Essays on Education and Labor Economics

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Alessandra Di Pietro

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Chapter 1

Wider Supply, Higher Demand? Evidence From a University Reform

with Berton F. and Bondonio D.

Abstract

To be competitive and turn into a strong knowledge economy Europe has to invest in human capital, boosting enrolment into higher education at no harm of graduation rates. Pushing people into education is expensive, and governments efforts seem not to pay off everywhere the same way. This paper takes advantage of a widespread reform and an administrative panel of degree-level data to assess the impact of an expansion in the supply of tertiary-education degrees on enrolment into higher education. Among other most popular incentives, increase in quantity of degrees offered is often overlooked in the literature because likely endogenous. Using a difference-in-differences set up, we find that the introduction of every new degree results in 3.3%-3.4% more enrollees. These results survive, in qualitative terms, to an instrumental variable approach[1].

[1]Data used in the analysis were provided by the former Italian National Committee for the Evaluation of the University System (MIUR-Ministry of Education, University and Research) for an impact evaluation study of the Italian university reform D.M. 509/99. We thank the Statistical office of MIUR, the National Committee for the Evaluation of the University System and Matilde Bini (LUISS University of Rome) for assistance in acquiring the data. We also thank the participants to the Fifth LEER Conference (KU Leuven) and to the seminars held at the Department of Economics and Statistics of the University of Torino and Collegio Carlo Alberto for helpful comments and suggestions

1.1 Introduction

A link between human capital and growth is well established in the literature (Barro 1998; Barro & Sala i Martin 1995). At the individual level this link translates into labor market and health related benefits, while the economy on the whole sees less pressure on earning differential between high skills and low skills workers (Card et al, 2000). Countries shall thus invest in education to increase human capital accumulation. Building a strong knowledge economy is one of the main goals of the EU, with a stated objective of having, by 2020, at least 40% of the population aged 30 to 34 that has completed higher education. For this reason, in many developed economies the challenge of attracting more people into tertiary education is very high in the policy agenda. Finding ways to raise higher education enrolment and completion rates, however, is not an easy task. Unsatisfying higher education participation rates are mainly due to two factors: higher education costs, which often prevent students from less endowed families to enrol; and asymmetries between the supply of higher education and the demand of high skills in the labor market- that result in limited wage premia for university degrees and vertical educational mismatch. While the limitation of higher education high costs has been widely studied, particularly in the US literature, the challenge of attracting more students by modifying supply – and fine-tuning it with labor market – have attracted much less scientific attention. Our study contributes specifically on this latter issue, aiming to estimate the causal effect of widening the supply of university curricula – a typical policy to make university supply more consistent with labor market demand – on tertiary education participation.

One of the main obstacle to causally identify the impact of these policies on higher educaton participation is often the endogeneity of the timing of the intervention, which is typically driven by the preferences of prospective students, or by labor market outlooks that would affect enrolments anyway. In order to overcome this limitation, in this paper we take advantage of the reform implied by the so-called Bologna Process. The Bologna Process takes its name from a meeting – held in Bologna in 1999 – among all European ministers of education. Its main goal was the harmonisation of the university systems across Europe, to encourage the allocation of skills throughout European countries by building by 2010 the European Higher Education Area (EHEA). The idea was to allow students graduating in one country to apply for jobs everywhere in Europe by being recognised their academic degrees. Implementing the Bologna Process at the national level implied normative changes of different intensity, depending on the pre-existing country-specific consistency with the model resulting from the Bologna meeting.

For a number of reasons, Italy emerges as a particularly apt case-study. First, as explained in Bondonio et al., 2018, the Bologna Process was introduced in Italy exogenously with respect to existing higher education participation and graduation trends. Departments were left with a very short time to implement the new rules. Second, as the Italian higher educational system was rather inconsistent with the educational model suggested by Bologna agreements – mostly because the latter envisaged three-year BA degrees followed by two-year master courses, while in Italy the single-tier model with four- or five-year degrees was largely prevalent at the time – its introduction implied a deep re-organizations of the teaching activities [2]. Most departments took advantage of this in order to update – and widen – their degree supply, as well documented in Figure 1.1. Third, among advanced economies Italy stands for the low level of education of its workforce: at the time the reforms were introduced, in 2000, only 11.6% of the population had completed tertiary education. This notwithstanding, Italy displays average levels of educational mismatch (McGuinnes et al. 2016).

How to attract more students has often been a challenge for higher education institutions and governments. In the late 70s US universities reached out to older, foreign and female students to increase enrolment rates. Back then, cohort size and earnings associated to degrees explained trends better than tuition fees or local unemployment (Card et al, 2000). As shown in Oppedisano (2011), coordination with labor market is also key nowadays to achieve results on enrolment and graduation rates (Freeman, 1981; Hastings et al. 2015). In the Netherlands in the 80s, it was national per capita income the main driver of enrolment into higher education (Huijsman et al, 1986). Literature shows mixed results when efforts aim at equality of opportunity, reaching students from low income households. Reducing college costs proved more effective when linked to incentive, being however beneficial for both enrolment and persistence (Deming et al. 2009). Tax based programs need to be well designed otherwise their impact is null (Hoxby et al., 2013, 2016). Expanding higher education supply did not work well niether in Italy in the late 90s, it did increase probability of enrolment but not that of completing the degree (Bratti et al., 2008).
Oppedisano (2011) is the closest reference to this work and deals with both location and variety of programs offered. Her work tests whether opening new small universities throughout the territory pays off in terms of enrolment rates. She observes a sample of individuals graduating from Italian high schools from 1995 to 1998, and shows that enrolment may grow, but at the expenses of on-time graduation rates. Moreover, spreading higher education on the territory by opening new small universities, getting geographically closer to new students, is beneficial only when matching local labor market needs, that means only for specific (scientific)

[2] See again Bondonio & Berton (2018) for a detailed description of the bureaucratic procedures.

departments. Another attempt to close the gap between students and universities in terms of phisical distance is also the aim of online universities. They increase overall enrolment and they do so by expanding the pool of students, not substituting existitng options (Goodman et al. 2016). Quality of institutions is also beneficial to enrolment, only when talking about top performing universities (Biancardi et al. 2019). All these measures, beyond being beneficial to enrolment, come at a higher cost for either countries or universities themselves. Reason to focus on supply expansion (be it updating or increasing number of degrees offered) is that it might cost much less. Some scholars focused on what changes Bologna Process entailed in the Italian context. Di Pietro et al. (2008) focus on drop out rates. They exploit survey data about high-school graduates in Italy, and show that the increased number of curricula introduced with the Bologna reforms reduced drop-out rate. Cappellari et al. (2008) found that high school graduates after the reform were more likely to enroll (10% higher) using Bologna reforms as an exogenous shock (reducing length thus costs). They also confimed negative trends on drop out rates.
Here too, since it is likely endogenous, a supply expansion has been little investigated.
We contribute to this stream of literature by taking advantage of a unique data source, namely the administrative records from the Statistical Office of the Ministry of Education (USTAT). This data allows to track the number of enrollees – distinguished by the year of first enrolment – at the university-department-degree level, over a time span from 1998 to 2005[3]. Also, we adopt a slight different perspective by having universities and not students as units of observations, as seen in most of the related literature (Bratti et al., 2008; Oppedisano, 2011; Card et al.,2000). Adopting a difference-in-differences (DiD) set up, we find that an expansion of higher education by one course, is responsible of an increase in the enrolment rate by around 3.3 to 3.4 percentage points. These results survive to the application of an instrumental variable (IV) approach. Using the reform itself as an instrument, downsizing our sample to engineering faculties as the only departments where length did not change, we show that the reform induced a increase of similar size to that of DiD model.

The remainder of this paper is organized as follows. In Section 1.2, we describe data and provide some descriptive statistics of the population under analysis. In Section 1.3 we discuss the context that allows our empirical analysis and introduce our main identification strategy, whose specifications and estimation results are described in Section 1.4. In Section 1.5 we show that our results survive to a different identification strategy, while Section 1.6 gives some concluding remarks.

[3] Data is organized in academic years; hence by, e.g., 1998 we mean academic year 1998-99.

1.2 Data

Microdata used for the analysis covers the whole universe of Italian university departments for a time-span of nine years, from 1998 to 2005. This data is provided by USTAT, the statistical office that collects the data for the Italian Ministry of Education. Every year, each university in Italy is required to send to USTAT the records about number of enrollees and of graduates, both distinguished by year of first enrolment. This grants a high degree of reliability and low measurement error. The interval observed captures few years before and few years after the implementation of the Bologna Process, that was introduced in Italy in 1999 through the Ministerial Decree no. 509 (DM 509/99, the so-called Zecchino Reform) and implemented between 2000 and 2001. It led to a switch from old cycles (four- to five-year long), to a new university system divided into two tiers. The first one includes three-year courses leading to the new Bachelor's degree. The second tier, leading to the Master's degree, lasts for two years. Few single-tier degrees did not change, lasting five or six years: Architecture, Pharmacy, Dentistry, Veterinary Science, Law, Medicine, Primary Education Sciences, and Chemistry (Istat, 2017). The Italian university system was made of 34 departments (facoltà, in Italian) in the first year of our time interval, which grew to 46 in the last year observed in our panel. Universities were 84 in 1998 and 86 in 2006. Number of universities did not change much, while number of departments and degrees offered by each of them steeply did. USTAT data covers both public and private Italian universities with degree-specific information on location (city, province and region) of the department in which the degree is offered; type and name of the degree; number of enrollees and graduated students sorted by the year of their first enrolment. This data is complemented by each university's foundation year, to capture its prestige; regional number of high-school graduates, as a proxy for higher education demand; and by the local youth unemployment rate, in order to control for labor market conditions. Our statistical unit is the single department-city, in order to ensure consistency over time in the units of observation, something we would not be able to grant using degree-specific figures. From the full sample of 505 departments observed over our time window we remove those units applying a cap on the number of new enrollees – i.e. Law, Medicine, Veterinarian Medicine and Pharmaceutical Studies. We are left with 354 departments, of which 29 introduced the reform in 2000, while the remaining 329 in 2001[4]. The resulting number of observation in our unbalanced panel is 2007.

[4]This distinction will be relevant for our identification strategy.

Figure 1.1: All degrees offered by type over time

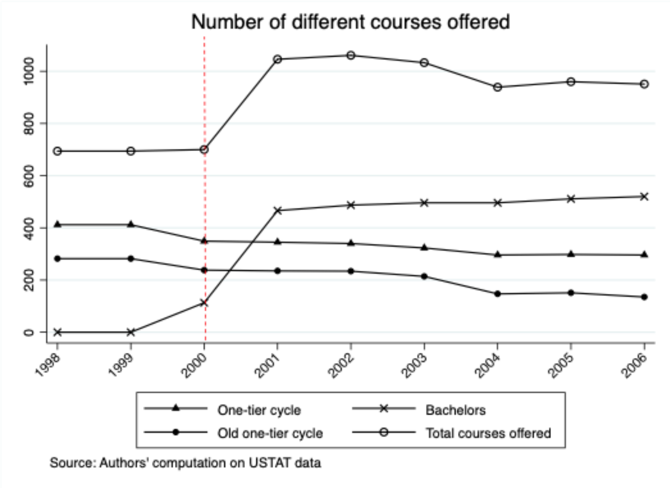


Table 1.1: Italian universities supply in the years of the reform

Type of courses	Activated a.a. 00/01		Activated a.a. 01/02	
	(v.a.)	(v.p.)	(v.a.)	(v.p.)
Degree - old (CDL)	1.273	52,1%	157	4.9%
Diploma - old (CDU)	968	39,6%	194	6,0%
Special purpose School - old (SDFS)	21	0,9%	10	0,3%
Bachelor - new (L)	182	7,4%	2.726	84,3%
Master of science - new (LS)			7	0,2%
Master degree one cycle - new (LSCU)			140	4,3%
Total	2.444	100,0%	3.234	100,0%

Source: CNSVU, 2004

1.3 Identification Strategy

As explained above and shown in Figure 1.1, during the time-frame under scrutiny most of the variation occurred in the number of degrees is related to the introduction of the Bologna reforms. As the latter has been shown to be largely exogenous to the existing higher education demand trends (Bondonio & Berton, 2018), we can conclude that the also the variation in the number of degrees offered in the years around 2000 and 2001 is largely exogenous to demand trends [5]. However, the introduction of Bologna reforms had autonomous effects on enrolment

[5]One may hence wonder why there has been a strong increase in the number of degrees offered, if no latent demand was there. Our answer is twofold. First, while there might be the willingness from a department to

trends, mainly because the duration of BA degrees was reduced from four or five years to three, something we can rationalize as a direct cost reduction. The main challenge in our approach is hence to separate the effect of the yearly change in the number of degrees offered from other autonomous effects of the Bologna reforms.

The specific Italian features of the Bologna Process provide us with a rather straightforward way to do it. The Ministerial Decree 509/99 provided the departments with eighteen months to implement the Bologna Process. The intention was to speed up its introduction as soon as possible, hence departments started immediately to prepare the paperwork. However, internal delays in the Minister of Education postponed the publication of some necessary regulations to August 2000. This implied that those departments that happened to have set their first faculty meeting early enough to apply the just issued regulations, were in a position to implement the Bologna reforms since academic year 2000/2001 (early adopters). The others, needed to wait until 2001/2002 (delayed adopters).

Table 1.2: Delayed vs Early adopters - Tested differences

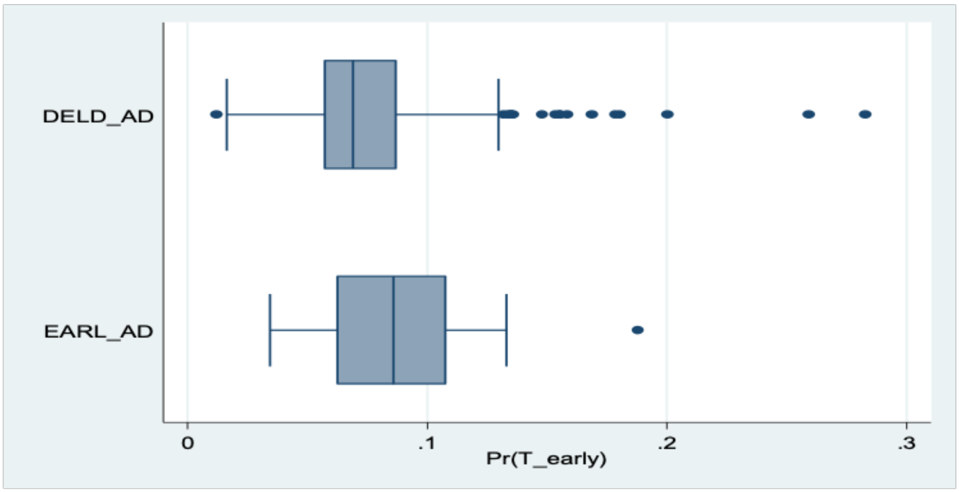
	Delayed	Early	Delayed vs Early
Yearly %Δ of 1st-yr Enrollees(1=1%)	-1.10	-6.09	4.99
	(22.81)	(11.59)	[0.29]
1-yr Retention Rate (1=1%)	77.50	77.73	-0.23
	(10.45)	(6.72)	[0.92]
Yearly Δ of 1-yr Ret. Rate (1=1 p.p.)	-0.47	1.56	-2.03
	(10.52)	(9.32)	[0.39]
2-yr Retention Rate (1=1%)	69.61	68.82	0.79
	(12.93)	(9.50)	[0.78]
Yearly Δ of 2-year Ret. Rate (1=1 p.p.)	-0.40	-0.85	0.46
	(14.13)	(13.84)	[0.88]
On-Time Graduation (1=1%)	29.08	32.72	-3.64
	(23.22)	(16.02)	[0.48]
Yearly Δ On-Time Graduation (1=1 p.p.)	6.17	4.17	2.00
	(10.15)	(10.70)	[0.39]

Notes: (.) standard errors; [.] p-values of T-tests; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

update the supply of degrees, the high bureaucratic costs implied in Italy may provide with a strong negative incentive to proceed. The Bologna Process made this costs compulsory, hence departments may have decided to take advantage of this opportunity. Second, creating new degrees represent also the opportunity for internal promotions; widening the supply of curricula may have been also a consequence of this internal pressure. Both motivations support the exogeneity of our interest variable during the observed period.

Table 1.1 displays some descriptive evidence on the main participation indicators, and show that no significant difference was in place between early and delayed adopters. To further reinforce the idea that the early adopters represent a random sample of the departments implementing the Bologna reforms, we have computed the probability to be an early adopter as a function of the variables included in Table 1.1, and then computed the distribution of this probability for the early and delayed adopters. Figure 1.2 shows the results, and confirms that the two distributions largely overlap.

Figure 1.2: Delayed and Early adopters - Box plot



We are therefore in front of a clear unintended delay-of-treatment situation, that is suited for the application of a DiD approach. In other words, we can estimate the effect of the time-change in the number of the degrees offered by each department during the years of the Bologna reforms net of other changes in the enrolment rate due to the same reforms by controlling the effect of the latter through a DiD specification that compares early and delayed units. Residual demand-driven components of the enrolment trend – e.g. changes in the number of high-school graduates or in the labor market conditions for the youth – are controlled for by including in the model an appropriate set of variables.

1.4 Model

Our estimates are obtained by first-differencing the following general linear specification:

$$Y_{it} = f[D_{it}, \rho_t, Tc_{it}, X_{it}, t * X_i, \alpha_i, u_{it}] \tag{1.1}$$

where Y_{it} is $ln(ENRL_{it})$ and $ENRL_{it}$ is the number of enrollees in department *i* in academic year *t*; D_{it} is the absolute number of degrees offered in department *i* during year *t*; $Tc_{it} = 0, 1$ with $c = 1, \ldots, 5$ is a set of five dummies taking on the value 1 when department *i* implements the reform in academic year *t* for the *c-th* consecutive year; $\rho_t = 0, 1$ is a set of yearly dummy variables (they identify the time-trend separately from Tc_{it} thanks to the delay of treatment; X_{it} is a set of department-specific time-varying characteristics (see Table 1.2.); $t * X_i$ is a set of department-specific time-unvarying characteristics interacted with the time trend (see Table 2); α_i is the fixed-effect department-specific error component; u_{it} is the i.i.d. error term with $E(u_{it}) = 0$ and $Var(u_{it})$=σ^2.
For the sake of robustness we estimate four different specifications of the model above. Specifications are defined in terms of different selections and functional forms for variables X_{it} and $t * X_i$. Specification I is the most statistically efficient, while specification IV has the most flexible functional form and the most complete set of controls.

Table 1.3. displays our estimation results. Irrespective of the specification used – what reinforce our prior that little room was left during those years for demand-driven components of enrolment rate – we find that one more degree offered is responsible for increasing enrolments by around 3%. Since the average number of pre-reform new enrollees was 208,526 per year, this implies an absolute effect of more than 6,800 new higher education students per year at the national level.

1.5 Robustness checks

The capability of model (1.1) to capture the causal effect of the variation in the number of degrees offered upon the enrolment rate relies upon the assumption that – conditional on

Table 1.3: Four Specifications: details

	I	II	III	IV
Log-change of the number of high-school graduates	X	X	X	X
Absolute change in the youth unemployment rate	X	X	X	X
Log-change of regional per-capita GDP		X		
Log-change of regional per-capita GDP in 1st quartile				X
Log-change of regional per-capita GDP in 2nd quartile				X
Log-change of regional per-capita GDP in 3rd quartile				X
Initial department size	X	X		
Initial dept. size in 1st quartile			X	X
Initial dept. size in 2nd quartile			X	X
Initial dept. size in 3rd quartile			X	X
Absolute change in the number of competing departments	X	X		
The number of competing departments is unchanged			X	X
The number of competing departments has grown			X	X
Region main city	X	X	X	X

Table 1.4: DiD estimation results

	I	II	III	IV
Number of observations	2007	2007	2007	2007
F-test (Prob.>F)	<0.0001	<0.0001	<0.0001	<0.0001
D_{it}	0.034***	0.033***	0.034***	0.034***
	(0.0036)	(0.036)	(0.0036)	(0.0036)

Source: own computations on USTAT data. Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

observables and time-invariant department-specific characteristics – the confounding effects of the Bologna reforms other than the change in the number of curricula, are captured by the DiD structure of the model. While, as explained above, we deem this structure robust to most sources of bias, admittedly there might be situations in which it is not. Imagine for istance that departments can be classified – based on some unobserved component – into heavy changers – those with a high propensity to renew their own teaching organization, for instance because they have a lower cost of implementing the needed procedures – and light changers, i.e. those with a lower propensity. As long as heavy and light changers differ based upon time-invariant characteristics, model (1) holds robust. However, if they differ due to time-variant unobserved features that are not captured by the structure of our model, we fail in identifying the causal effect under scrutiny. One possibility, for instance, could be that both the enrolment rate and the number of degrees offered depend on the departments' governing body, which in Italy are renewed every three years.

In order to make our model more robust to this, we exploit more directly the part of variation in number of degrees offered (explained by the implementation of the Bologna process) through an IV approach. In other words, we use the department-specific year of introduction of the new Bologna BA courses as an istrument of the yearly change of the absolute number of degrees supplied by each department. In symbols, our main (second-stage) IV equation is:

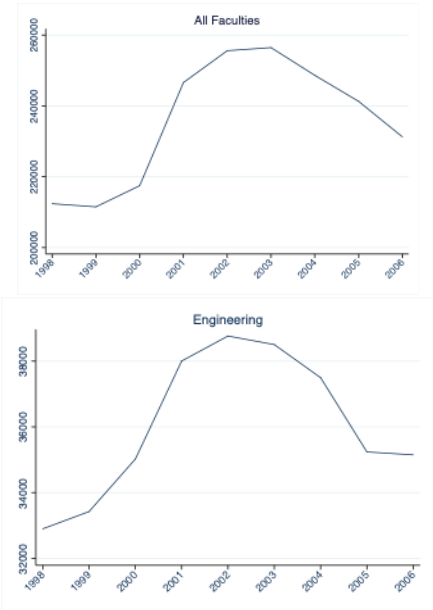
$$\Delta ENRL_{it} = g(\Delta D_{it}, \Delta X_{it} T_t, \epsilon_{it}] \tag{1.2}$$

where $\Delta ENRL_{it}$ represents yearly changes in enrolment rates, g is a linear function, T_t are year dummies, and ϵ_{it} is the idiosyncratic error component. In the first stage of the model, the department-specific first year of introduction of the reform is used as identifying restriction:

$$\Delta D_{it} = h(\tau_{it}, \Delta X_{it}, T_t, \varepsilon_{it}] \tag{1.3}$$

This approach provides us with more robustness to unobserved time-varying components that may affect both the enrolment rate and yearly change in the number of degrees offered by each department. In order to use the first year of introduction of the reform as an instrument in the first stage, we need to drop it from the main equation, hence giving up to control for other features of the Bologna reforms – most importantly, the reduction in the duration of the BA courses – that for sure had an independent impact on the dependent variable. To hold on our exclusion restriction to be acceptable, we need to restrict our analysis to those departments where the Bologna Process did not imply any reduction in courses' duration. More in details, in the sub-sample used for the IV analysis we allow only for departments who split a five-year one-tier course into a Bachelor of three years and a Master of two, but such that a student who enrols and wants to continue towards a profession needs to complete both tiers. The adoption of this criteria led us with a dataset of all Engineering departments in Italy. Enrolment trends comparing the whole sample and the Engineering departments only appear however rather similar (Figure 1.3).

Figure 1.3: Enrolment trends, main sample vs. engineering departments



Source: USTAT, Miur

Table 1.4 displays the estimation results. The first column shows, for the sake of comparability, a standard OLS regression in which ΔD_{it} is not instrumented. The supply of one more curriculum in the engineering departments increases the number of enrolled students by nine units. The comparison with column two shows that this figure is overestimated by one unit, providing support to the suspect that departments more prone to update their supply of degrees are also more attractive to prospective students also for some other unobserved reasons. Indeed, the IV estimate suggests that the true impact is of (less than) eight students. Clustering the standard errors at the department level (column three) increases the precision of our estimates. Eventually, the F-statistics of the first stage – well above the critical threshold identified in the literature – confirms the validity of our instrument. Size of IV coefficients proves our DiD results robust.

Table 1.5: IV estimation results

	OLS	IV	IV clustered
Number of observations	624	624	624
F statistics for the excluded instrument		44.25	51.68
R-squared	.109	.108	.108
$ln(D_{it})$	.058*	.037	.037
	(.026)	(.066)	(.051)

Notes: own computations on USTAT data; standard errors (.); *** p<0.01, ** p<0.05, * p<0.1

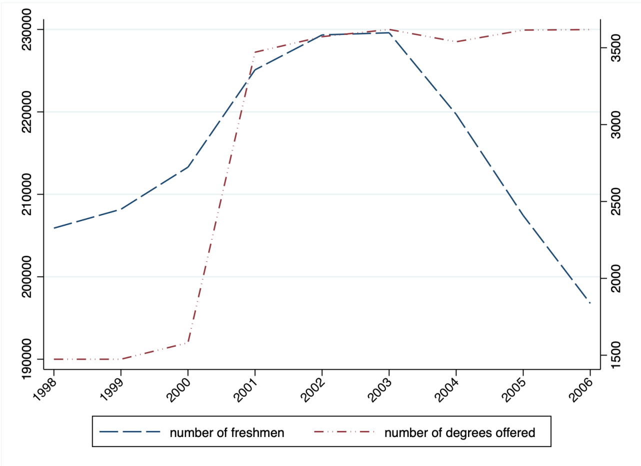
1.6 Concluding remarks and future research

Policies aimed at increasing the particiption to higher education are top-agenda issues in an era in which knowledge is the main factor of long-run growth. Cost reduction has already been proved to be effective, but – in particular in countries where most universities are public – the burden upon the public budget may be very high. In this paper we assess the impact upon enrolments into tertiary education of a different type of policy, namely an expansion of university degrees supply. The cost implied by this strategy can indeed be very low, as widening the set of curricula can be often obtained by offering more combinations of already existing classes. Our study focuses on a very apt case-study – Italy – where the share of work-age population holding a tertiary degree appears dramatically low, and where students have a traditionally low freedom, once enrolled, to build their curriculum according to their preferences, and where henceforth a richer composition of curricula may be very attractive to high-school graduates. Moreover, we take advantage of a unique dataset – the microdata from the Statistical Office of the Ministry of Education – and of a reform, implied by the Bologna Process, that we can exploit to prevent endogeneity. Using a difference-in-differences set up, we find that one more degree offered implies an increas of the new enrollees by more than 3%. A robustness check through an instrumental variable approach supports qualitatively these results. Of course, a larger number of enrollees can be obtained at the price of lowering the quality of university students. For this reason, our next research will be devoted to study the impact of an increase of the number of the curricula offered on the retention rate of first-year enrollees, and on their (on-time) graduation rate. Should the students' quality be lower, we will observe a negative impact on these outcome variables.

1.7 Tables and Figures

Figure 1.4 visually illustrates the steep increase number of degrees experienced around the year of the reform.

Figure 1.4: Degrees and new enrolled over time



We reproduce here the entire output of the IV model. Outcomes have been transformed in log to make results comparable between the two specifications.

Table 1.6: Results on Δ number of enrolled students

	OLS	IV	IV clustered
Δ L	8.861***	7.776**	7.776***
	(1.898)	(3.159)	(2.389)
Δ unemployment 15-24	-0.0982	-0.0987	-0.099
	(1.075)	(1.065)	(0.907)
Δ HSG	0.00128	0.00133	0.0013
	(0.00296)	(0.003)	(0.002)
size1998	-7.84e-05	0.0001	0.0001
	(0.002)	(0.002)	(0.001)
foundation year	0.0101	0.0103	0.0103*
	(0.010)	(0.009)	(0.005)
Constant	-8.293	-8.916	-8.916
	(18.69)	(18.58)	(9.612)
Year dummies	YES	YES	YES
Observations	624	624	624
F statistic for excluded instrument		44.25	51.68
R-squared	0.109	0.108	0.108

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Robust standard errors in parentheses. Optimal instruments are included in all IV specifications.

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Chapter 2

Imperfect Substitutability Between Old And Young Workers

with Carrozzo S.

Abstract

Employment rate of older workers has increased over the last decade in Italy. Meanwhile youth employment rate has experienced a big decline. These divergent employment paths raise a question about the substitutability between old and young workers. To answer such question, we propose a novel identification strategy to estimate the elasticity of substitution in production between old and young workers. We start setting the labor demand functions for both groups within the same region-occupation-time group to estimate such elasticity. Then, we develop a theoretical model that shows towards-zero estimation bias induced by time correlations within each region-occupation-time group. To overcome this estimation problem, we use a set of instruments based on yearly employment changes by age and citizenship. Using yearly Italian administrative data for the period 1995-2004, we exploit a number of pension and labor migration reforms to create a set of exogenous instruments to time correlations within a region-occupation-time group. Our results show that old and young employees within the same region-occupation-time cell experience imperfect substitutability in production.

2.1 Introduction

May increases in both life expectancy and retirement age affect youth employment opportunities? Most developed countries experience a decline in either youth employment rate or youth participation rate together with an increase in older participation rate. In 2018, France's and Italy's youth unemployment rates were still larger than pre 2008-crises, 20.08% and 32.2% (OECD database) respectively. While, the U.K.'s and the U.S.'s youth participation rates were 5% and 4% (OECD database) lower than pre 2008-crises, respectively. At the same time, all developed countries experience an increase in participation and employment rate for workers older than 55. These divergent patterns raise a question on the existence of a large degree of substitutability between old and young workers.

Substitutability between old and young workers is an outstanding question in labor literature. On the one hand, the *lump of labor* concept claims that old and young workers compete for a scarce good: a job. Boeri et al. (2017) show that the 2011 sudden increase in the retirement age of *baby-boomers*, the generation born between the end of the World War II and the late '50, due to a pension reform has negatively affected youth employment in Italy. Mohnen (2019), using 1980-2017 U.S. data, finds that the effect of an increase in the retirement age on the youth employment is wider the larger older worker share in low skilled jobs. Bertoni and Brunello (2017) produce same results in Italy between 2004 and 2015. Bovini and Paradisi (2018) find that the effect of an increase in Italian retirement age on youth labor outcomes is wider the larger share of manufacturing workers over the period 2009-2015. On the other hand, the existence of imperfect substitutability between old and young workers should lower the competition for the same job. Brugiavini and Peracchi (2010) find that delaying retirement has a positive impact on the youth employment rate in Italy between 1997 and 2004. Gruber and Wise (2010) find a positive effect of an increase in older participation rate on youth employment rate by studying labor markets of several developed economies from the late '70s to the beginning of the new century. Munnell and Wu (2012), using 1977-2011 U.S. data, show that an increase in older employment leads to better labor outcomes for young workers, raising both wages and employment rate. Our paper fills in by offering a novel identification strategy to estimate the old-young elasticity of substitution in production.

In our paper, the elasticity of substitution between old and young workers is the ratio of the percentage change in old-young employment ratio (labor gap) to the percentage change in the old-young wage ratio (wage gap) within the same region-occupation-year cell. We estimate the inverse of such elasticity to identify the causal relation of an increase in labor gap on wage gap. The greater is the identified effect, the smaller is the substitutability between old and young workers. In other words, under imperfect substitutability we observe a smaller effect on the age-group wage not affected by the employment increase.

To carry out our analysis we use a nested constant elasticity of substitution (CES) production function to derive the relation between labor gap and wage gap. A detailed employees dataset allows us to estimate the elasticity. Nested CES production function is suitable to identify the elasticity of substitution between old and young workers for two reasons. First, the nested CES dimensions, in our case region-occupation-age-year, allows to control for different demand shifts. Second, the linearity of log first order conditions enables to study the old-young elasticity of substitution using linear estimators. We use 1995-2004 Work Histories Italian Panel (WHIP) employee data to estimate such elasticity. We restrict the sample to 1,426,340 full-time male workers in the private sector as they experience larger employment spells and, hence, accumulate on-the-job human capital at a constant pace. We aggregate data on employees to build total employment and average wage per region-occupation-age-year cell.

Estimating the effect of a labor gap change on the wage gap is not trivial as long-run dynamics might bias the estimates. In the short run, age-specific labor supply shocks might lower the wage gap through labor gap, but the occurrence of general equilibrium adjustments restores the previous wage gap equilibrium in the long run. Hence, labor supply shocks might have a negative effect on wages in the short run, but a positive one through general equilibrium adjustments in the long run. The net effect might be null, showing inverse-elasticity estimates biased towards zero, since the two effects offset each other. We call the general equilibrium adjustment mechanism *offsetting mechanism*, because it offsets any wage disequilibrium in the long run. Since the *offsetting mechanism* is unobservable and positively correlated with the labor gap, elasticity estimates are upward biased.

Our paper contributes to solve this puzzle with two main innovations. First, we develop a theoretical model to understand how the *offsetting mechanism* biases the estimates. The idea is that the *offsetting mechanism* begins to adjust the disequilibrium a year after the labor supply shock applies. Hence, we model the *offsetting mechanism* as a function of past labor supply shocks. Assuming that the model holds, only an instrument at current year uncorrelated with past labor supply shocks identifies the elasticity. To the best of our knowledge, this way of studying *offsetting mechanism* bias is a novelty in the elasticity of substitution estimation literature.

Second, we provide a novel set of instruments to estimate the elasticity of substitution. As mentioned above, we must find an instrument uncorrelated with past labor supply shocks to identify such elasticity. One candidate is labor gap in first differences, because first differences sweep away past trends. However, labor gap in first differences might be correlated with region-occupation-year unobservable heterogeneity. In order to avoid this endogeneity issue, we combine the age dimension, old and young, with the citizenship dimension, native and foreign, to create four instruments. Each instrument is the ratio of yearly region-occupation-age-citizenship employment change to the total yearly region-occupation-age employment. The idea is to exploit a deeper dimension aiming at lowering the correlation between unobservable heterogeneity and instruments. To strengthen our identification strategy, we exploit a set of age-citizenship specific reforms enacted in Italy between 1995-2004. Reforms were enacted to save the Italian social security system from default by increasing both the retirement age and the workers per retiree. These reform shocks are suitable to identify our elasticity of substitution as uncorrelated with the region-occupation-year specific labor market characteristics.

We find that an increase in the labor gap lowers the wage gap by around 16% within the same region-occupation-year labor market. Further, the effect corresponds to an elasticity of substitution around 6, because in our theoretical model the effect reflects the negative inverse of such elasticity. The elasticity of substitution value range starts from 0, perfect complementarity, to infinity, perfect substitutability, our findings are closer to zero than infinity showing an imperfect degree of substitutability between old and young workers. Our findings are in line with the existing literature on old-young elasticity of substitution (Borjas, 2003; Card and Lemieux, 2001; D'Amuri et al., 2010; Manarcorda et al., 2012; and Ottaviano and Peri, 2012) as scholars find very similar results for different countries in different periods.

We provide a set of robustness checks and sensitivity analyses to test our results. First, we change the weights used to estimate the elasticity, because different weights may lead to different point estimates (Borjas, et al. (2012)). We use wage gap variance as a weight in our baseline estimates, while we weight for total employment in every region-occupation-year cell to test our results. Results do not change. Second, we test our identification with the foreign employment instrument. This instrument is very common in the literature and it is widely used to estimate the old-young elasticity of substitution. We show that the instrument is weak in our specification. Third, we assume that labor supply shocks identify the effect, through our instruments, excluding region-occupation-year demand shocks. We use temporary laid-off workers as a labor demand shock instrument to check our assumption. The instrument is weak and estimates are not significant. Fourth, we evaluate whether our parameters of interest are time-varying. We interact with our instruments with a linear trend increasing the set of instruments from four to eight. The results do not change. Hence, our baseline specification is robust to time dimension.

Related literature.— The literature on old-young substitutability in production exploits demographic changes to understand the degree of complementary among several age groups. Freeman (1979) is one of the first to study the degree of substitution among workers belonging to different cohorts. He estimates the elasticity of substitution between *baby-boomers* and previous cohorts in the US. He finds that an increase in the young labor supply has a larger effect on younger workers' wage than on older workers' one. This result shows workers belonging to different cohorts are imperfect substitutes in production. Katz and Murphy (1992) extend the analysis by exploiting the industry level variability. They identify demand shocks with technological shifts and labor shocks with demographic cohort characteristics. They show that both have a role in setting out the degree of imperfect substitutability across different age groups. A further extension of Katz and Murphy (1992) is Card and Lemieux (2001), where they improve the accuracy of elasticity of substitution estimates by taking into account both time effects and cohort effects. The underlying intuition relies on different salary paths among cohorts over time. By exploiting "baby-boomer" shock in the U.S., Canada, and the UK in a nested constant elasticity of substitution, they are able to make cross-country comparisons of the results. They estimate an elasticity of substitution among different age groups in the range of 4 to 6 by proving that additional fixed effects play an important role to exclude any possible bias due to supply or demand shifts. Borjas (2003), D'Amuri et al. (2010), Manarcorda et al. (2012) and Ottaviano and Peri (2012) extend Card and Lemieux (2001) exploit foreign labor force as instrument to estimate old-young elasticity of substitution, but thier estimates do not show any significant difference.

All the mentioned scholars do not pay much attention to long-run effects, while Llull (2018) points out that demand for different labor inputs depend on past labor supply shocks[1]. He shows that human capital accumulation is one of the main drivers to adjust wage disequilibrium in the long run. Also Jaeger et al. (2018) show that firms anticipate the labor supply shifts by adjusting the capital level. These mechanisms happen when labor force increases are stable across years. However, they only focus on foreign labor supply shocks, while we address the long-run bias issue by taking into account native labor supply shocks as well. We provide an estimation strategy that complements the literature on old-young elasticity of substitution estimate and adds an other piece to general equilibrium adjustment puzzle. Our estimation method relies on Arellano and Bover (1995) who exploit the first differences to identify the long run parameter in a dynamic panel framework. The underlying intuition is the same, but we apply that in a static framework.

[1]People reshape their human capital accumulation after experienced labor supply shocks.

The article proceeds as follows. Section 2.2 describes the institutional background over the considered time span. Section 2.3 presents the theoretical framework. Section 2.4 shows the data and the descriptive statistics. Section 2.5 discusses the empirical strategy. Section 2.6 shows the results. Section 2.7 presents robustness checks. Section 2.8 concludes.

2.2 Institutional Background

At the turn of the 20th century, Italy has experienced a number of labor market reforms mostly tackling the supply side. Among others there were pension reforms and migration flows regulations. Depending on the type of reform, different cohorts of workers were involved.' What follows is a brief review of all these different policies, grouped by theme.

2.2.1 Pension Reforms

The age threshold defining the active population of a country clearly affects the size of labor force, and pension reforms play an important role in setting such a threshold. The idea behind reforms in the '90s was keeping older workers in the labor market as longer as possible. This is due to an increase in life expectancy and experts were casting doubts on the sustainability of a pay as you go pension system. Two main pension reforms characterize the end of the century, Dini reform in 1995 and Prodi reform in 1997. As mentioned, the main aims were containment of public spending and curbing early retirement. The very first attempt to postpone retirement age (gradually) occurs with Amato reform, in 1992. In 1995, Dini reform, (L.335/1995), raised the age and contribution requirements for seniority pension. The change was gradual and finished in 2008. Prodi reform in 1997 further increases age and contribution requirements for seniority pensions.

2.2.2 Migration Reforms

Italy has long been a country of emigration. First regulations on immigration flows date back to the 80s. Up to that moment legalization of immigrant workers mainly happened through amnesties. In the '90s, a pool of migration laws enacted and included an amnesty to legalize migrant workers who had been working (or living) in the country for a year before. In 1990, Martelli law, L. 39/1990, was the first to regulate economic immigration in the country and legalize 215,000 foreign workers. This law imposed restrictions to incoming flows, and set a maximum number of workers to be accepted each year, based on foreseen Italian labor market needs. Dini decree, in 1995, allowed for the legalization of 244,500 immigrant workers. In 1998, the Turco-Napolitano law (L 40/1998) implemented major changes. This law represented the milestone for migration regulation in Italy. It involved inclusion of migrant workers within the labor force and made procedures and rules smoother and clearer. It allowed immigrants a temporary visa through the sponsorship channel to look for a job. Together with this reform, other 217,000 workers were regularized. Political debates spurred by increased migration flows conveyed into the Bossi Fini law (L. 189/2002). That stopped the sponsorship system and introduced stricter limitations to immigration. Few months after the enactment, the situation in black market was dramatic and, therefore, the two Ministers,Bossi and Fini, promoted the largest amnesty in Europe (634,700 immigrant workers were legalized). As such, some scholars used it to better understand the impact of amnesties on labor market outcomes. Devillanova et al. (2014) exploit it as a natural experiment and show that an increase in employment probability follows the prospect of legal status. Size of this increase is two third of the increase in employment rate illegal immigrant experience in the five years after entering the country. Di Porto et al. (2019) show the short term impact of 2002's regularization, with most of the legalized workers staying in the legal labor market for long. Amnesty regularized 62% of regular immigrants in the country in 2002 (Barbagli et al., 2004).

2.3 Model

2.3.1 Theoretical Framework

In order to study the elasticity of substitution between old and young workers we use a nested constant elasticity of substitution (CES) approach. Most of the prominent studies (e.g., Card and Lemieux, 2001; Borjas, 2003; Ottaviano and Peri, 2012) have used an aggregate production function to estimate the elasticity of substitution between old and young workers. An aggregate model provides an overview of national labor market but loses information about differences among local labor markets. We prefer to add the regional dimension to take into account local differences in labor force. We assume an identical Cobb-Douglas production function in each region *r* at time *t*:

$$Y_{rt} = A_{rt} K_{rt}^{\alpha} L_{rt}^{1-\alpha} \tag{2.1}$$

where Y is the output, A is exogenous total factor productivity, K is the physical capital, L is a CES aggregate of different types of labor, and α is the income share of capital. L_{rt} includes workers who differ by occupation and age, respectively. Let

$$L_{rt} = [\theta_{rBCt} L_{rBCt}^{\frac{\sigma-1}{\sigma}} + \theta_{rWCt} L_{rWCt}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

where *BC* (*WC*) indicates blue collar workers (white collar workers) and σ is the elasticity of substitution between blue collar and white collar workers ($0 \leq \sigma < \infty$). The θs are the region-occupation-time specific productivity parameters, with $\theta_{rBCt} + \theta_{rWCt}$=1. Finally, every occupation-specific labor input is a CES aggregate of imperfect substitute age-specific labor inputs. In particular,

$$L_{rst} = [\gamma_{rsOt} L_{rsOt}^{\frac{\lambda-1}{\lambda}} + \gamma_{rsYt} L_{rsYt}^{\frac{\lambda-1}{\lambda}}]^{\frac{\lambda}{\lambda-1}} \quad s = BC, WC \tag{2.3}$$

where *O* (*Y*) indicates old worker (young worker) labor input and λ, our parameter of interest, is the elasticity of substitution between old and young workers, with $\lambda \geq 0$. γs are the region-occupation-age-time specific productivity parameters, with $\gamma_{rsOt} + \gamma_{rsYt}$=1. We get the old (young) labor demand within each region-occupation-year cell by assuming that marginal product of old (young) labor is equal to the old worker (young worker) wage. Using logs, the age specific labor demand within each region-occupation-year cell is equal to:

$$ln(w_{rsat}) = ln(A_{rt} K_{rt}^{\alpha} L_{rt}^{-\alpha}(1-\alpha)) + \frac{1}{\sigma} ln(L_{rt}) + ln(\theta_{rst}) - (\frac{1}{\sigma} - \frac{1}{\lambda}) ln(L_{rst}) + ln(\theta_{rsat}) - \frac{1}{\lambda} ln(L_{rsat}) \tag{2.4}$$

Taking the difference side by side of labor demands for old and young workers, we get rid of all terms on the right-hand side, but the difference between productivity parameters and the difference between old and young labor demands:

$$ln(\frac{w_{rsOt}}{w_{rsYt}}) = ln(\frac{\theta_{rsOt}}{\theta_{rsYt}}) - \frac{1}{\lambda} ln(\frac{L_{rsOt}}{L_{rsYt}}) \tag{2.5}$$

Hereafter, we define the wage difference between the old and young worker as "wage gap" and the employment difference between old and young workers as "labor gap".

2.3.2 Labor gap between old and young by citizenship

In this subsection, we show how local and foreign labor supply shocks affect the labor gap between old and young workers. We assume that the employment level for old and young workers within the same region-occupation-year cell is a function of native and foreign employment[2] :

[2]A wide range of literature (e.g. D'Amuri et al., 2010, Manarcorda et al., 2012 and Ottaviano and Peri, 2012) use a CES aggregate of native and foreign labor inputs in every age-specific group. We do not assume any functional form to avoid any constraint on the age-citizenship elasticity of substitution.

$$L_{rsat} = f(L_{rsaNt}, L_{rsaFt})) \tag{2.6}$$

where N (F) indicates native (foreigner) characteristics. We assume that each age-specific labor input is continuously differentiable and the first derivative with respect to citizenship dimension is greater than zero. Looking at differential[3] in discrete form we obtain:

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc}\frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc}\frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \tag{2.7}$$

where

$$\beta_{Oc} = \frac{\partial L_{rsOt}}{\partial L_{rsOct}} \qquad \beta_{Yc} = \frac{\partial L_{rsYt}}{\partial L_{rsYct}} \tag{2.8}$$

with c indicating if they are either natives or foreigners[4]. Each β is assumed to be fixed[5]and measures the elasticity of labor gap differential change with respect to a specific subgroup differential change, where a subgroup is the total number of workers with age a and citizenship c.

This decomposition allows us to understand how labor supply shocks affect the labor gap. By imposing β_{OF}=β_{YF}=β_F and rearranging the terms we get:

$$\frac{\Delta(ln(L_{rsOt}) - ln(L_{rsYt}))}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} = \beta_F + \beta_{ON}\frac{\frac{\Delta L_{rsONt}}{L_{rsOt}}}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} - \beta_{YN}\frac{\frac{\Delta L_{rsYNt}}{L_{rsYt}}}{\frac{\Delta L_{rsOFt}}{L_{rsOFt}} - \frac{\Delta L_{rsYFt}}{L_{rsYFt}}} \tag{2.9}$$

The left-hand side is the elasticity between a change in old-young labor gap and a change in old-young foreigner labor gap, where the denominator represents a change in foreign employment. We show that the effect of a foreign labor supply shock is not constant, but it depends on old and young native labor supply change.

This is an important result, in the literature a very common assumption is the exogeneity of foreign labor supply shock with respect to native employment. In our model, instead, the effect of a foreign labor supply shock on old-young labor gap depends also on native labor

[3]In Appendix for the mathematical derivation.

[4]This methodology is very similar to one developed by Amiti et al. (2019) that provide a decomposition of a firm price differential.

[5]In the empirical section we allow parameters to vary over time.

supply shocks (if any).

In the Empirical Strategy Section we take into account this finding to estimate the elasticity of substitution.

2.4 Data

The empirical analysis is based on the information on the wages and employment of old and young workers drawn from the 1995-2004 Work Histories Italian Panel (WHIP) dataset. The WHIP also contains information on citizenship that we use to create our set of instruments.

The WHIP database includes information on social securities records of 2,164,829 employees from 1995 to 2004, around 140,000 observations per year. Since our aim is to provide with a new identification strategy using a standard theoretical framework, we follow the literature to create wage and employment variables.

The main sample is restricted to men aged 18-64 working in the private sector. We narrow the analysis only to male employees as old and young females do not accumulate constantly experience in their working life showing larger substitutability (Freeman, 1979). Further, foreign females in Italy are usually employed as either caregivers or domestic helper, while native females are often employed in the public sector (Venturini and Villosio, 2008). We narrow the analysis only to private sector as public sector has more rigid labor dynamics. EU15 foreign workers are excluded from the analysis to avoid confounding effects due to similarities between EU15-foreign and Italian workers. Including EU15 workers in native (foreign) group might overestimate (underestimate) the elasticity of substitution. Further, the EU15 worker exclusion allows us to focus our attention on foreigners with different skills with respect to natives. We take the gross average log daily wage as wage measure[6]. Unfortunately, we have only information on total contribution days, where one contribution day is equal to 8 hours spent at work. The lack of information on hours spent at work does not allow us to include part time jobs as they differ by hours spent at work per day. Due to this missing information we are not able to homogenize the daily wage of part-time workers. Hence, we prefer to consider only full time workers. To measure the cell-specific employment we, first, measure the days spent in each region-occupation-age-year cell to the total worked days in a year per every worker. Then, we sum these shares to obtain the total employment in each region-occupation-age-year

[6] We get rid of the first and last percentile of the distribution in order to avoid any confounding effect due to outliers.

cell. We follow this procedure to overcome the assignment of a single worker to different region-occupation-age-year cells since there are some workers that change either working region or job within a year. Following the literature (i.e. Card, 1999), we assign the 'old' label for workers age over 38[7].

Table 2.1 and Table 2.2 show that young workers are the main group in the labor market. The old-young employment ratios are 0.5 for blue collars and 0.69 for white collars, it means that there are 10 young blue collar workers (white collar workers) for every 5 old blue collar workers (7 old white collar workers). This evidence shows that old employees fill more white collar jobs than the blue collar ones. We get an other supporting evidence of previous finding by studying blue collar-white collar employment ratios by age. Ratios are 2.96 and 2.08 for young and old employees, respectively. These findings show old employees compete much more for white collar jobs. Hence, a labor supply shock due to an increase in retirement age affects much more young white collar workers than young blue collar workers. While, a labor supply shock due to a new migration flow affects much more young blue collars than young white collars. In Table 2.3 and 2.4 we report log daily wages for blue and white collars, respectively. In every table, we have information on log daily wages in each macro region-age[8] cell over 1995-2004 period. Wages are deflated to 2001 euro by using OECD's Italian CPI series. We observe an overall sharp increase of real wages until 1999, followed by a decline and a renewal until 2004. Looking at the difference between the old and young average log daily wages, we see a declining path for blue collar wage differences, while there is no evidence of such trend for white collars. This finding suggests that old and young white collar workers are more substitute than old and young blue collar workers. Young blue collar wage does not respond to migration and pension reforms, while old blue collar wages lower over time by decreasing the gap with young blue collar workers. Instead, young white collar workers do not fill the wage gap with old white collar workers over time, showing a larger substitutability. Although these evidences are only descriptive, we might consider them as a first evidence on the degree of substitutability between old and young workers.

Finally, Figure 2.1 shows the trend for each instrument from 1985-2004. Each instrument is the ratio of yearly region-occupation-age-citizenship employment change to the total yearly region-occupation-age employment, then, we have four subgroups: old natives, young natives, old foreigners and young foreigners. Yearly changes are very noisy from 1995 to 2004, they do

[7]The explanation is that workers accumulate on-the-job human capital with a lower pace when they are age over 38.

[8]North includes: Emilia Romagna, Friuli Venezia Giulia ,Lombardia, Liguria, Piemonte and Valle d'Aosta, Trentino Alto Adige, Veneto. Centre includes: Lazio, Marche, Toscana and Umbria. South and Islands include: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna and Sicilia

not follow a common path as observed for young and old natives in the previous periods. We exploit this heterogeneous variability to estimate old-young elasticity of substitution.

2.5 Empirical strategy

In this section we explain how to implement our theoretical findings in an empirical setting in order to estimate the elasticity of substitution between old and young workers. We estimate the equation (5) in Section 3. As shown in Section 4, we use as dependent variable the difference between average log daily wage of old and young workers for each region-occupation-year cell (wage gap). Independent variable is the difference between the total employment of old and young workers for each region-occupation-year cell (labor gap). The old-young elasticity of substitution, $1/\lambda$, may be biased towards zero since labor gap might be positively correlated with long run *offsetting mechanism*. We try to figure out how long run adjustment may bias our estimates.

2.5.1 The *offsetting mechanism* function

We substitute log of old-young productivity ratio with a broad set of fixed effects and an error term. We assume fixed effects capture part of productivity variability and the left part is nested in the error term. We are not able to fully control for productivity shifts by using region-occupation-year fixed effects. The inclusion of these fixed effects would capture all the variability in old-young employment ratio not allowing us to estimate the old-young substitutability parameter. The new estimating equation is:

$$ln(\frac{w_{rsOt}}{w_{rsYt}})) = \phi_{rt} + \phi_{rs} + \phi_{st} - \frac{1}{\lambda} ln(\frac{L_{rsOt}}{L_{rsYt}}) + \varepsilon_{rst} \tag{2.10}$$

where ϕ_{rt} and ϕ_{st} capture every time productivity shift in each regional and occupation labor market, respectively. ϕ_{rs} captures any time invariant characteristic in each region-occupation labor market. ε_{rst} stands for whatever time variant residual components in every specific region-occupation labor market.

The error component is most probably correlated with the labor gap. The main concern is that the unobservable heterogeneity in each region-occupation-year cell nested in the erratic term might occur to offset any wage disequilibrium. We call that *offsetting mechanism* because

it offsets wage gap changes, e.g. triggered by labor supply shocks.
We want to shed light on this mechanism and on the correlation between labor gap and the *offsetting mechanism*. By assuming labor gap has a stable AR(1) process, we can see this process as MA(∞) process:

$$ln(\frac{L_{rsOt}}{L_{rsYt}}) = \sum_{k=1}^{t} \beta^t \epsilon_{rsk} + ln(\frac{L_{rsO0}}{L_{rsY0}}) \tag{2.11}$$

where $\epsilon_{rsk} = \Delta ln(\frac{L_{rsOk}}{L_{rsYk}})$, the last term is the yearly variation in the labor gap. Hence, on the right-hand side of Eq. (11) we have the sum of all labor gap yearly variations until t plus the initial condition. When $\Delta ln(\frac{L_{rsOk}}{L_{rsYk}}) \neq 0$, there is a change in the wage gap and the *offsetting mechanism* starts adjusting later in time. Assuming that *offsetting mechanism* fully offsets wage shift in the following period[9], we nest the *offsetting mechanism* process in the error term:

$$\varepsilon_{rst} = \xi_{rst} + f(\epsilon_{rst-1}) \tag{2.12}$$

where ξrst is a random effect uncorrelated with the labor gap and $f(\epsilon_{rst-1})$ is the *offsetting mechanism* that depends on lag of yearly labor gap variation, ϵ_{rst-1}. As a result, this *offsetting mechanism* has a positive correlation with the labor gap biasing old-young elasticity of substitution estimate[10].
Offsetting mechanism function takes into account only the previous period labor gap change and not the current one. This structure allows us to exploit the current change as exogenous to the *offsetting mechanism* function.

The described mechanism is in line with papers that use new wave of migrants as an instrument to estimate the old-young elasticity of substitution (e.g. Borjas, 2003; Ottaviano and Peri, 2012), since yearly labor supply shocks are uncorrelated with previous ones[11].

2.5.2 A short run instrument for a long run effect

In the previous subsection, we discussed the structure of the *offsetting mechanism* process nested in the error term and the features that an instrument must have in order to identify the

[9] Adding more lags results hold.
[10] Because the $Cov(ln(\frac{L_{rsOt}}{L_{rsYt}}), f(\epsilon_{rst-1})) > 0$
[11] Jaeger et al. (2018) point out that the exogeneity of migration inflows depends on previous wave of migrants. If the flow of new migrants is stable across years, the labor demand can foresee the new inflow and adjust itself before it comes up.

elasticity parameter. In our setting, we exploit variations based on current foreign and native labor supply shocks. We exploit the elements on the right-hand side of Eq. (7) as instruments, where each of them takes into account yearly change in each region-occupation-age-citizenship cell[12]. This methodology is very common in the macro literature, especially in dynamic panel data models[13].

In order to identify the true parameter and rule out all the time correlations between the instruments and the error term, we assume that employment time series in every subgroup is a random walk:

$$\Delta L_{rsact} = \varepsilon_{rsact} \tag{2.13}$$

where, the first differences are equal to the error at current period. Testing this assumption we cannot reject the presence of unit root for every region-occupation-age-citizenship group[14].

The main concern is that the instruments might still depend on unobservable characteristics within region-occupation-year cell. To overcome this problem, we exploit Italian reforms enacted over the period 1995-2004. Between 1995 and 2014, Italy has enacted a series of national policies that have affected the labor supply of all considered categories across years. They provide us with exogenous variation to identify the effect as they are not labor market specific. This continuous treatment has allowed us to exploit short run effects as instrument.

2.6 Results

Table 2.5 shows the old-young elasticity parameter, $-\frac{1}{\lambda}$, by using different estimators. All regressions are weighted by the inverse of the wage gap variance to reduce the bias of the cells with small sample size[15]. In the first two columns we show the results by using ordinary least

[12]In the Appendix B, we compute parameter distortion when we first order differences as instrument and *offsetting mechanism* function is linear. The estimated distortion is very small and equals to $-\frac{T}{(T-2)(T-1)}$, in particular it is smaller than the Nickell's one (Nickell, 1981).

[13]Arellano and Bover (1995) were the pioneers of this identification strategy that exploits the short run changes (i.e. first differences) to instrument levels. They use the lagged first differences as an instrument for the lagged value of the dependent variable that is their explanatory variable.

[14]P-values of Harris-Tzavalis unit-root test are: 1.00 for old foreign labor supply, .798 for young foreign labor supply, .1406 for old native labor supply and .9995 for young native labor supply

[15]There is a wide debate about the weight to be used. OP (2012) use the sample size in every specific cell as weight, while Borjas et.al (2012) in a comment to their paper say that is better to use the inverse of the wage variance.

squares, OLS. As discussed in previous sections, the estimates are biased towards zero both without and with the time-occupation fixed effects. This finding is in line with the literature, that highlights the positive correlation between labor gap and *offsetting mechanism* in every region-occupation-year cell.

In the following six columns we use IV methodology by exploiting different estimators. From the third to the sixth column, we show the results by using two stage least squares, 2SLS, and the limited information maximum likelihood, LIML. As pointed out by Angrist and Krueger (1991), 2SLS and LIML estimates have to be very close in an overidentified framework because asymptotically they have the same distribution. The point estimates are -0.250 and -0.259 for 2SLS and LIML without occupation-time fixed effects and -0.168 and -0.171 for 2SLS and LIML including them. The quite similar results do not show any problem in the specification. Furthermore, the specifications pass the F-statistic and the overidentification tests. The former is 45.46 and 14.69, respectively, without and with occupation-time fixed effects and the other one cannot reject the null hypothesis of good specification at a significance level of 5%. The last two columns show the estimates with a continuously-updated GMM estimator, that allows for heteroskedastic and autocorrelation disturbances, we add this estimation in order to take into account of a possible correlation among different shocks. Estimates confirm the previous results.

In Table 2.7 we show the estimates with employment cell weight to be sure that wrong weights drive our estimates. The estimates are quite similar, not showing any difference to use different weights. Results in Table 2.5 and 2.7 prove that there is not difference between the wage variance weight and employment-cell weight when the model is well specified.

In Table 2.8 we use a control function approach[16]. This approach used by Wooldridge (2015) is suitable for our aim, because residuals contain the endogeneity source that we cannot control in our model. In this way by adding this part in the main regression we control directly for the bias. Residuals' parameter captures the *offsetting mechanism* of shocks. Indeed, as showed in Table 2.8, the estimate has the opposite sign of our old-young elasticity parameter and more or less the same magnitude.

Hence, by using the control function approach we have not only the elasticity parameter but also the relative bias. In particular when we add the occupation-time fixed effects the parameter is even closer in absolute value to the elasticity estimate.

Old-young elastacity of substitution, λ, is between 4 and 6. The results are in line with Ottaviano and Peri (2012), Borjas (2003) and Card and Lemieux (2001) estimates when they use 8 level of experience and 4 level of education. Our result differ from Ottaviano and Peri

[16]In the control function approach you have to run an IV first stage, then get the residuals and put them in the main regression.

(2012), when they use old and young as a proxy for experience. They find an elasticity of substitution around 3[17]. This result shed lights on time correlation bias.

2.7 Robustness checks

2.7.1 The comparison with migration instrument

Ottaviano and Peri (2012) and Borjas (2003) exploit foreign workers as instrument to identify age-group elasticity of substitution[18]. They assume that foreign labor supply shocks in the foreign labor force in each region-occupation-year cell, once added fixed effects, identify the elasticity of substitution between old and young workers.

In subsection 4.2 we find that the effect of a change in foreign labor supply on the labor gap is not constant since it depends on native labor supply changes. In order to take that into account, we consider both native and foreign labor supply shocks in each region-occupation-age-citizenship cell aiming at having an unbiased estimate.
In this subsection, we compare our specification with the one used by Borjas (2003) and Ottaviano and Peri (2012) by using their instrument to estimate the elasticity of substitution between old and young workers.

Table 2.9 shows estimates close to Ottaviano and Peri (2012)[19] when we do not control occupation-time fixed effects. The results change when we add them. The parameter is not more significant with standard error quite large. Our explanation is that large standard errors are due to the correlation between instrument and error term. The missing information on native labor supply changes in other skilled categories might create a correlation between the foreign instrument and the *offsetting mechanism* process.

In our setting we add both native and foreign labor supply changes, which help us to rule

[17] Their estimate is equal to -0.31

[18] An other instrument widely used by researchers is the shift-share instrument (Altonij and Card, 1991) that exploits migrant enclaves in the previous decades to create an instrument exogenous with respect to current economic conditions. Unfortunately we cannot compare our methodology with that, because our dataset does not have information later than 1985 and because the level of inflows in decades before 1995 is almost null or is selected among high skilled workers (before 1990 in Italy there was not a labor migration policy, so for migrant was almost impossible to come in Italy with a labor VISA.)

[19] Our estimates are little bit larger because we use a regional approach as opposed to a national one. For this reason the bias is smaller than Ottaviano and Peri (2012).

out any possible correlation with the long run adjustments.

2.7.2 Labor demand shocks

In our paper we exploit short run changes in every region-occupation-age-citizenship cell. We state that the short run changes are supply driven assuming that the possible labor demand shocks are captured by fixed effects. In this section we test this assumption by using an instrument that is based on labor demand shock.

We exploit the information on unemployment support mechanisms provided in our dataset. The Italian government helps firms to face crisis periods by paying part of employee salaries for a given period[20], when employers suspend temporary employment relationships. During the suspension firms cannot hire other workers in order to hold the benefit and, at the same time, employees cannot engage in another job. This tool has been created mainly to help the manufacturing sector, where most of the workers are engaged. We, thus, use the information whether a worker is in this program to capture a labor demand shock due to a firm's temporary crisis.

Our first stage is the labor gap on the log of the number of temporary suspended workers. The sample is reduced to 322 observations from 1996-2004 since we have some cells that do not experience any temporary suspension. Table 2.10 shows the results. The estimates are not significant and F-stat of the instrument is very low. The F stat is very low showing how a labor demand-driven instrument is not suitable to provide an exogenous variation to identify labor gap.

2.7.3 Relaxing time invariant assumption on the first-stage parameters

In subsection 4.2 we have assumed that the derivatives of each specific region-occupation-age labor input with respect to a change in both native and foreign employment is constant over time. In this subsection we show the results when derivatives vary over time.
In order to add a time dimension to parameters, we multiply the instruments by a linear time trend[21]. Rearranging Eq. (7) we get:

[20] The so called "Cassa Integrazione"

[21] We try also to interact time dummies with every instrument. The results are not different from adding a linear trend.

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc}(1 + \textit{trend})\frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc}(1 + \textit{trend})\frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \quad (2.14)$$

Table 2.11 shows the results using this broader set of instruments that takes into account of time dimension. The results are quite similar to the time constant ones. Hence, without loss of generality, we can assume time invariant parameters.

2.8 Conclusions

How much old and young workers are substitutes in production is of great interest worldwide. Demographic changes have affected the composition of the labor force. This paper tries to shed light on the degree of substitutability between old and young workers in production.

In line with the tradition on this topic, we use a nested-CES framework at regional level to derive the elasticity of substitution between old and young workers. The choice of a local approach allows us to rule out any possible misleading effect due to huge differences across Italian regions. We can get a more precise estimate of the overall elasticity of substitution controlling for different local growth patterns.

In the literature, adding specific skill fixed effects is generally used to control for different demand shifts. Still, possible biases might remain due to log-run factors. In particular, skill-specific unobservable long-run adjustments offset any variation suited to study the effect of a skill-specific labor force change on the skill-specific wages biasing the elasticity estimates towards zero. Studying the dynamics of the *offsetting mechanism*, we identify the bias and create an instrument to overcome the omitted variable problem. We exploit the variation triggered by Italian reforms to create a set of instruments exogenous to skill-specific . The estimated elasticity of substitution is between 4 and 6, in line with previous findings.

In a global scenario, young workers concern about the longer working life of some old workers. Our results show old and young workers are imperfect substitution in production. Hence, policies aiming at reducing the youth unemployment should not consider the early retirement as a solution. Instead, they should look at specific characteristics of young workers to increase the match between firms needs and young worker skills.

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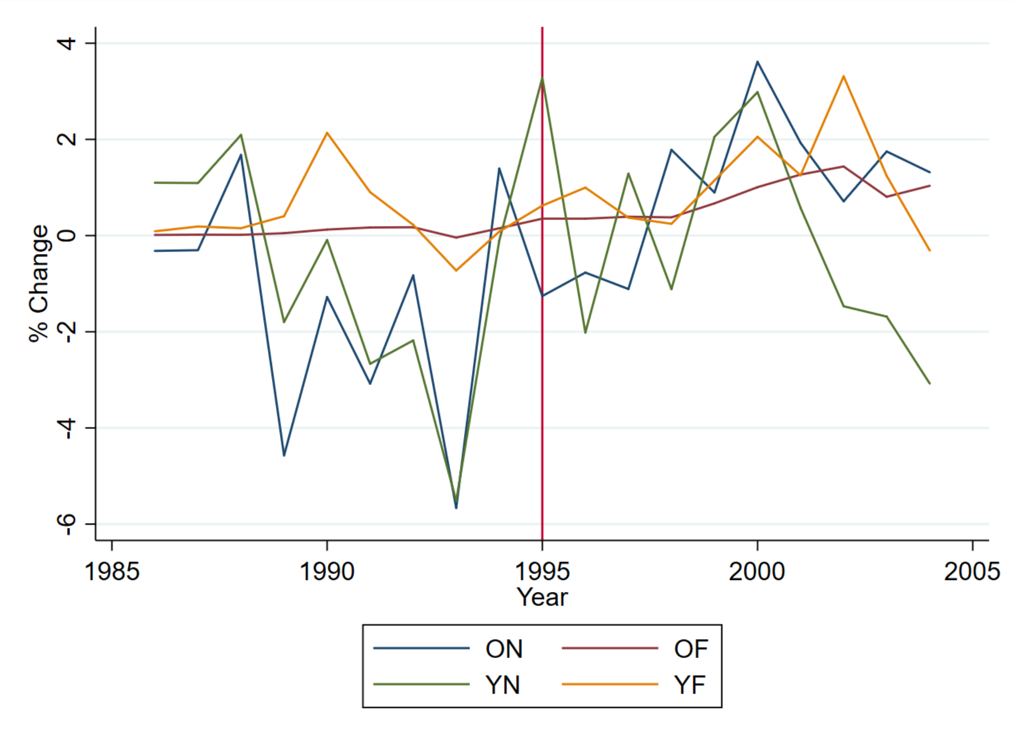
Tables and Figures

Figure 2.1: Ratios of age-citizenship yearly employment changes to the relative yearly age employment between 1985 and 2004



ON: old natives. OF: old foreigners. YN:young native. YF: young foreigners.

Table 2.1: Blue collar subgroup shares within all sample, within the subgroup sample and within the sector sample

	Old Natives			Young Natives			Old Migrants			Young Migrants		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Agricolture and forestry	0.016	0.052	23.563	0.039	0.067	56.897	0.001	0.059	2.011	0.012	0.130	17.529
Fishery	0.037	0.119	25.168	0.095	0.164	65.007	0.003	0.136	2.153	0.011	0.122	7.672
Mining	0.180	0.583	39.390	0.249	0.431	54.639	0.010	0.450	2.277	0.017	0.184	3.694
Manufacturing	15.098	49.036	30.582	28.953	50.143	58.648	1.036	44.917	2.098	4.281	46.720	8.672
Water, electricity and gas suppliers	0.745	2.419	64.234	0.406	0.703	34.989	0.005	0.204	0.405	0.004	0.047	0.372
Constructions	4.845	15.736	31.798	8.391	14.532	55.069	0.385	16.705	2.529	1.616	17.633	10.604
Retailers and wholesale,	2.863	9.299	27.549	6.915	11.976	66.533	0.145	6.293	1.397	0.470	5.128	4.521
Hotels and restaurants	1.297	4.213	22.245	3.540	6.130	60.704	0.183	7.932	3.137	0.811	8.854	13.914
Transports, storage and communications	3.706	12.037	39.364	4.782	8.281	50.785	0.239	10.352	2.536	0.689	7.516	7.314
Financial	1.756	5.703	24.396	3.952	6.844	54.907	0.285	12.348	3.957	1.205	13.149	16.740
Real estate, rentals and R&D	0.247	0.803	33.897	0.421	0.729	57.695	0.014	0.603	1.907	0.047	0.517	6.500
Subgroup Obs		157,193			294,790			11,775			46,781	

Notes: (1) subgroup share in the row sector with respect to all sample;(2) subgroup share in the row sector with respect to subgroup sample; (3) subgroup share in the row sector with respect to row-sector sample. Sample from 1995 to 2004.

Table 2.2: White collar subgroup shares within all sample, within the subgroup sample and within the sector sample

	Old Natives			Young Natives			Old Migrants			Young Migrants		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Agricolture and forestry	0.211	0.524	35.649	0.380	0.650	64.184	0.000	0.000	0.000	0.001	0.117	0.167
Fishery	0.045	0.111	62.069	0.027	0.047	37.931	0.000	0.000	0.000	0.000	0.000	0.000
Mining	0.149	0.370	54.332	0.123	0.211	44.946	0.000	0.000	0.000	0.002	0.235	0.722
Manufacturing	15.853	39.413	40.263	22.978	39.356	58.358	0.229	41.749	0.582	0.314	37.207	0.797
Water, electricity and gas suppliers	2.148	5.340	68.379	0.966	1.655	30.755	0.018	3.336	0.583	0.009	1.056	0.284
Constructions	1.901	4.725	40.121	2.747	4.704	57.977	0.044	8.025	0.930	0.046	5.458	0.972
Retail and Wholesale,	6.193	15.396	31.181	13.364	22.890	67.286	0.083	15.149	0.419	0.221	26.232	1.114
Hotels and restaurants	0.503	1.250	35.977	0.834	1.428	59.632	0.013	2.435	0.956	0.048	5.692	3.435
Transports, storage and communications	3.720	9.249	49.022	3.779	6.473	49.798	0.040	7.304	0.528	0.049	5.869	0.652
Financial	8.566	21.295	41.936	11.633	19.924	56.950	0.101	18.485	0.497	0.126	14.965	0.618
Real estate, rentals and R&D	0.935	2.326	36.892	1.554	2.662	61.292	0.019	3.517	0.761	0.027	3.169	1.054
Subgroup Obs		81,266			117,956			1,109			1,704	

Notes: (1) subgroup share in the row sector with respect to all sample;(2) subgroup share in the row sector with respect to subgroup sample; (3) subgroup share in the row sector with respect to row-sector sample. Sample from 1995 to 2004.

Table 2.3: Average log daily wage for male blue collar workers, 1995-2004

Macro Region	Broad Experience	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
North	Old	4.4465	4.4394	4.4551	4.4504	4.4455	4.4258	4.4259	4.4154	4.4040	4.4255
	Young	4.2900	4.2879	4.3038	4.3111	4.3045	4.2988	4.2974	4.2924	4.2915	4.3116
Centre	Old	4.4341	4.4239	4.4318	4.4214	4.4174	4.4127	4.3780	4.3712	4.3611	4.3762
	Young	4.2591	4.2570	4.2639	4.2703	4.2615	4.2619	4.2587	4.2425	4.2473	4.2639
South and Islands	Old	4.4278	4.4087	4.4175	4.3898	4.3941	4.3781	4.3700	4.3526	4.3514	4.3596
	Young	4.2612	4.2430	4.2471	4.2269	4.2184	4.2410	4.2381	4.2430	4.2397	4.2609

Notes: The table reports the mean of the log daily wage of workers in each region-age group. All wages are deflated to 2001 euro using the Italian CPI index from OECD database.

Table 2.4: Average log daily wage for male white collar workers, 1995-2004

Macro Region	Broad Experience	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
North	Old	4.9591	4.9633	4.9865	4.9917	5.0035	5.0045	4.9935	4.9927	4.9949	5.0029
	Young	4.6578	4.6478	4.6752	4.6835	4.6943	4.6969	4.6991	4.7036	4.6916	4.7041
Centre	Old	4.9576	4.9545	4.9712	4.9756	4.9598	4.9522	4.9507	4.9392	4.9479	4.9503
	Young	4.6336	4.6288	4.6339	4.6441	4.6497	4.6499	4.6426	4.6455	4.6350	4.6320
South and Islands	Old	4.8804	4.8644	4.8806	4.8623	4.8648	4.8614	4.8413	4.8333	4.8241	4.8364
	Young	4.5260	4.5136	4.5329	4.5257	4.5026	4.4920	4.4916	4.4737	4.4747	4.4880

Notes: The table reports the mean of the log daily wage of workers in each region-age group. All wages are deflated to 2001 euro using the Italian CPI index from OECD database.

Table 2.5: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, weighted by the inverse of dependent variable variance

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893***	-0.0157	-0.259***	-0.171***	-0.250***	-0.168***	-0.215***	-0.164***
	(0.0322)	(0.0366)	(0.0518)	(0.0510)	(0.0494)	(0.0499)	(0.0461)	(0.0484)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.000298	0.000745	0.000298	0.000745	0.000298	0.000745
F-stat			45.46	14.69	45.46	14.69	45.46	14.69
P-value J-stat			0.0773	0.389	0.0742	0.386	0.0742	0.386
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of the wage ratio variance. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.6: First stage and Reduced Form weighted by the inverse of dependent variable variance

	First stage		Reduced Form	
$\frac{\Delta L_{rsOFt}}{L_{rsOt-1}}$	1.399	-0.0254	-0.659***	-0.138
	(0.907)	(0.716)	(0.213)	(0.253)
$\frac{\Delta L_{rsYFt}}{L_{rsYt-1}}$	-0.448*	-0.160	0.102	0.0300
	(0.246)	(0.521)	(0.105)	(0.183)
$\frac{\Delta L_{rsONt}}{L_{rsOt-1}}$	0.433***	0.508***	-0.0850**	-0.0658*
	(0.119)	(0.0918)	(0.0391)	(0.0393)
$\frac{\Delta L_{rsYNt}}{L_{rsYt-1}}$	-0.743***	-0.569***	0.166***	0.115**
	(0.107)	(0.105)	(0.0520)	(0.0538)
Skill x Time FE	NO	YES	NO	YES
Observations	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of wage ratio variance. The explanatory variables are measured as the yearly change in the old (young) native (foreign) group over the total old (young) employment. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.7: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, weighted by the size of independent variable

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0897***	-0.0168	-0.258***	-0.167***	-0.249***	-0.164***	-0.210***	-0.158***
	(0.0306)	(0.0343)	(0.0499)	(0.0492)	(0.0472)	(0.0480)	(0.0436)	(0.0470)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.000108	0.000190	0.000108	0.000190	0.000108	0.000190
F-stat			51.22	18.00	51.22	18.00	51.22	18.00
P-value J-stat			0.0525	0.402	0.0490	0.400	0.0490	0.400
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the size of every region-occupation-time cell. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.8: Control function estimates of elasticity of substitution $\frac{1}{\lambda}$

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	Control Function (1)	(2)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.250***	-0.168***
	(0.0435)	(0.0509)
Residuals	0.209***	0.180***
	(0.0559)	(0.0568)
Skill x Time FE	NO	YES
Observations	342	342

Notes: All regressions include region-year fixed effects and region-skill fixed effects. The reported standard errors are clustered by region-skill. The regressions are weighted by the inverse of the wage ratio variance. Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.9: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$ by exploiting foreign employment as instrument

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893***	-0.0157	-0.298***	-0.0167
	(0.0322)	(0.0366)	(0.104)	(0.338)
Skill x Time FE	NO	YES	NO	YES
P-value Lm-stat			0.00981	0.415
F-stat			5.285	0.336
Observations	342	342	334	334

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. The instrument is the log oh the total region-occupation-time specific foreign employment. LM test is for underidentification test and F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap). Time span covers from 1996-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.10: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, by exploiting temporary laid-off workers as instrument

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0915***	-0.0264	-0.268	0.0263
	(0.0310)	(0.0535)	(0.220)	(0.796)
Skill x Time FE	NO	YES	NO	YES
P-value Lm-stat			0.100	0.619
F-stat			1.055	0.106
Observations	342	342	322	322

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The regressions are weighted by the inverse of the wage ratio variance. The regression are run only on the manufacturing sector. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. The instrument is the log of the total number of temporary laid-off workers. LM test is for underidentification test and F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap). Time span covers from 1995-2004. * p<0.10, ** p<0.05, *** p<0.01

Table 2.11: Estimated old-young elasticity of substitution, $-\frac{1}{\lambda}$, by adding a linear trend to instruments

$ln(\frac{w_{rsOt}}{w_{rsYt}})$	OLS (1)	OLS (2)	LIML (3)	LIML (4)	2SLS (5)	2SLS (6)	GMM-CUE (7)	GMM-CUE (8)
$ln(\frac{L_{rsOt}}{L_{rsYt}})$	-0.0893***	-0.0157	-0.268***	-0.168***	-0.249***	-0.164***	-0.189***	-0.144***
	(0.0322)	(0.0366)	(0.0532)	(0.0556)	(0.0476)	(0.0541)	(0.0353)	(0.0406)
Skill x Time FE	NO	YES	NO	YES	NO	YES	NO	YES
P-value Lm-stat			0.00321	0.00808	0.00321	0.00808	0.00321	0.00808
F-stat			46.73	12.09	46.73	12.09	46.73	12.09
P-value J-stat			0.208	0.802	0.192	0.798	0.192	0.798
Observations	342	342	342	342	342	342	342	342

Notes: All regressions include region-year fixed effects and region-occupation fixed effects. The reported standard errors are clustered by region-occupation. The dependent variable is the log ratio of average old and young worker wages in a region-occupation-age-time-specific cell and the explanatory variable is the log of the ratio between old and young employment inside the same cell. LM test is for underidentification test, F statistic is for weak identification test (Cragg-Donald or Kleibergen-Paap) and J test is for overidentification test. Time span covers from 1995-2004. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

2.9 Appendix A

By defining labor gap for old and young workers as function of native and foreigners, we get

$$ln(L_{rsOt}) - ln(L_{rsYt}) = ln(f(L_{rsONt}, L_{rsOFt})) - ln(f(L_{rsYNt}, L_{rsYFt})) \tag{2.15}$$

Computing the differential, we get:

$$\begin{aligned} d(ln(L_{rsOt}) - ln(L_{rsYt})) =& d(ln(f(L_{rsONt}, L_{rsOFt})) - ln(f(L_{rsYNt}, L_{rsYFt}))) = \\ = \frac{1}{L_{rsOt}} \frac{\partial L_{rsOt}}{\partial L_{rsONt}} dL_{rsONt} &+ \frac{1}{L_{rsOt}} \frac{\partial L_{rsOt}}{\partial L_{rsOFt}} dL_{rsOFt} - (\frac{1}{L_{rsYt}} \frac{\partial L_{rsYt}}{\partial L_{rsYNt}} dL_{rsYNt} + \\ &+ \frac{1}{L_{rsYt}} \frac{\partial L_{rsYt}}{\partial L_{rsYFt}} dL_{rsYFt} \end{aligned} \tag{2.16}$$

Labor ratio differential in discrete is:

$$\Delta(ln(L_{rsOt}) - ln(L_{rsYt})) = \Sigma_c(\beta_{Oc} \frac{\Delta L_{rsOct}}{L_{rsOt}} - \beta_{Yc} \frac{\Delta L_{rsYct}}{L_{rsYt}}) \qquad c = N, F \tag{2.17}$$

where

$$\beta_{Oc} = \frac{\partial L_{rsOt}}{\partial L_{rsOct}} \qquad \beta_{Yc} = \frac{\partial L_{rsYt}}{\partial L_{rsYct}} \tag{2.18}$$

with c indicating if they are natives or foreigners.

Appendix B

By assuming that the residuals, x, obtained by applying Frisch–Waugh–Lovell theorem to labor gap first difference, follow an AR(1) process:

$$x_{rst} = \rho x_{rst-1} + \varepsilon_{rst} \tag{2.19}$$

By subtracting x_{rst-1} on both sides we obtain:

$$\Delta x_{rst} = (\rho - 1)x_{rst-1} + \varepsilon_{rst} \tag{2.20}$$

By substituting the first difference in the labor demand we have:

$$ln(\frac{w_{rsOt}}{w_{rsYt}}) = \beta \Delta x_{rst} + u_{rst} \tag{2.21}$$

Where y_{rst} is the residuals from wages by using the Frisch–Waugh–Lovell theorem and t goes from 2 to T. We omit to multiply the parameter from the first stage regression.

$$\operatorname*{plim}_{N\to\infty} \widehat{\beta} = \beta + \frac{\operatorname{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})(u_{rst} - u_{rs.})}{\operatorname{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})^2} \tag{2.22}$$

$$\operatorname*{plim}_{N\to\infty} \widehat{\beta} - \beta = \frac{\operatorname{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})(u_{rst} - u_{rs.})}{\operatorname{plim}_{N\to\infty} \frac{1}{N}\Sigma_{i=1}^{N}(x_{rst} - x_{rs.})^2} = \frac{A}{B} \tag{2.23}$$

$$A = \underbrace{E[x_{rst}u_{rst}]}_{\text{endogeneity bias}} \underbrace{-E[x_{rst}u_{rs.}] - E[x_{rs.}u_{rst}] + E[x_{rs.}u_{rs.}]}_{\text{Nickell bias}} \tag{2.24}$$

$$B = E[x_{rst}^2] - 2E[x_{rst}x_{rs.}] + E[x_{rs.}^2] \tag{2.25}$$

Let u_{rst} equals to the sum of a random effect and a *offsetting mechanism*:

$$u_{rst} = \xi rst + f(\varepsilon_{rst-1}) \tag{2.26}$$

Let $f(\epsilon_{rst-1})$ linear and function of labor supply shock at t-1:

$$f(\epsilon_{rst-1}) = \varepsilon_{rst-1} \tag{2.27}$$

Let ρ is equal to one:

$$\Delta x_{rst} = \varepsilon_{rst} \tag{2.28}$$

Then A turns into:

$$A = E[\varepsilon_{rst}\varepsilon_{rst-1}] - E[\varepsilon_{rst}\varepsilon_{rs.-1}] - E[\varepsilon_{rs.}\varepsilon_{rst-1}] + E[\varepsilon_{rs.}\varepsilon_{rs.-1}] \tag{2.29}$$

Showing the time means of A:

$$A = E[\varepsilon_{rst}\varepsilon_{rst-1}] - \tfrac{1}{T-1}E[\varepsilon_{rst}\textstyle\sum_{j=2}^{T}\varepsilon_{rsj-1}] - \tfrac{1}{T-1}E[\textstyle\sum_{j=2}^{T}\varepsilon_{rsj}\varepsilon_{rst-1}] +$$

$$\frac{1}{(T-1)^2}E[\sum_{j=2}^{T}\varepsilon_{rsj}\sum_{j=2}^{T}\varepsilon_{rsj-1}] \tag{2.30}$$

Solving covariates:

$$A = 0 - \frac{1}{T-1}\sigma_{\varepsilon}^2 - \frac{1}{T-1}\sigma_{\varepsilon}^2 + \frac{1}{(T-1)^2}(T-2)\sigma_{\varepsilon}^2 \tag{2.31}$$

$$A = -\frac{T}{(T-1)^2}\sigma_{\varepsilon}^2 \tag{2.32}$$

Doing the same for B:

$$B = E[\varepsilon_{rst}^2] - 2E[\varepsilon_{rst}\varepsilon_{rs.}] + E[\varepsilon_{rs.}^2] \tag{2.33}$$

$$B = E[\varepsilon_{rst}^2] - \frac{2}{(T-1)}E[\varepsilon_{rst}\sum_{j=2}^{T}\varepsilon_{rsj}] + \frac{1}{(T-1)^2}E[\sum_{j=2}^{T}\varepsilon_{rsj}^2] \tag{2.34}$$

$$B = \sigma_{\varepsilon}^2 - \frac{2}{T-1}\sigma_{\varepsilon}^2 + \frac{1}{(T-1)^2}(T-1)\sigma_{\varepsilon}^2 \tag{2.35}$$

$$B = \sigma_\varepsilon^2 \frac{T-2}{T-1} \tag{2.36}$$

Computing the ratio between A and B:

$$\frac{A}{B} = -\frac{T}{(T-2)(T-1)} \tag{2.37}$$

Chapter 3

Selection of Italian Teachers: Is Mine Better Than Yours?

Abstract

Italian high school teachers need to satisfy certain criteria to be eligible for tenure jobs. Constitution states tenure is allocated on a merit base, proven with an open public examination. Different demographic cycles have shrinked and enlarged the quantity of teachers needed over time, not coping very well with selection procedures. This might have impacted the overall quality of high school teaching, to the possible harm of students. This work wants to assess the role different pathways into teaching play in shaping students future opportunities. Thanks to a rich and novel dataset, made of administrative data on teachers and schools (in Veneto) we can compute each school's share of teachers who passed a public exam. To assess the impact on student's future chances we use a comprehensive measure of high school quality provided by Fondazione Giovanni Agnelli. Schools where higher share of tenure positions are merit based help their students more in their later chances into tertiary education, yet the impact is small in size.

3.1 Introduction

It is often stated that education lies at the heart of a prosperous country. Quality of teachers is one of the most relevant education input according to many scholars (see, for example, Rivkin, Hanushek, and Kain 2005; Rockoff 2004; Sanders and Horn 1994; Sanders and Rivers 1996). Although assessing their quality is not straighforward (Hanushek e Rivkin, 2010; Darling-Hammond, 2012). In Italy, claims that public exams are too difficult to properly select teachers are all over the media when one public exam is announced. In times when no public exam is planned, public opinion strongly advocates for new ones.

Need of teachers varies along with demographics and school system innovation, while dismissal of poor teachers hardly happens. Properly working selection into jobs represents therefore a good chance to guarantee high teaching quality.

Outcomes of italian education system are worrisome. Teachers are among the worst paid of OECD countries (89%, and progress also at a much lower rate), among the oldest, and have been long experiencing a failure of consideration[1]. Students performance qualify always at the end of international rankings. Differences across regions are not neglible either. Investment in education is still lower than many other OECD countries (89% of OECD average). A number of studies have investigated reasons of such bad outcomes, also trying to relate them to education inputs. What has not been widely explored yet, to the best of the author's knowledge, is whether the selection of teachers into tenure jobs impacts high school graduates competences, in terms of performances at university or in the labor market.

Selection of teachers has undergone several adjustments over the years. Steep increase of students enrolled in the early 70s found no response in the number of teachers officially qualified for the job. This meant that many teachers were hired despite a proper certificate to practice the profession. As long as they held a degree or diploma they could be hired in a tenure job. By doing some work they started gaining some seniority, which with law 477/73 became a criteria of selection into different types of open competitive exams and jobs (> 360 work days). About 200.000 teachers obtained a tenure job with law 477/73.

Since 1982 there have been some open competitive exams aimed at officially entitling teachers to work. They did differ in degrees of complexity and number of days worked played a key role in determining what type of competitive exams each candidate was entitled to sit for[2]. One other major problem that also arised with these public open exams was the uncertain timing. Law 417 of 1989 stated that ordinary exam had to be held every three years (it was every 2

[1] Real wage of teachers is 0.72 of highly educated full time professional wage in Italy, EU23 ratio is 1, OECD 2018

[2] The so called "sessioni riservate", in art.35 L270/1982 or art.11 L417/1989 Ex-DL 357/89

years, according to L. 270/1982). Yet the first one after 1989 was in 1999. The following was in 2012, then 2016 and 2018. One every ten year, then two in six years. One possible explanation for slow planning is that evaluation of teachers through an open examination means assessing competences of thousand candidates. Still, in times when ordinary open competitive exams were not announced, schools had to adapt. Teachers were hired regardless and had just to wait for a couple of years for their position to be regularized through amnesties (Art. 2L124/1999), leading to same result as if they did successfully pass an open competitive exam.

This way of proceeding resolved in the existence of three different types of rankings, and to differently selected teachers obtaining same jobs. Tenure jobs are allocated with a 50% rule from merit rankings and depletion rankings. When two slots are available one teacher is picked from merit ranking (i.e. passed a public exam) and one is picked from GaE (depletion ranking). It used to be 30% for merit rankings and 70% for deplation (according to L.1074/1971, before 1st October 1975). Rankings from open exams work at regional level, while depletion rankings work at the provincial one. This allocation procedure allows to consider the school share of merit rankings' teachers random enough to other school characteristics that might also influence students' performances.
Given the key role teachers play in the development of a country's human capital, it seems interesting to exploit variation in selection to define whether there are paths working better than others, or to find out differences are negligible.

This paper assesses the effects of pathways into teaching on students outcomes. Such analysis is possible thanks to a rich dataset made of administrative information on what selection each teacher went through to enter the profession. An indicator will help capturing the share of teachers that have passed a public exam on the total of teachers in each upper secondary school. Provided we do not have students performance data at the classroom level, the indicator was built at the school one. The analysis is performed on Veneto region. Student performances are expressed with an indicator built by Fondazione Giovanni Agnelli (hereafter FGA), weighting both average grades and number of credits obtained in the first year of university by three different cohorts of high school graduates (a.y. 2014/2015 to 2016/2017). This indicator evaluates schools that mostly train students for university. Another indicator applies for schools which train students for labor market. The share of employed students and how close their studies are to their job are the quality indicators for professional and technical schools (the vocational training path). Main contribution of this work is the innovative dataset that allows to observe how many teachers obtained a tenure job successfully passing a public exam. It is public available data but it is not in a format ready to be at scholars disposal. Information is spread across districts, provincial and regional administrative public boards.

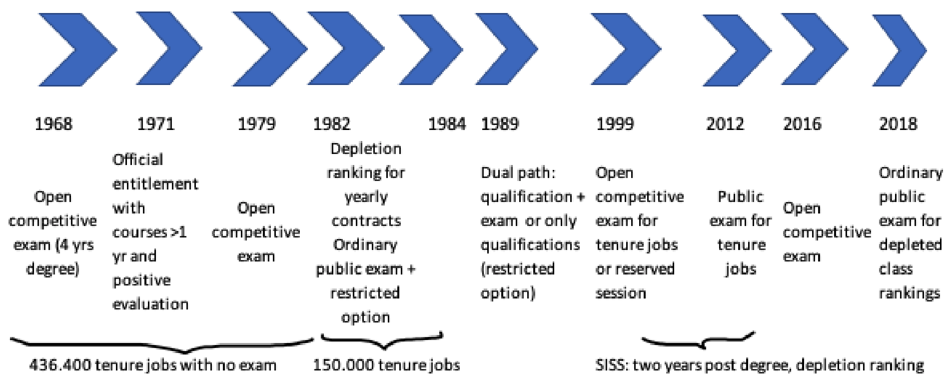
Gathering this data and look at teachers through this lens represents a novel approach to a known topic. Similar works have been performed in the US (Boyd et al, 2009; Douglas et al., 2008). Nothing similar has been done regarding the italian teachers job market, mostly because of low data availability.

The remainder of the paper proceeds as follows. Section 3.1 will provide a description of the Italian context. Section 3.2 will describe in detail how the dataset has been built and what main information it provides. Section 3.3 will develop the analysis, by first focusing on the index used as dependent variable. Section 3.4 will present some conclusive remarks.

3.2 Institutional context

In 1978, 83% of tenure teachers obtained their jobs without successfully pass an open competitive exam (Berardi,2001). Since then, a model where rule and exception interchanged regularly kept imposing one restriction and relaxing entry barriers with amnesties the moment after. Figure 3.1 tries to shed some light on teachers' recruitment process, it pins down the history of open competitive exams, amnesties and alternative paths into tenure jobs.

Figure 3.1: Teacher selection path over the period 1968-2016



Italian teachers selection follows a complicated path. Few reforms have attempted to re-design selection process into the profession yet most of them had to focus as well on all awaiting candidates from previous years rankings (Moscati, 2010). To be a teacher in Italy you can either be only allowed to the job market (i.e. you can be hired on a temporary base only), or you can be entitled to (and you are allowed a permanent contract, tenure job). Which one of the two depends on your qualifications as well as on government planning. Different times of italian history have called for both expansive and more restrictive phases, in terms of requirements to practice the profession. Problems of more expansive phases, whereby the need of teachers push towards relaxing entry barriers, are the negative spillovers in future times. If not yet entitled teachers start being employed longer than just short substitutions they start gaining seniority, which is also a criteria to advance in the rankings.

Three different types of ranking exist in Italy. Merit rankings are made of all teachers who succefully passed a public competitive exam. Those are the entitled teachers who are eligible for tenure. Then there are the so called depletion ranking (GaE), where since 2008 no new prospective teacher can be included. They are indeed aimed at depletion. Candidates in these rankings are eligible for tenure too, as well as for annual substitutions. The last type of ranking is the Institutes' ranking (each institute has one) where only short (shorter than the entire year, from september to august) substitute teaching is possible. When tenure positions become available, the law states that 50% of the available slots are assigned to teachers in the merit ranking, the other half in the depletion ranking. Law 417 in 1989[3] institutionalized the so called *dual selection path* that will last until depletion of GaE rankings. In the period between last ordinary public exam (1999) and the one in 2016 several other ways to prepare teachers took place. Meanwhile teachers could ask to be inserted in both deplation rankings (provincial level) and institutes one (up to 20 different high schools). Each prospective teacher can apply to only few different subjects, based on type of studies and admission criteria.

One goal of this paper is also trying to sort out all these different selection paths. What cohort one prospective teacher belongs makes a huge difference. If a person wants to become a teacher and graduates from university when no public exams takes place, her chances to get a tenure positions are low (not null just because of deplation rankings). Quite the opposite is the one who chooses not to sit for the exam (or worse, do not pass it) and yet because of some time in schools (substitutions contracts) gains seniority and enters either depletion or institute rankings. From there to tenure job they would face similar trajectories. It is interesting to understand whether this has any impact on students.

Quality of teachers is a widely discussed topic in the literature. Few studies focus though

[3]Art. 1, comma 109 letter c) of law 107/2015, to hire teachers and educational professionals art. 399 comma 1 del T.U. Istruzione still applies, until total depletion of related GaE rankings. (MIUR)

on selection because data is not easily available. Public examinations do not come without any cost. Checchi et al. (2016) underline how critical a tough selection is to hire high quality teachers. Selection has to be finetuned between the risk of hiring not too qualified candidates, and the one of rejecting possible good candidates. Other contributions to the literature around selection of school teachers comes from US. Lowering standards to increase number of teachers in New York led to small differences in mathematics and english students scores, and those differences disappeared over time (Boyd et al. 2006). The impact of certification released by the National board for prefessional teaching standards in the US proved ineffective in enhancing student's achievement (Harris et al. 2008). These results seem in contrast with what we would expect, so that proving the ability with a certificate has no positive effect on students' performances, while lowering standards does not harm students much. Unespected results like these make even more the case for a contribution on Italian schools.

3.3 Data

Data used in this paper is administrative data, mostly gathered from state education department provincial agencies. Each province has its own administrative agency with main tasks of allocating teachers into schools and managing rankings. Information has been gathered from each of the seven public boards, and from the regional one. Data on schools and teachers in each schools is available at the beginning of each academic year, with name of the school where each new tenure teacher is assigned. A measure of high schools quality in Veneto comes from FGA's website *Eduscopio.it*.

The analysis is performed on these original datasets merged together. First one is data from all provincial boards with new tenure jobs. Then we added information from all different rankings (mostly depletion and merit but also some institutes). These rankings have also different lives. Depletion rankings (at provincial level since 1961, L. 463/1978) have been updated every year up to 2008. They are now updated every three, but with no chance of new entries. Merit rankings originate at regional level from every new open tenure exam, and last up to depletion. This kind of open exam are announced every time a subject class has lots of vacancies. Last two (useful for the analysis[4]) were the ones in 2012 and 2016. Institutes's ranking are updated on a three year basis.

Teachers have been listed according to the school where they obtained a tenure job, and to

[4]there has been one in 2018 too but teachers obtained tenure jobs in the next academic year, which is out of our study interval

the class of subjects they belong to. Information on whether they passed an exam or not was taken either from tenure jobs notification, when merging with merit rankings directly, from institute's rankings or from movement bulletins. Movement bulletins only display information of tenure teachers who got positive reply to their request of moving to a different schools. This information will turn useful in developing the analysis. Schools' mechanographic code and teachers' name are the two key variables on which the merging process takes place. Not all merit rankings were available, some of those we observe rankings for are foreign languages, italian literature, history and philospy, physics, maths (corresponding to A245, A345, A446, A050, A037, A028, A049 etc.). Class codes have been updated in 2016. This might have created some noise despite careful data gathering and cleaning. Merit rankings involved in the analysis correspond to 1999 open exam, 2012 and 2016 exams. Exclusion of 1989 ranking was forced by being only paper archive, same for 1982 open exam. It is certainly a loss of useful information. While most of tenure professors who passed 1982 exam have already retired[5], the same cannot be claimed for 1989 exam. Adding them would definitely help the precision of the estimates, involving teachers aged 50 or more. Not having 1982 or 1989 merit rankings at disposal does not mean though that we do not capture any, by looking at intra regional movements or institutes rankings some of this information is still available (we can't attribute them exactly to either one of the two because variable is a dummy which takes value 1 if entry path was public exam only).

The focus is on Veneto's high schools, distributed across seven provinces. Observations listed in the first dataset are 596 (mechanographic codes, which associate to each institute). Some of them will necessarily be dropped because of the merging process with another rich source of information that will consitute our dependent variable, FGA indicator. This comprehensive measure allows to capture the quality of the school by looking at how recently graduated students perform in the year after completing high school. More details on the index will follow in the next paragraph.

3.3.1 FGA Indicator

A measure of school performance has for long been missing in the Italian education context. The one provided for the first time in 2014 by FGA fills this gap. Knowing what graduates are able to achieve once they complete high schools is important for middle school students (and families) to make more informed choices. This is indeed the main goal of the project

[5]Average age in the other three open exams ranges from 34 to 39, it is thus likely that the majority already reached retirement age and according to Battistin at al. (2009), public employees tend to retire as soon as they are entitled to.

textitEduscopio, allowing families to compare high schools located close by. The availability of three different pools of administrative data made this measure possible. Information on high schools, students (ANS) and university students (ANSUL) comes from MIUR (Ministero dell'Istruzione Università e Ricerca). With these rich datasets at their disposal it was possible to compare all types of high schools with the future they prepare their students to. Each high school is measured with respect to what its final goal is. Since 2010, there are three different types of secondary education in Italy: Lyceum (*Liceo*), Technical Insitutes (*Istituti tecnici*) and Professional Institutes (*Istituti professionali*). Students who graduate from Lyceum (Classic, Linguistic, Scientific or Social Sciences) have their natural progression into universities (91% from Classic Lyceum enrols at university); those who graduate from professional schools aim at the labor market. Technical schools qualify in the middle, a relatively sizeable share of their graduates opts for enrolment at universities. Because of this, technical schools are evaluated on both exit paths. Lyceums are evaluated on the university career of their students, Professional schools on students performance on the labor market. Ideally it would have been interesting to have a single measure for quality of future options granted by each type of school. We opted for not merging the two variables produced in *Eduscopio* into one. Professional and Technical Institutes are evaluated on the share of employed students one year after graduation, and how close to their studies their job is. Picking either one of the two would compromise the high quality of the comprehensive measure in use for university careers. Success at university is twofold, it matters both how well students perform on average, and how far they manage to progress in terms of credits obtained. This is why FGA builts a robust indicator considering both variables. Average grades indicator comes as follows:

$$averagegrade_t^{ij} = \frac{\Sigma_{k=1}^{n_i} grade_{tk}^{ij} * CFU_k^{ij}}{\Sigma_{k=1}^{n_i} CFU_k^{ij}} \tag{3.1}$$

Obtained credits are computed this way:

$$progress_t^{ij} = \frac{\Sigma_{k=1}^{n_i} CFU_k^{ij}}{\overline{CFU}^{ij}} \tag{3.2}$$

In between the authors of textitEduscopio (and thus FGA indicator) perform a standardization on the university outcomes so to freely assume that results are as comparable as students all chose same course at the same university (for more detailed explanation on FGA indicator see Bernardi et al., 2018).

The final indicator is the weighted average of both measures:

$$indicatorFGA^j = 0.5 * averagegrade^j + 0.5 * progress^j \tag{3.3}$$

This indicator could pose some challenges when we want to express that as a mere result of teachers impact on students, since it is based on a time period that start immediately after completion of studies[6].

Yet the quality of education is indeed measurable by the oppurtunities it offers later on in life, when this means allowing smooth transition into higher education. We thus employ this measure as overall high school quality. The index is not built with a huge time gap. FGA index looks at three different cohorts of high school graduates, and computes indicators for the first year after graduation, where there is still little room for something to offset the effect of a good education. The very aim of this index is indeed guiding middle school students and parents in the choice of high schools, which reinforce the idea that it could represent a way of evaluating high schools. As a further proof of the validity of this indicator (and to fight doubts on whether time gap is too large to infer quality of high schools) there is a work of Aina et al. (2019) where school quality indicator (FGA) is tested and shows to help explaining up to third year of studies, not just the first one, impacting also on time graduation. First year of university is considered to be a good signal of how studies will progress (60% of those who abandon do not sit for any exam in the first year). Another important information is that students considered belong to three different cohorts (2014/15 up to 2016/2017). Reason for that is robustness of measure, this way not relying too much on a single group of teachers and students. Minimum conditions to be included in the indicator's list of schools apply. In absolute terms, students opting for universities should be more than 21 within the three cohorts of high school graduates. Only schools that send at least one out three students to university have been considered in the analysis. Imposing these two conditions

[6]To measure schools' performance one could argue Invalsi test scores would be more precise. Invalsi is a standardized test used in italian schools, from primary to upper secondary. They could capture the quality of teaching at very moment such teaching is provided, at class level, avoiding the gap we and the aggregate level we observe in our FGA indicator. The way Invalsi data are collected prevents this information to be usable for this analysis. Plus data are not of public use, results disclosure is discretion of each schools' principal.

grants less noise and measurement errors (Bernardi et al. 2019). This also means dropping from the dataset all those schools that do not qualify for the FGA indicator. They could be either too small or with different goals than sending students to universities[7]. The number of schools eventually considered in the analysis is presented in Table 3.1. Technical institutes (technologic major) and scientific lyceum are the most frequent in the dataset (namely 19.35% and 18.41%). The number of students enrolled at universities coming from Veneto's high schools is 56.246, representing 7,8% of the total.

Table 3.1: Descriptives, 2019/2020

Dependent variables	N	Mean	St. dev.	Min	Max
Average grade	380	25.571	1.292	21.82	28.63
Progress	380	66.125	11.01	13.79	96.43
Indicator FGA	380	64.607	12.61	27.41	87.79

Notes: The table reports the mean of the two indicators (progress and average grade).

[7] in this first version of the study we also drop those professional and technical institutes that qualitfy for labor outcomes, since we only used FGA indicator, available for university carreers only

3.4 Empirical strategy

The model employed revolves around the two key variables described above. To measure schools quality we use FGA indicator, as dependent variable. As for now, a linear model fits the purpose of the analysis. Our main regression is:

$$FGA_i = meritshare_i + X_i \tag{3.4}$$

where X is a set of controls that allows the relationship with the dependent variable to be mainly driven by the share of merit awarded tenure positions in each school *i*. They capture the average age of teachers in school *i*, school *i* size (in terms of tenure jobs) and location (whether a school is located in the main city or in another municipality.

Another interesting control that can be added to better isolate the impact of our variable of interest is the share of temporary contracts and tenure contracts each school has. This information tells us more about unobserved characteristics of the school that might impact future chance of students irrespective of teachers selection. The only academic year this information is availabe is 2010/2011. This is not a problem since it gives us a picture of some times before the interval of time we do observe in our data (2014/15 up to 2016/2017)[8].

One different way to proceed could be clustering FGA indicator into four categories to also include in the first group of schools those who do not qualify to have an indicator computed, then perform a multinomial logit model. This would avoid leaving behind some observations, increasing size of the sample and therefore precision of estimates. When treating our dependent variable as continuos (while working with all observations) we would know it is censored at one point, yet we would exploit the variability a cluster would reduce. One key assumption we made in order to perform the analysis needs further discussion. Since the allocation of one teacher is given the very year she gets the tenure job, we have to assume that she will not leave that school for the period that goes from tenure to the interval we observe students in (2014-2016). It as a strong assumption, the impression is that teachers do move despite the tenure contract. Yet, by gathering data on open exam also from movement bulletins within the region, and keeping for each teacher the last observation over time for the analysis we might not have misplaced any teacher in the time interval under analysis. Should there be some bulletins left behind, it would be completly random and would not affect estimates. Furthermore, a report on italian teachers mobility shows that for tenure teachers the figure

[8]The way this information is provided prevented it from being usable in this version of the paper.

is about 11%[9], which is lower than figures on all teachers because mobility within schools happens only in a voluntary way, forced mobility does not involve tenure jobs (FGA, 2009). Also most of teachers' movements happen within the region (96.2%), reinforcing the argument that i captured most of them already. In the pooled dataset used for the analysis we gather more than 11556 tenure teachers, divided between those who passed an open exam and those who did not. Total number of teachers in the Veneto region was 18945 in 2014 (Istat).

Table 3.2: Output

FGA Indicator	(1)	(2)
Share of merit teachers	.145**	0.324**
	(0.047)	(0.108)
Size of tenure jobs		0.002*
		(0.001)
City		-0.003
		(0.052)
Average age teachers		-0.004
		(0.005)
Constant	4.161***	4.233***
	(0.014)	(0.276)
Controls	NO	YES
R-squared	0.050	0.137
N	166	42

Notes: * p<0.05, ** p<0.01, *** p<0.001

The dependent variable has been transformed in logarithm. Table 3.2 shows some simple although encouraging results. A positive and significant coefficient means there is something this new data could explain, also considered how much the dataset shrinks when merged with quality measures and the information missed in this process. Adding some controls makes number of observations drop singificantly. The information that also size of tenure jobs matter is relevant, and confims the idea that a large share of teachers on temporary contract does not benefit much students. Share of well prepared and thouroghly examined teachers might contribute positively in shaping students future careers.

[9]Apparently this figure could be lower should some other career improvements be set up. Right now, getting closer to home or to better schools is the only available move tenure teachers have.

3.5 Conclusive Remarks

Results presented so far are far from complete. Limitations due to the complexity of building a dataset are many. More controls should be added to the model. As mentioned, the share of temporary contracts each school has in force would improve the estimation. It would be informative of the size of tenure jobs shares and on school characteristics we cannot observe. This information is available for 2010/2011 and is provided by MIUR for each academic year so, upon request, it should be possible to include it. It would be intresting to build the shares giving different weights to different subject classes. Other specification of the model, like the multinomial logit with the indicator clustered in four categories could help assessing robustness of these results, not excluding those high schools that right now have been dropped. Same exercise should also be carried on vocational training and labor market first year performances, including both Professional and Technical institutes. Robustness checks of the analysis could be running this model with a different dependent variable, using Invalsi data instead of FGA indicator. Being timewise closer to teachers' performance, precision and informative value of the estimates might increase. Trying this model on a different region might also help testing its robustness. Although this does come at the cost of building another dataset for the purpose. It is certainly too early to discuss implication, but should these results test robust to different specification or datasets this work will provide new evidence in support of more radical changes in teachers selection paths.

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