effect works is **task specialization**: the arrival of skilled immigrants pushes skilled natives (French skilled workers) towards more language-intensive and managerial tasks, while skilled immigrants specialize in more technical tasks (research and innovation).
- This is consistent with institutional de facto characteristics of the French system.

Share of migrants and high-skilled migrants over total population, in France



Tab 1: Share of Immigrant workers over total French workforce	
year	*Share of immigrant workers over total French workforce*
1995	6.12%
1996	5.35%
1997	5.38%
1998	5.40%
1999	5.19%
2000	5.24%
2001	5.22%
2002	5.31%
2003	5.64%
2004	6.18%
2005	9.40%
2006	9.84%
2007	9.92%
2008	11.22%

Source: INSEE-DADS 1995-2008.

Tab 2: Share of high-skilled and Tech-workers migrants over total french workforce			
	Share of migrants:		
year	*High-Skilled*	*Tech-workers*	*Tech-Workers and Professors*
1995	2.84%	0.31%	0.44%
1996	2.50%	0.29%	0.39%
1997	2.61%	0.27%	0.37%
1998	2.61%	0.29%	0.38%
1999	2.58%	0.28%	0.38%
2000	2.71%	0.26%	0.36%
2001	2.68%	0.28%	0.39%
2002	2.76%	0.33%	0.42%
2003	3.04%	0.51%	0.62%
2004	3.36%	0.52%	0.64%
2005	4.90%	0.99%	1.14%
2006	5.21%	1.02%	1.24%
2007	5.30%	1.01%	1.19%
2008	5.97%	1.24%	1.45%

Source: INSEE-DADS 1995-2008.

Tab 7: Top-5 Occupations by share of immigrants		
Occupation	*Mig Sh in the occupation*	*Migrants in the occupations over tot migrants in France*
Ouvriers non qualifiés de type artisanal	27%	10.4%
Ouvriers qualifiés de la manutention, du magasinage et du transport	20%	4.0%
Ingénieurs et cadres techniques d'entreprise	14%	6.9%
Contremaîtres, agents de maîtrise	14%	3.1%
Contremaîtres, agents de maîtrise	13%	9.7%

Source: INSEE-DADS 1995-2008.

Identification: modified version of Card instrument

- Endogeneity due to unobservable local characteristics that affect both patenting activity and the share of skilled immigrants in the population.
- For example, skilled immigrants may be attracted to locations where firms are carrying out innovation activity and, as a consequence, the labor-market is stronger for them.
- On the other hand, it might be that skilled immigrants are more likely to be hired in less attractive locations.
- We use the following instruments for the share of high-skilled migrants and high-skilled natives:

$$\widehat{SN}_{jt}/(\widehat{N}_{jt}+\widehat{M}_{jt})$$

$$\widehat{SM}_{jt}/(\widehat{N}_{jt}+\widehat{M}_{jt})$$

$$sh_{FR,j,1980} = \frac{N_{j,1980}}{\sum_j N_{j,1980}}$$

$$sh_{c,j,1980} = \frac{M_{c,j,1980}}{\sum_j M_{c,j,1980}}$$

$$skillsh_{FR,j,1980} = \frac{SN_{j,1980}}{\sum_j SN_{j,1980}}$$

$$skillsh_{c,j,1980} = \frac{SM_{c,j,1980}}{\sum_j SM_{c,j,1980}}$$

$$\widehat{N}_{jt} = sh_{FR,j,80} N_t \quad \text{and} \quad \widehat{M}_{jt} = \sum_c sh_{c,j,80} M_{ct}$$

$$\widehat{SN}_{jt} = \sum_c skillsh_{FR,j,80} N_t \quad \text{and} \quad \widehat{SM}_{jt} = \sum_c skillsh_{c,j,80} M_{ct}$$

Table 3: Pre-trend test for IV exogeneity.

Dep var:	Δ patents across districts			
	1990-1970	1980-1960	1970-1950	1960-1940
	(1)	(2)	(3)	(4)
$\Delta\ IV_{2011-1995}$	0.092	0.074	0.015	0.051
	(0.087)	(0.120)	(0.190)	(0.227)
Observations	93	93	93	93
R-squared	0.166	0.238	0.211	0.281
Fixed Effects	Region	Region	Region	Region

Dependent variable is the log difference in the number of patents in the district over different sub-periods. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

District-level regressions

- District-level regressions controlling for region fixed effects: they include both the high-skilled immigrant share and the high-skilled native share; both these variables are instrumented with the Card instrument.
- District-level regressions controlling for district fixed effects: they include the high-skilled immigrant share, which is instrumented with the Card instrument; the high-skilled native share is either not included or, if it is included, it is not instrumented (because the instrument is too weak).
- District-level first and long-difference estimations

Table 2: Patents and high skilled migrants in the district. Baseline OLS and 2SLS with region FE.

Dep var:	# Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrant (sh)	0.100***	0.240**		
	(0.020)	(0.098)		
High Skill Natives (sh)	0.079***	0.074***		
	(0.010)	(0.016)		
Techies Migrant (sh)			0.112***	1.218***
			(0.029)	(0.303)
Techies Natives (sh)			0.099***	0.040
			(0.014)	(0.043)
Estimator	OLS	2SLS	OLS	2SLS
Region Fixed Effects	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
IV: High Skill Migrant (sh)	no	yes	no	yes
IV: High Skill Natives (sh)	no	yes	no	yes
Observations	1,598	1,598	1,598	1,598
Cluster	dep	dep	dep	dep
F-test first stage		25.58		8.940
Coeff first stage Mig sh		0.950***		0.287
Coeff first stage Nat sh		4.867***		3.104***
F-test (H0: equal coeff)		0.140		0.000

Dependent variable is the log of the number of patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 4: Fixed effects explained variance (R^2).

Dep Var:	Included Fixed Effects		
	Region	District	District-Year
Observed Native High Skill (Share)	0.595	0.938	0.968
Imputed Native High Skill (Share)	0.499	0.987	0.990
Imputed Native High Skill (Level)	0.457	1.000	1.000
Imputed Native (Level)	0.599	1.000	1.000
Imputed Migrants (Level)	0.434	0.890	0.906

Table 5: Correlation between the share of high skilled natives and migrants (observed and imputed) across districts.

Dep var:	Share High-Skilled Migrants					
	Observed			*Imputed*		
	(1)	(2)	(3)	(4)	(5)	(6)
Sh High-Skilled Nat	-0.211**	-0.401***	-0.013	0.004	0.000	0.026
	(0.089)	(0.103)	(0.028)	(0.004)	(0.000)	(0.017)
Specification	Level	First Diff	Long Diff	Level	First Diff	Long Diff
Observations	1,598	1,488	93	1,598	1,488	93
R-squared	0.700	0.539	0.308	0.905	0.314	0.438
Fixed Effects	Dep Year	Year	Year	Dep Year	Year	Year

Dependent variable is the share of high-skilled immigrants in level, first and long (1995-2011) difference (observed and imputed). ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 6: Patents and high skilled migrants in the district. OLS, 2SLS and IV PPML estimations.

Dep var:	# Active patents in the district (ln)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Skill Migrant (sh)	0.015	0.024**	0.237***	0.210***	0.245***	0.217***	0.151**	0.242***
	(0.010)	(0.012)	(0.045)	(0.049)	(0.060)	(0.059)	(0.068)	(0.0602)
High Skill Natives (sh)		0.018*		0.057***				
		(0.010)		(0.020)				
VA per firm (ln)					-0.106	-0.151	-0.256	-0.218
					(0.383)	(0.369)	(0.361)	(0.362)
Capital/VA					-0.191	-0.156	-0.075	-0.222
					(0.189)	(0.182)	(0.173)	(0.195)
Tot VA (ln)					0.246	0.291	0.398	0.424
					(0.427)	(0.418)	(0.405)	(0.389)
Estimator	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	IV PPML
Region Fixed Effects	No	No	No	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV: High Skill Migrant (sh)	no	no	yes	yes	yes	yes	yes	yes
IV: High Skill Natives (sh)	no	no	no	no	no	no	no	no
Base year IV	1980	1980	1980	1980	1980	1990	1975	1980
Observations	1,598	1,598	1,598	1,598	1,598	1,598	1,598	1,598
Cluster	dep	dep	dep	dep	dep			dep
F-test first stage			23.13	10.42	20.43	20.44	23.82	
Coeff first stage Mig sh			1.167***	1.288***	1.231***	0.753***	1.109***	1.232***

Dependent variable is the log of the number of patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 9: Patents and high skilled migrants in the district. 2SLS long difference specification.

Dep var:	# Active patents in the district (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrant (sh)	0.881***	0.996***		
	(0.298)	(0.376)		
Techies Migrant (sh)			1.475***	1.701***
			(0.437)	(0.563)
VA per firm (ln)	1.195	1.410	0.764	0.897
	(1.111)	(1.319)	(0.905)	(1.065)
Capital/VA	-0.298	-0.330	0.356	0.443
	(0.522)	(0.558)	(0.443)	(0.462)
Tot VA (ln)	-1.128	-1.326	-0.588	-0.691
	(1.336)	(1.567)	(1.112)	(1.245)
Δ Patents Nat 1900-1800		-0.047		-0.059
		(0.125)		(0.112)
Δ Patents Mig 1900-1800		-0.037		-0.045
		(0.105)		(0.095)
Δ Tot Patents 1980-1970		0.137		0.183
		(0.142)		(0.161)
Estimator	2SLS	2SLS	2SLS	2SLS
Specification	Long Diff.	Long Diff.	Long Diff.	Long Diff.
Observations	94	93	94	93
Year Fixed Effects	yes	yes	yes	yes
Cluster	dep	dep	dep	dep
F-test	21.62	17.89	34.65	30.40
Coeff first stage	0.425***	0.425***	0.254***	0.249***

Dependent variable is the difference in the log of the number of patents in the districts. Standard errors adjusted for clustering by district. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Firm-level regressions

- We construct the patents variable at the firm level but we keep the explanatory variable (the skilled-migrant share) at the district level.
- We are able to control for firm-level characteristics.
- We also explore heterogeneity with respect to firm-level characteristics. We find that high-productivity, capital-intensive and large firms are those for which the effects are stronger.

Table 10: High skilled migrants and firms' patenting activity. Baseline OLS and 2SLS. Within specification.

Dep var:	# Active patents in the firm (ln)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High Skill Migrant (sh)	0.009**	0.010**	0.111***	0.116***	0.115***	0.118***				
	(0.004)	(0.004)	(0.028)	(0.029)	(0.028)	(0.032)				
Techies Migrant (sh)							0.175***	0.184***	0.184***	0.186***
							(0.045)	(0.047)	(0.046)	(0.051)
VA per firm (ln)		-0.014**		-0.013*	-0.013*	-0.013*		-0.012*	-0.012*	-0.012*
		(0.006)		(0.007)	(0.007)	(0.007)		(0.007)	(0.007)	(0.007)
Capital/VA		0.021*		0.036***	0.035***	0.036***		0.038***	0.038***	0.038***
		(0.011)		(0.011)	(0.011)	(0.011)		(0.012)	(0.012)	(0.012)
Tot VA (ln)		0.041***		0.051***	0.051***	0.051***		0.053***	0.053***	0.053***
		(0.014)		(0.014)	(0.014)	(0.014)		(0.014)	(0.014)	(0.014)
Estimator	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Specification	Within	Within	Within	Within	Within	Within	Within	Within	Within	Within
IV Baseline Year			1980	1980	1990	1975	1980	1980	1990	1975
Firm-District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,937	56,937	56,937	56,937	56,937	56,937	56,937	56,937	56,937	56,937
Cluster	id rt	id rt	id rt	id rt			id rt	id rt	id rt	id rt
F-stat first stage			16.29	16.29	17.49	13.30	16.64	16.58	17.85	13.38
Coeff first stage			0.958***	0.953***	0.583***	0.845***	0.607***	0.603***	0.365***	0.535***

Dependent variable is the log of the number of patents in the firm. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 11: High skilled migrants and firms' patenting activity by type of firm. Baseline OLS and 2SLS. Within specification.

Dep var:	# Active patents in the firm (ln)					
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrant (sh)	0.008**	0.009**	-0.005	0.074***	0.094***	-0.107
	(0.004)	(0.004)	(0.007)	(0.024)	(0.026)	(0.096)
High Skill Migrant (sh) x High Prod	0.004			0.092**		
	(0.004)			(0.038)		
High Skill Migrant (sh) x High K/L		0.002			0.086**	
		(0.005)			(0.042)	
High Skill Migrant (sh) x Big Firm			0.015**			0.229**
			(0.007)			(0.109)
Capital/VA	0.021*	0.021*	0.021*	0.037***	0.043***	0.039***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
VA per firm (ln)	-0.014**	-0.014**	-0.014**	-0.011	-0.010	-0.008
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Tot VA (ln)	0.041***	0.041***	0.041***	0.052***	0.055***	0.059***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS
Firm-District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,937	56,937	56,937	56,937	56,937	56,937
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
F-stat first stage				7.149	8.182	5.871
Coeff first stage High Skill Mig				0.958***	0.954***	0.754***
Coeff first stage Interaction				1.241***	1.287***	1.110***

Dependent variable is the log of the number of patents in the firm. High productive, high capital intensive and big firms are those above the $75^t h$ percentile of labor productivity, capital intensity and size distribution. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 12: High skilled migrants and firms' patenting activity by district of firm localization. Baseline OLS and 2SLS. Within specification.

Dep var:	# Active patents in the firm (ln)			
	(1)	(2)	(3)	(4)
High Skill Migrant (sh)	0.010**	0.001	0.182***	0.014
	(0.004)	(0.004)	(0.070)	(0.050)
High Skill Natives (sh) x Big City	-0.003		-0.084	
	(0.006)		(0.063)	
High Skill Migrant (sh) x Mig patenting 800-900 ¿ 0		0.010**		0.095*
		(0.004)		(0.055)
Capital/VA	0.021*	0.021*	0.041***	0.036***
	(0.011)	(0.011)	(0.013)	(0.011)
VA per firm (ln)	-0.014**	-0.014**	-0.011	-0.012*
	(0.006)	(0.006)	(0.007)	(0.007)
Tot VA (ln)	0.041***	0.041***	0.055***	0.053***
	(0.014)	(0.014)	(0.014)	(0.014)
Estimator	OLS	OLS	2SLS	2SLS
Firm-District Fixed Effects	Yes	Yes	Yes	Yes
Sector-Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	56,937	56,937	56,937	56,937
Cluster	id rt	id rt	id rt	id rt
F-test			3.175	3.573
Coeff first stage High Skill Mig			1.424**	0.775***
Coeff first stage Interaction			1.039***	1.509***

Dependent variable is the log of the number of patents in the firm. Big cities districts are: Paris, Lyon and Marseilles. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

The effect is likely to work through four different channels:

1. as is the case with trade, skilled immigrants are the conduit through which **knowledge flows** from their countries of origin to France – this is the channel analyzed by Kerr and Lincoln (2010);

2. since immigrant workers are characterized by **greater mobility** than native workers – and this is the case in France as well – we investigate whether they facilitate knowledge diffusion across French firms;

3. ***task specialization***: the arrival of skilled immigrants pushes skilled natives (French skilled workers) towards more language-intensive and managerial tasks, while skilled immigrants specialize in more technical tasks (research and innovation).

4. to the extent skilled migrants are positively **self selected**, they will be characterized by greater unobserved ability compared to skilled native workers with the same observable skills.

Task specialization

- See Peri and Sparber (2009) for low-skilled immigrants and Peri and Sparber (2011) for high-skilled immigrants.
- Due to lower language/communication abilities or other (institutional or de facto) constraints, skilled immigrants tend to specialize in more technical tasks (such as in STEM occupations or more broadly in occupations related to research) while skilled natives tend to specialize in language-intensive occupations or administrative/managerial occupations.
- The case of France is special from this point of view as the education system (through Grandes Ecoles) is set up in such a way that outsiders (both French workers who did not go to Grandes Ecoles and foreign workers who studied abroad) are less likely to have access, in practice, to top managerial positions within firms, hence they focus on research/innovation/technical tasks.

Table 14: The impact of migrants on the share of **natives** employed in each firm's layer (production workers, intermediate professions and management). 2SLS estimations.

Dep var:	# Prod. workers (share over tot natives)		# Interm. Profession (share over tot natives)		# Management (share over tot natives)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrant (sh)	-0.776**	-0.496	-0.206	-0.284	0.942***	0.754**
	(0.380)	(0.361)	(0.307)	(0.310)	(0.280)	(0.294)
Capital/VA		0.915**		-0.829***		-0.131
		(0.372)		(0.315)		(0.315)
VA per firm (ln)		-3.453***		-1.188***		4.339***
		(0.360)		(0.308)		(0.300)
Tot VA (ln)		3.724***		-0.266		-3.205***
		(0.418)		(0.363)		(0.379)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Specification	Within	Within	Within	Within	Within	Within
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,267	56,267	56,267	56,267	56,267	56,267
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
F-test	16.30	16.28	16.30	16.28	16.30	16.28

Dependent variable is the share of natives employed in each firm's layer over total firm's employment. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 15: The impact of migrants on the share of **natives** employed in production occupation: decomposition specific occupations.

Dep var:	Unskilled blue collar (share over tot natives)	Skilled blue collar (share over tot natives)	Production white collar (share over tot natives)
	(1)	(2)	(3)
High Skill Migrant (sh)	0.684**	-1.013**	-0.167
	(0.327)	(0.397)	(0.223)
Capital/VA	-0.353	1.195***	0.073
	(0.307)	(0.359)	(0.219)
VA per firm (ln)	-2.772***	-2.535***	1.854***
	(0.273)	(0.334)	(0.229)
Tot VA (ln)	2.171***	2.740***	-1.188***
	(0.342)	(0.424)	(0.251)
Estimator	2SLS	2SLS	2SLS
Specification	Within	Within	Within
Firm-District FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Observations	56,267	56,267	56,267
Cluster	id rt	id rt	id rt
F-test	16.28	16.28	16.28

Dependent variable is the share of natives employed in each firm's layer over total firm's employment. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Table 16: The impact of migrants on the share of **natives** employed in managerial occupations: decomposition across sales executives, engineers, other professionals (including CEO). 2SLS estimations.

Dep var:	# Sales Executives (share over tot natives)		# Engineers (share over tot natives)		# Other Profess. (share over tot natives)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Skill Migrant (sh)	0.506**	0.444**	0.240	0.204	0.195	0.106
	(0.207)	(0.210)	(0.206)	(0.215)	(0.140)	(0.140)
Capital/VA		-0.245		0.113		0.002
		(0.241)		(0.221)		(0.185)
VA per firm (ln)		1.568***		1.586***		1.186***
		(0.219)		(0.247)		(0.179)
Tot VA (ln)		-1.000***		-0.859***		-1.346***
		(0.295)		(0.254)		(0.181)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Specification	Within	Within	Within	Within	Within	Within
Firm-District FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,267	56,267	56,267	56,267	56,267	56,267
Cluster	id rt	id rt	id rt	id rt	id rt	id rt
F-test	16.30	16.28	16.30	16.28	16.30	16.28

Dependent variable is the share of natives employed in each firm's layer over total firm's employment. Standard errors adjusted for clustering by firm and region-year. ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels respectively.

Conclusion

- Skilled migration to France (and Europe) in general plays an important role in terms of innovation.
- In countries, such as Italy, where immigrants are for the most part of low-skilled, we should encourage skilled migration as well.
- This is an important topic which should enter policy discussions on immigration in Europe.