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Summary

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Keywords: brain drain, corruption, panel data, gravity, zip, ppmlhdfe

JEL Classification: D73 F12 R23

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Nemo Propheta in Patria: Empirical Evidence from Italy[1]

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Abstract

In recent years, young brain drain within Italian provinces has increased at higher speed than ever. While is premature to assess whether this process is transitory or permanent, it should be analysed and monitored by researchers and policy makers for its many socio-economic consequences. Previous empirical studies have demonstrated that Italian net skilled migration is influenced by economic factors, such as income per capita and employment, and, with a less extent, by the search of places endowed with more amenities. In the crossroad between these factors, this paper investigates corruption as key element of the Italian skilled mobility. To this end, a comprehensive framework with Zero-Inflated Poisson and Pseudo-Poisson Maximum Likelihood with High Dimensional Fixed Effects models for bilateral data on the Italian students' flows is used. Results suggest the dual role of push and pull mechanisms at play, as high corruption incentivizes Italian skilled mobility to destinations that, instead, exhibit lower corruption. Moreover, sensitivity of the prospective tertiary students to corruption varies according to their field of study of interest. Finally, empirical evidence on skilled flows from the lagging Mezzogiorno to the North of Italy, suggests that the push and pull effects of corruption stir up the endurance of the well-known socio-economic dualism between these two parts of the country.

Keywords **brain drain**, **corruption**, **panel data**, **gravity, zip**, **ppmlhdfe**

JEL Classification: **D73 F12 R23**

[1] The present working paper was presented during the 62nd Edition of RSA conference organized by the Italian Economics Society (S.I.E) on October 29th, 2021, in an online parallel session named "Italian Economy". Still, the same work was presented at SIDE Italian Society of Law and Economics (ISLE) on December 16th, 2021, on the online parallel session named "Corruption" at University of Trento, Italy

1. Introduction

Net skilled migration constitutes a bulk of interest for researchers of several fields of study including (endogenous) economic growth. The economic growth path of a country depends crucially by its technological change and human capital accumulation, through schooling and learning-by-doing (Solow, 1956, Arrow, 1962, Romer, 1987, Lucas, 1988). Nonetheless, increasing human capital has usually been considered an efficient policy to stir up growth (Beine et al., 2014). Usually, researchers have long sustained the pessimistic view of brain drain. In fact, brain drain from sending places is conceived as human capital depletion with negative spill-over effects meanwhile brain migration to receiving places turns a gain because such places acquire and plausibly retain skilled individuals (Beine et al., 2014). In contrast, a recent wave of research has emerged around the theory that net skilled migration generates beneficial effects for sending places, by partly or totally compensating for the costs of losing talents (Beine et al., 2014). More precisely, skilled individuals who emigrate from native places leave out opportunities, in terms of employment or living standards, for those who remain. Besides, the costs of emigrants is attenuated if origin places receive larger remittances and other benefits from skilled returns. Thus, inequalities between sending and receiving places can be mitigated. Several studies have identified economic and socio-cultural factors, such as the search for better job opportunities, income, quality of life and quality of institutions as relevant causes for skilled mobility (Poprawe, 2015; Nifo and Vecchione, 2014; Charron et al., 2013; Dotti et al., 2013; Biagi et al., 2011). On the other hand, few part of the recent literature has already demonstrated the negative effects of corruption on growth (Savovic, 2021; Corrado and Rossetti, 2018; Lisciandra and Millemaci, 2016) and even fewer part of it has proved corruption as remarkable social factor that positively affects skilled flows from source contexts (Cooray and Schneider, 2016; Poprawe, 2015; Dimant et al., 2013). Thus, understanding how corruption influences skilled mobility is an issue of crucial importance for researchers and policymakers due its severe economic consequences. However, the push contours of corruption are more defined than its pull side. Although it is easy to find that high corruption positively affects young skilled flows, there is not obvious evidence in the recent literature that skilled individuals are attracted to destinations where corruption is relatively low. This is partly explained by the fact that resident students from origins have perfect information on the high number of unlawful cases of their context (such as achieving goals without merit but just for favouritism, nepotism and/or political connections) and decide to move to destinations where they surmise that corruption is relatively low. Hence, they may presume it because they gather information from newspapers, web, media, parents and friends, who already live in the designed destinations. However, such information is far from perfect because it is likely to be reported in incomplete way, based on individuals' knowledge rather than objective facts mainly. Hence, the contours of the pull effect of corruption at destinations are feeble and need to be further analysed. For that reason, the aim of this paper consists of investigating whether corruption acts not only as push but also as pull factor, that attracts skilled individuals to destinations, after they gather information on the quality of the context of their designed receiving place. This happens because young skilled individuals, at the beginning of their university career, are more sensitive to legal concerns for living better-off in society. Besides, they know that opportunities of their careers depend on the competitiveness and meritocracy of their local labour market. Thus, they are looking forward to having chances to live in places where deserving rewards are likely to occur fairly. Thus, the decision of students to move from their native provinces is complex because there are many causes behind. Moving for study-reasons may refer to move in search of higher standards of life, meant as a mix of economic and socio-cultural elements related to higher welfare, social mobility, greater availability of services and infrastructures at disposal (Nifo and Vecchione, 2014). Another interesting aspect, that is novel in the literature of brain drain and corruption, consists of investigating whether the sensibility to corruption varies among prospective tertiary students, who decide to enrol to academic courses belonging to different fields of study. In fact, it is plausible that sensibility to corruption may differ per student as it reflects his/her diverse attitudes to meritocracy and politically correct policies and that may strongly or not influence his/her decisions to move/remain from/at his/her homeplace.

While cross-country and cross-section studies on brain drain are particularly investigated in the literature, within-provinces analysis is relatively scanty and scarce. One of the most developed countries characterized by ample movements of skilled individuals across its main areas is Italy. In fact, Italy represents an interesting study-case because it registers one of the highest levels of skilled emigration rate among the other developed European countries (11 percent -%- against 3 percent -%- in France and 6 percent -%- in Germany in 2017)[2]. Besides, the peculiar and enduring dualism of North and South of Italy may be exacerbated by high skilled emigration from the southern area. As reported by SVIMEX (Italian Association for the Industrial Development of Mezzogiorno), from 2002 to 2017, the number of movers from Mezzogiorno is about 2 million, out of which almost 150.000 in 2017 only. Given that number, almost 50.4 percent (%) of those who move are students (66.557) while 33 percent (%) are already graduated (21.970). Besides, from 2010 to 2017, the net skilled migration from the South increased more than double than the net skilled migration from the North and is still following an increasing path: as reported by Figure 1, southern skilled movements rise of 4 percent (%) against the 2 percent (%) of skilled movements occurring from the North[3]. In addition, Figure 2 shows that between 11 percent (%) and 13 percent (%) are provincial skilled movements occurring from the South while between 8 percent (%) and 10 percent (%) represent the provincial skilled movements from the Centre-South to the North[4]. This implies severe economic consequences on growth of each different macro-area: as reported by SVIMEX, from 2007 to 2017, the difference in economic growth between the Centre-North and the South was 9.6 percent (%) against 5.3 percent (%) if skilled mobility from the South never existed. Hence, in the last ten years, Italian provinces have experienced an increasing trend of skilled movements that has achieved a peak to higher levels as never before. It is not possible to know if this phenomenon will stop or rise even further, although the advent of external shocks may cause a reverse trend of skilled mobility. An example is provided by the widespread of Coronavirus disease that has determined the likely return

[2] Data are provided by OECD (2022) "*International Migration Statistics Database*"
[3] Data are taken by M.I.U.R and elaborated by the author with STATA
[4] Data are taken by M.I.U.R and elaborated by the author with STATA

Figure 1. *Skilled migration rate Italian area 2010-2017 (source: M.I.U.R)*

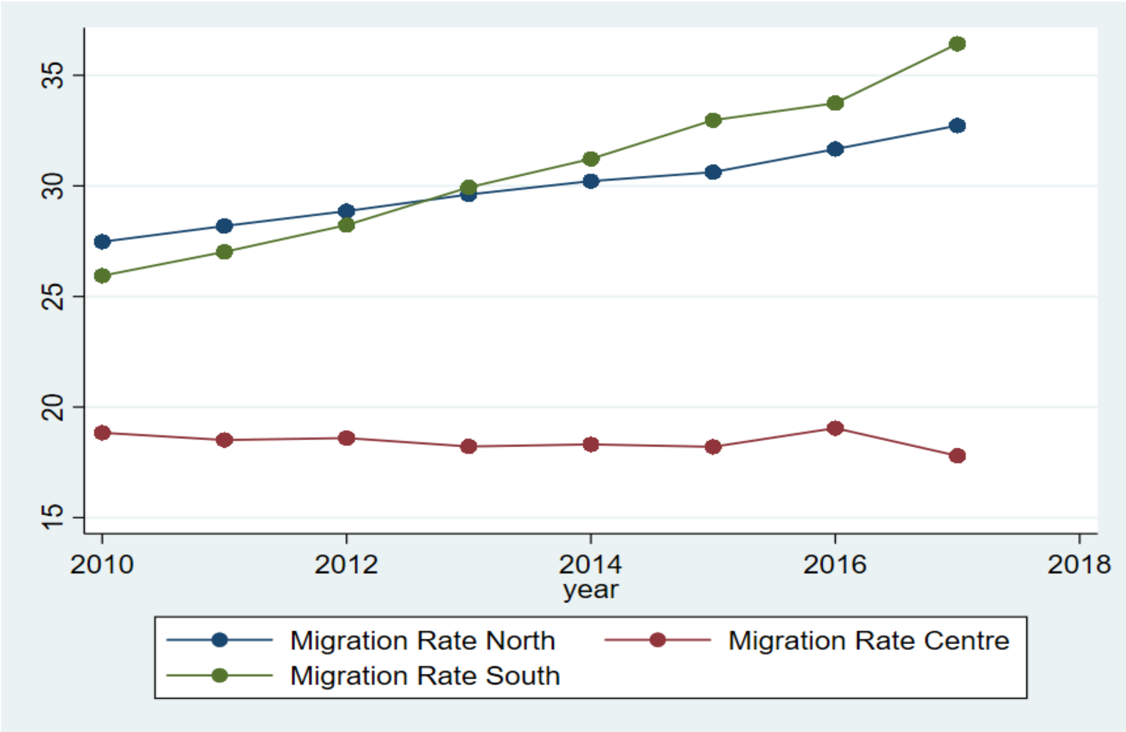
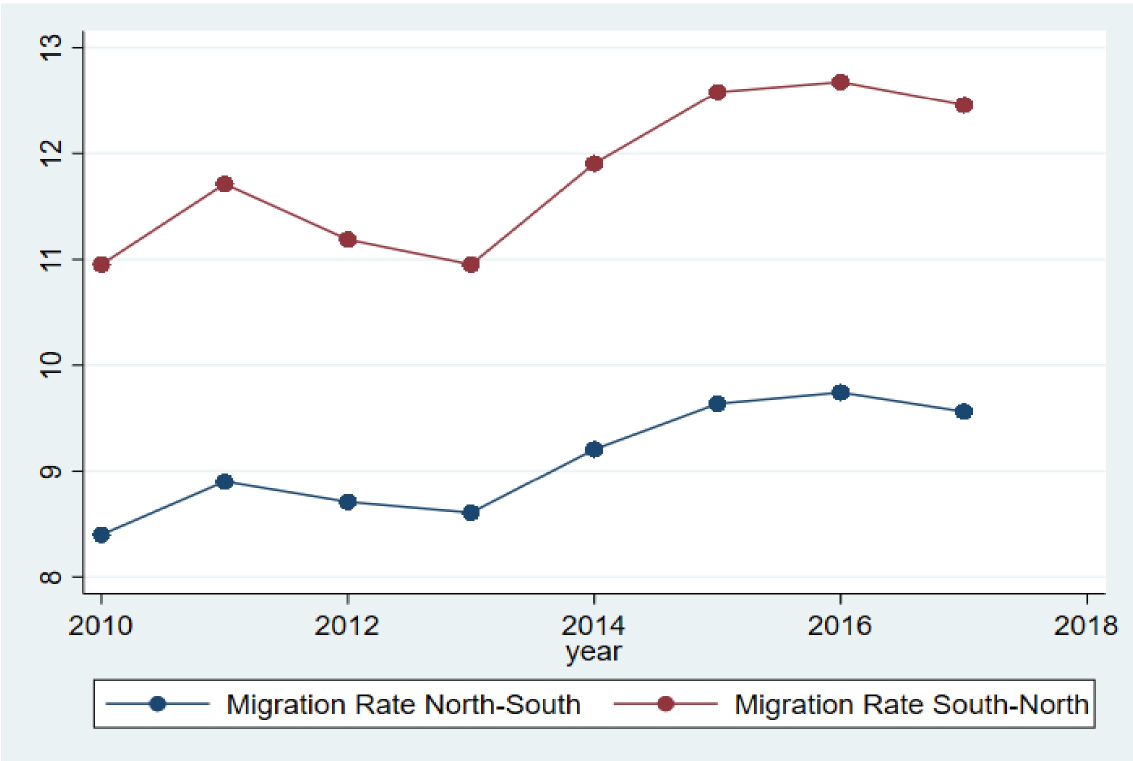


Figure 2. *Net skilled migration rate to total migration Italian macro-area (source: M.I.U.R)*

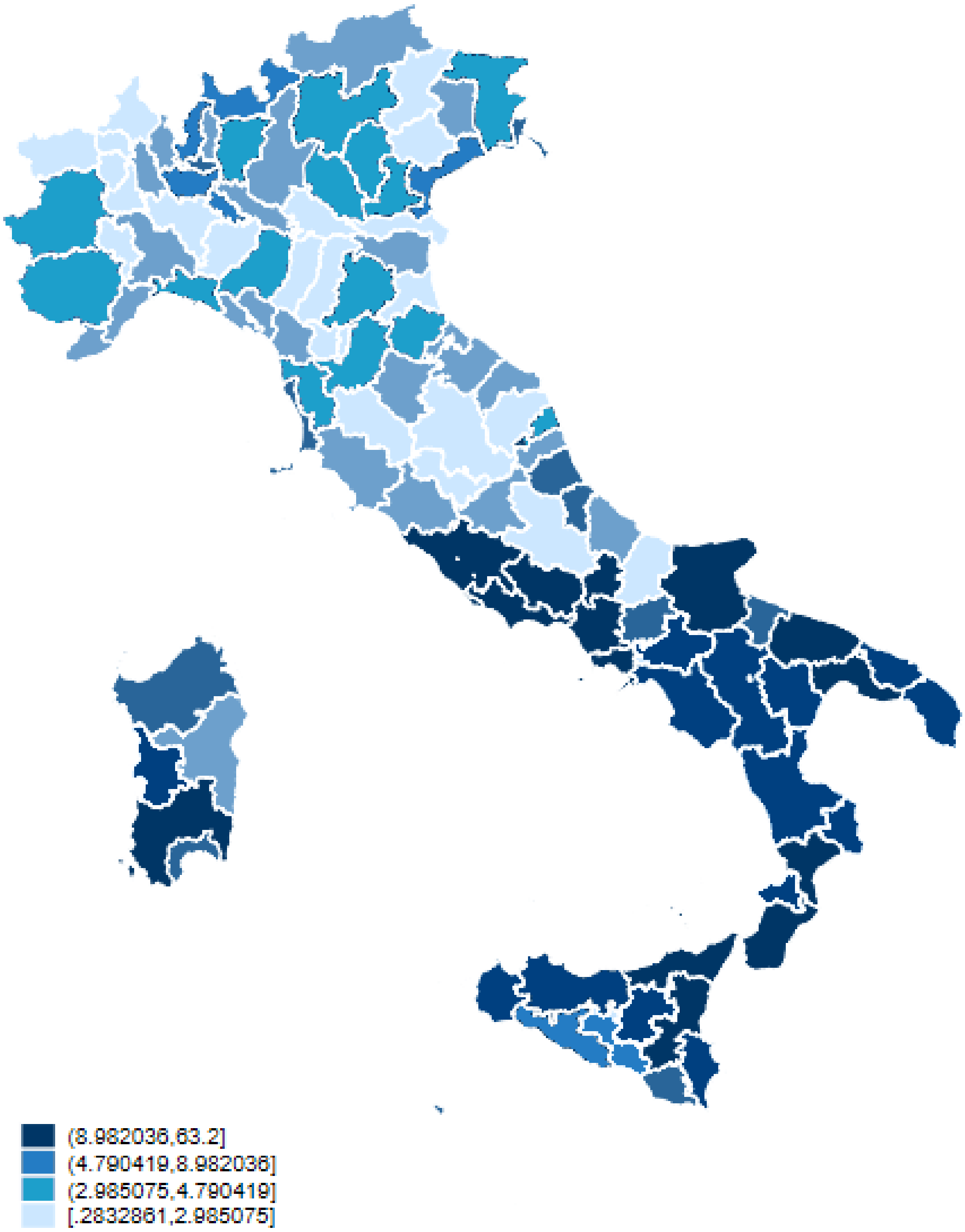


of skilled people to their homeplace, as a recent survey of Il Sole 24 Ore reports: on 23 percent (%) of skilled emigrants interviewed, 1 student over 5 has decided to return in Italy and 1 student over 4 has decided to return to his/her origin place. Undoubtedly, the return of talents can reduce the harmful effects of losses at origin but also remittances, sent by workers to support their families at origin, are remedies against the negative consequences derived by net skilled escape. As reported by Bank of Italy, remittances in Italy rise from 0.3 percent (%) in 2010 to 0.5 percent (%) of GDP in 2017[5] only. Similarly, corruption is a widespread phenomenon alongside brain drain in Italy. As reported by the Corruption Perception Index (CPI), published by Transparency International (TI), Italy is ranked on 52nd place over 180 global countries, on 20th place over 27 European countries, for considerable presence of corruption in 2020[6]. Besides, as evidenced by the Global Corruption Barometer (GCB), one of the most detailed survey of people's views on corruption and experiences of bribery in the 27 EU countries, almost 34 percent (%) of interviewed people believe that corruption increased in the previous 12 months in Italy (2021)[7] against the 26 percent (%) in Denmark (2021)[8] and 16 percent (%) in Finland (2021)[9]. In addition, GCB reports that almost 3 percent (%) of users paid a bribe and used personal connections to access public services in the last 12 months in Italy (2021) against 1 percent (%) of users of public services in Denmark and Finland respectively (2021)[10].

Furthermore, corruption within Italian provinces varies and is higher for provinces that are in the southern macro-area. As Figure 3 reports, from 2010 to 2017, the annual average corruption is between 9 percent (%) and 60 percent (%) for the centre-southern provinces whereas it is below 9 percent (%) for the northern provinces[11].

[5] Data are available at: Personal remittances, received (% of GDP) - Italy | Data (worldbank.org)
[6] The list of countries ranked for Corruption Perception Index (CPI) for year 2020 is available at: Italy Transparency.org
[7] Data of the Global Corruption Barometer for Italy are available at: Results European Union Transparency.org
[8] Data of the Global Corruption Barometer for Denmark are available at: Results European Union Transparency.org
[9] Data of the Global Corruption Barometer for Finland are available at: Results European Union Transparency.org
[10] These reported data can be viewed at: Results - European Union - GCB - Transparency.org
[11] The map is realized by the author with STATA with data provided by RE.GE ISTAT upon request

Figure 3. *Annual Average Corruption within Italian Provinces 2010-2017 (source: RE.GE ISTAT)*



Hence, descriptive statistics reveal that both phenomena are widespread within Italian provinces and need to be studied by researchers and monitored by policymakers constantly. Although hypothesis of the push effect of corruption on skilled (not skilled) migration have been studied by researchers so far, this paper investigates the dual push-pull role of corruption over young Italian brain drain. To this end, this study adopts a methodology with elements of novelty that consists of i) using an original tri-panel dataset with bilateral data aggregated at Italian provincial level, providing more detailed information on skilled mobility than cross-section and cross-country data can afford, ii) modelling net skilled migration with the aid of a recently released gravity model (the Pseudo Poisson Maximum Likelihood Model with High Dimensional Fixed Effects) apart from more standard methods belonging to the Poisson family models (Zero Inflated Poisson model), iii) investigating under-explored factors that may influence students' decisions to emigrate, and iv) checking the validity of results by adopting strategies that prove the coexistence of robustness and completeness in the empirical analysis if models are correctly implemented. Results suggest the presence of push and pull mechanisms of corruption at play over young skilled mobility. Besides, the sensitivity of prospective tertiary students to corruption varies according to their field of study of interest. Also, corruption significantly affects long-distance skilled movements from the Centre-South to the North of Italy mainly. Hence, this paper offers interesting cues for adopting public policies necessary to overthrow inequalities within provinces affected by corruption and net skilled migration mostly. Fighting against corruption and brain drain is not only an important short and medium-term policy concern but has even more relevant consequences in the long run as it might have long-lasting effects on human capital accumulation and distribution at odds that may strength inequalities within Italian provinces.

The present paper is organized as follows: Section II delineates the core literature that yields the basis for formulating the main research hypotheses. Then, Section III describes data used and the methodological approaches adopted. Finally, Section IV presents the main results corroborated by additional analyses as robustness check while Section V provides the conclusion to the paper.

2. Literature Review

Human mobility is an interesting but complex phenomenon due to not uniquely identifiable cause (Faggian et al., 2017). A conspicuous part of literature on net skilled migration has already indicated the main determinants and patterns of students' mobility. Three main streams of research can be identified. The first group of studies considers students' preferences, personal attitudes and their family background as key elements that exercise influence over mobility from source to destination places to enrol at a given university (Weisser, 2020; Ciriaci 2013, Biagi et al., 2011 Kellcgtermans and Verbovern, 2010). The second group of studies considers local quality of university as main decisional element for pre-graduated students to move away (Beine et al., 2014, Ciriaci, 2013; Dotti et al., 2013; Van Bouwel and Veugelers, 2013). The third group, instead, indicates the quality of life and labour opportunities as decisive factors for skilled flows. In fact, the *jobs versus people' debate*, whether people following job opportunities or better quality of life determine people's location decisions, is still an open issue on which policy makers are interested to learn the main causes of skilled mobility (Ketterer and Rodriguez-Pose, 2015). Besides, the efficiency of institutions and the widespread civic sense encourage skilled people to move from origin, where these factors are scarce, to different destinations, where, instead, these elements are predominant (Auer et al., 2020; Nifo and Vecchione, 2014; Dotti et al., 2013; Biagi et al., 2011; Mayda, 2009). Furthermore, corruption has been already recognized as promoting factor of migration and net skilled migration. Dimant et al., 2013, in a cross-country dataset, demonstrate that corruption is the main push factor of average migration and tends to diminish the returns to education. Cooray and Schneider, 2016, in a cross-country dataset, find that as corruption increases, the emigration rate of high-skilled individuals increases while the emigration rate of medium and low-skilled migrants, increases at initial levels of corruption and then decreases beyond a certain threshold, depicting a non-linear relationship apparently[12]. Poprawe, 2015, in a cross-section dataset with bilateral data, finds that high level of corruption at origin province encourages emigration while discourages immigration. In fact, Poprawe,

[12] For more details, see **Cooray and Schneider, 2016**

2015, offers a complete study on the dual effects of corruption over (not skilled) average migration. In doing so, the author evaluates data of 230 world countries, taken by World Bank's Global Migration Database Ozden et al., 2011[13], from 2000 to 2010, with the Negative Binomial Model. Then, the author adds robustness analyses made with the Extreme Bound Analysis (EBA) and Pseudo Poisson Maximum-Likelihood (PPML) models with heteroscedasticity-robust standard errors à la Santos Silva and Tenreyro, 2010. However, in contrast to the present paper, Poprawe, 2015 considers the average migration rate as main dependent variable while the Corruption Perception Index[14] (CPI) for origins and destinations, from 2000 to 2010, as proxy of the independent variable for corruption. Then, opposite to Dimant et al., 2013 and Cooray and Schneider, 2016, the present paper uses a tri-panel dataset with upgraded bilateral data, a non-negative count dependent variable of prospective tertiary students and a more objective-based measure of corruption as main independent variable. Thus, this study expands upon the scanty literature of within-province investigation of corruption and Italian young brain drain and tests the following main hypotheses:

H_1: High corruption acts as push factor for young skilled mobility from origin provinces

H_2: Low corruption acts as pull factor for young skilled mobility to destination provinces

These hypotheses are not mutually exclusive because the occurrence of the first event does not necessarily imply the occurrence of the second event. Until now, the traditional literature on corruption and brain drain has evidenced the push effect of corruption but this study tries to fill the gap with the existent literature and to acquire knowledge on the pull effects of corruption. In fact, individuals, who are exhausted of corrupted homeplaces, prefer to move to destinations where corruption is lower generally. Hence, they gather information on the context of their targeted

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[13] This dataset cover data for 230 world countries. For more details see: Ozden, C., Parsons, C. R., Schiff, M., Walmsley, T. L. (2011) "Where on earth is everybody? The evolution of global bilateral migration 1960–2000", *World Bank Economic Review*, 25(1), 12–56.

[14] Treisman, 2007, Corruption Perception Index (CPI) is provided by Transparency International (TI) and measures how public users perceive the spread of corruption among politicians and officials. CPI rank countries from 0 to 10, where 0 indicates high level of perceived corruption while 10 indicates low level of perceived corruption. To avoid the distorting effect on scoring caused by shocks, such as exposure to scandals, the score combines assessments from the last two years.

destination with the help of their family's members and/or friends, social media and/or newspapers, recognizing that their designed destinations are effectively characterized by lower level of corruption. However, alternative hypotheses should be considered. On one hand, students who do not migrate from corrupted origins are those who are motivated to pursue better quality of life and do not engage in corrupted activities, creating a virtuous circle that lowers the existent level of corruption. On the other hand, students who do not migrate from corrupted origins are those who are probably less sensitive to corruption and engage in criminal activities, generating a vicious circle that increases the existent level of corruption further. However, even if the two hypotheses are not verified, these ones cannot be necessarily interpreted as evidence that corruption is not a remarkable factor because the null outcome can be determined by the interplay of the two opposite effects derived by escaping from corruption at origin and fighting against corruption by remaining in the native places.

On the premises of these hypotheses, this paper explores an aspect that has never been handled for the Italian case so far. In past times, prospective tertiary students of Medicine or Engineering, even due to the physical absence of certain courses in the university of origin province, tended to emigrate more than prospective tertiary students of Law or Economics. However, in last years the number of prospective tertiary students of Social and Physical Sciences, who emigrate, increases more than the number of students of Life Science[15]. Thus, this paper investigates whether corruption differently influences skilled mobility trends and tests the third hypothesis as follows:

H_3. Sensibility to corruption varies among prospective tertiary Italian students who choose to enrol to courses belonging to different fields of study (Social Science, Physical Science and Life Science).

Hence, by comparing the magnitude of the estimated coefficients, this study analyses whether prospective tertiary students of Law are more sensitive to corruption and emigrate more than prospective students of Biology or Medicine and/or differences of these types are not discernible.

[15] From 2010 to 2017, the number of prospective tertiary students of Social Science (ERC-1) who emigrate rise by 8 percent (%) as well as the number of prospective tertiary students of Physical Science (ERC-2) rise by 16 percent (%) whereas the number of prospective tertiary students of Life Science (ERC-3) decreases by a mild 5 percent (%) (source: own elaboration with data provided by M.I.U.R)

Furthermore, part of the literature has poorly examined the Italian skilled movements occurring between places located at different distances. For example, Michaeli et al. 2021, retain that long-distance skilled mobility from the South to the North of Italy is driven by the search of higher civicness due to stringent enforcements of civic behaviour in the North that makes migration more attractive for the southern skilled individuals. A tentative analysis is offered by Biagi et al., 2011, who examine the main determinants of long-and short-distances (not skilled) migration within Italy. Thus, this paper reproduces this framework and investigates if corruption maintains its effects over long-distance movements by testing the following fourth hypothesis:

H_4: Corruption maintains its push and pull effects when long-distance skilled mobility is considered

Biagi et al., 2011, find that economic factors have greater influence over long-distance flows, while quality of life related factors affect short-distance flows. However, the analysis is based on data of Italian migration for two years (2001-2002) that may not still reflect the current causes of skilled mobility. Besides, these data are not sufficient for concluding that short movements occur due to search of better quality of life instead of economic conditions in the long run. Another limit of this study is represented by the fact that those who do not migrate are not considered. In addition, it does not take explicitly account of regional or provincial fixed effects nor they cluster standards errors with Negative Binomial Regression model (NBREG). However, the present paper tries to overcome those methodological limits faced by Biagi et al., 2011, by adopting the novel Pseudo Poisson Maximum Likelihood (PPML), with the gravity set-up (Santos Silva and Tenreyro, 2006).

Another critical aspect that is treated in this paper concerns endogeneity. Generally, the common approach relies on the Instrumental Variable (IV) regression with the lagged instruments of the main variables and/or alternative instruments. For example, Mayda, 2009, uses the lagged value of per worker GDP at home and abroad as instrument on emigration rate. Dotti et al., 2013, opt to instrument the dependent variable of enrolled students with its past values. Besides, Biagi et al., 2011, use the two-stage GMM regression with three alternative instruments for per capita GDP and unemployment, such as the performance of football teams, the industry mix employment and the number of ATM machines per 10,000 inhabitants at destination. Also, Beine et al., 2014, argue that the choice of destination is determined by two factors mainly: the costs of moving and search of better quality of university. An interesting aspect on the costs of moving is represented by the network effect between origin and destination. In fact, the presence of compatriots at destinations tends to act as a magnet for autochthonous people. Interestingly, this effect increases with the level of education at destination: higher level of movers' education in the hosting places is associated to higher students' flows of the same nationality in the same hosting place. In doing so, Beine et al., 2014, use data of 180 origin and 13 destination OECDs from 2004 to 2007 and combine Poisson with IV model, by using "guest worker program" as proxy for network flows[16].

Thus, the present study does not limit itself to investigate the potential reverse causality between corruption and skilled flows but also analyses the network effect of skilled mobility from origin to destination, by adopting a new two-stage IV procedure à la Wooldridge, 2018 (Drivas et al., 2020)[17].

In sum, this paper introduces several elements of innovation that consist of i) the adoption of a count dependent variable that indicates the number of prospective tertiary students who decide to enrol to the university (this variable takes into account those students who enrol to their local university of their native province as well as those who, instead, decide to enrol to university located to different destinations), ii) the usage of a newer variable for corruption that is objective-based measure instead of the perception-based indices exploited by the literature[18], iii) the adoption of a newer procedure to deals with endogeneity in gravity model[19], iv) the use of different variables for quality of university and quality of life respect to the ones adopted by the literature so far. A more detailed description for data, sources and models is provided by the following third section titled *Data and Model.*

[16] Guest worker programs were implemented after the second world war in many industrialized countries to attract economic migrants for the explicit purposes of working in specific industries like coal mines or steel factories. They were mostly dropped at the beginning of the 70's. Those bilateral agreements led to the building of important diasporas in the destination countries before 2000.

[17] See *Subsection-Endogeneity* of **Section IV-Results**

[18] See **Section III – Data and Model**

[19] See **Section IV – Results**

3. Data and Model

3.1 Data

Young Italian brain drain was studied by constructing an original tri-panel dataset that is balanced and consists of 20.808 total observations, made by the combinations of 51 Italian origin provinces (*i*), where there is one university at least (we consider the larger one) and 51 Italian destinations provinces (*j*), analysed from 2010 to 2017 (T)[20]. The dependent variable, the number of prospective tertiary students who enrol to local universities, has a considerable number of zeros (0s), about 16.332 over 20.808, and it is not comparable with cross-section and cross-country studies existing in the literature. The reason to adopt a restricted sample of provinces with one university relies on examining the voluntary skilled mobility not forced by the absence of local university but by other non-specified reasons[21]. For that reason, Italian origin provinces that have not local university are excluded from estimations ex-ante, because, by definition, they do not attract flows. Also, those students that move away from Italy to attend tertiary education abroad are not included in the analysis because it would be beyond the purpose of this study and requires different methodologies to be implemented.

The data source used for the Italian brain flows is the Italian Ministry of Education, University and Research (M.I.U.R), while data on corruption within Italian provinces, on quality of Italian universities and on economic features within Italian provinces are taken from different sources as the Italian Centre for Investments and Social Studies (CENSIS), the Italian Ministry of Education, University and Research (M.I.U.R), the Italian University Group of ALMALAUREA and Italian National Institute of Statistics (ISTAT), respectively. Data sources and descriptive statistics are reported by Tables 1 and 2 of *Appendix A*.

[20] A detailed list of Italian provinces for origin and destination is illustrated by **Table A.3** of **Appendix A**

[21] A detailed list of Italian university for origin and destination is illustrated by **Table A.4** of **Appendix A**

3.2 Model

This study reproduces the bilateral net skilled migration within Italian provinces with the gravity set-up[22]. In analogy with the Newton's law of gravity, resident students' flows can be predicted according to the following formula[23] :

$$I_{ij} = K \frac{M_i^{\beta_1} M_j^{\beta_2}}{d_{ij}^{\beta_3}} \qquad [1]$$

where I_{ij} represents the interaction term of the number of prospective tertiary students of origin province *i* who move to university located in origin province (*i*) or destination province (*j*), K is a proportionality constant, M_i indicates the mass of origin province, M_j is the mass of destination province while d_{ij} indicates the Euclidean distance between origin and destination provinces. In addition, β_1 is the coefficient that estimates flows from mass origin *i*, β_2 flows that are attracted to mass destination *j* and β_3 is an impedance factor reflecting distance decay between masses *i* and *j* (Dotti et al., 2013). Given Equation [1], the above gravity set-up is estimated by an econometric model, as described by Dotti et al., 2013, with the following form:

$$I_{ij} = f\,(\text{origin characteristics, destination characteristics, distance, controls}) + \varepsilon_{ij} \quad [2]$$

where I_{ij} represents the count dependent variable of the number of young Italian students who enrol to university at origin/destination provinces. Besides, additional count dependent variables are added, indicating the number of prospective tertiary students who apply to courses of Social Sciences (ERC-1), Physical Sciences (ERC-2) and Life Science (ERC-3), respectively[24]. Equation [2] reports variables which are two-fold featured for Italian origin (*i*) and destination (*j*) provinces, the Euclidean distance, a set of controls and provinces-specific variables, which consist of geographic dummies for central and southern provinces (origin and destination), which are meant to control for the traditional North–South migration flows that characterize Italy (Dotti et al., 2013). The error term is included.

[22] A theoretical framework of gravity models is illustrated in *Additive Notes* of **Appendix C**
[23] Dotti et al., 2013, report the same gravity model with similar specification. For more details, see Dotti et al., 2013
[24] A detailed list that describes each graduate course per study field is reported by **Table A.5** of **Appendix A**

The main independent variable is corruption (origin and destination). It refers to the number of crimes reported to prosecution departments resulting in criminal proceedings. Contrary to the traditional literature of crime and corruption, where scholars adopt perception-based indices for corruption[25] in the absence of alternative proxies, this paper uses a more objective-based proxy for meritocracy, that provides the idea of students' preferences to live in fair contexts where merit is fully awarded and the possibility to move upward in the society to achieve a respected *status quo* is likely to occur without the exploitation of political connections, social groupings and/or cronyism. Specifically, this variable encompasses Italian corruption crimes from 2010 to 2017 reported from the Annals of Criminal Statistics (Re. Ge) published by the National Institute of Statistics (ISTAT). This measure collects the number of crimes according to in the Italian penal code from art. 314 to art. 322-bis, which cover bribery by and to public officials, judicial bribery, promised bribery and incitement to bribery, embezzlement, misuse of public funds, undue receipt of economic benefits and extortion by virtue of office. Some of these crimes are very often related to bribery. Besides, all reported crimes, grouped together in the official statistics, are those referred to a court. This avoids the distortions usually existing in the number of crimes reported simply to the police, which do not account of posterior dismissed charges[26]. However, this proxy presents some criticisms. First, it can be evaluated as a measure of crime detection due to the effort of prosecution departments to investigate and impose criminal charges and may determine the underestimation of such phenomenon even if in the dynamic framework, this aspect becomes irrelevant. Second, the number of detected crimes can be affected by the different quality of activities performed by different prosecution agencies (Treisman, 2007). Then, as corruption increases, underreporting or reduced number of investigations can occur. This may be due to lack of trust to the judiciary or the time constraints facing the investigation that become more

[25] The most used perception-based indices in international studies are the Corruption Perception Index (CPI) provided by Transparency International (TI), the Worldwide Governance Indicator (WGI) provided by World Bank (WB) and the International Country Risk Guide (ICRG) provided by Political Risk Services Group (PRSG).
[26] There is evidence of robustness of this proxy. For more details, see Lisciandra and Millemaci, 2017.

binding. However, this negative result can be mitigated by the spill-over effects of the investigative activity in crime reporting, maintaining this issue still debatable (Lisciandra and Millemaci, 2017). Then, Equation [2] uses alternative gravity variables of distance and masses (origin and destination). In particular, time (expressed in minutes) is used in place of the traditional Euclidean distance (expressed in kilometres) and indicates the time necessary to travel from source to destination provinces by car. Besides, time captures general migration costs that a person sustains when he/she moves to places far from his/her home. High time needed to travel by car from origin to destination, higher the general migration costs that, in turn, disincentive people to move (Dotti et al., 2013). Also, average population (origin and destination) is used as mass variable that describes the capacity of places to draw flows. Consistently with the prediction of the gravity model, large urban agglomerates attract many individuals because of great number of services and facilities hosted (Beine et al., 2014). As to university-specific characteristics, this paper adds size of university and quality of university (origin and destination). First, larger universities are preferable because they offer more students' services (libraries, study-rooms cafeteria, gym), didactic, extra-didactic, career facilities and international programs (inclusive of ERASMUS programs) than smaller universities (Ciriaci, 2013). Then, quality of university is constructed by taking the average of the standardized values of age, grade, expected per capita income, expected time to find a job when students get graduation from their three-years course program at least[27]. All these factors adapt to students' expectations in evaluating their university choices because they arguably care of the 'working prospects' for learning specific-skills required to find a valuable job tomorrow. In addition, quality of life is added. It is given by the average of the standardized values of mortality rate, working formation, gender difference in employment, the presence of green urban areas, childcare and eldercare[28] that are indicators related to the personal health and social well-being, that, in turn, influence individuals' standards of living[29].

[27] For details related this variable, see *Additive Notes* **of Appendix C**
[28] Data source is ISTAT
[29] For details related this variable, see *Additive Notes* **of Appendix C**

Then, as control variables, this paper uses per capita real GDP and employment (origin and destination). Specifically, employment controls for safety while per capita real GDP does not only capture welfare effects but also the capacity of high-income families to bear students' costs of studying far from their homeplaces (Ciriaci, 2013). Also, the present analysis inserts dummies that indicate the presence of airports, ports and high-speed railway stations (origin and destination). These infrastructures favour mobility and engrave general costs of moving within places (Dotti et al., 2013). Finally, variables of law enforcement are used as controls for the underestimated cases of corruption. In fact, law enforcements indicates the efficiency of judicial system to detect and punish illegal behaviours to guarantee safety and security for the entire society (Treisman, 2007).

Estimations of Equation [2] are performed by adopting Zero Inflated Poisson (ZIP) and the cutting-edge Pseudo-Poisson Maximum Likelihood with High Dimensional Fixed Effects (PPML or PPMLHDFE) proposed by Long (1997) and Santos Silva and Tenreyro (2010), respectively. These models belong to the Poisson family models. General Poisson belongs to the Generalized Linear Model (GLM) class of popular non-linear regression models based on the exponential family of distributions. Final estimates of these two models are compared in order to check signs and significances of their estimates. While ZIP allows to consider the highly skewed distribution of the dependent variable and overdispersion, assuming that there are two different types of observations in the data, those who have a zero count with a probability of 1 (0 group), and those who have counts predicted by the standard Poisson (not 0 group) (Long, 1997), PPML presents statistical properties that renders this model suitable for bilateral panel data because of i) relaxing assumption of knowledge of distribution of the non-negative dependent variable, ii) providing more natural way to deal with great number of zeros of the dependent variable as ZIP, iii) dealing better with sources of heterogeneity within larger panel-type dataset instead to resort to log-linear regressions (Correia et al., 2019), iv) allowing flexibility with multiple fixed effects and interactions (Fally, 2015), v) `ppmlhdfe` command of Correia et al. (2020) favours less time-consuming estimation of parameters of interest even in presence of multiple fixed effects (Santos Silva and Tenreyro, 2010). Besides, a recent article written by Correia, Guimaraes and Zylkin (2020) promotes PPML as valid tool that can detect and discard observations that do not convey relevant information for the estimation process. Thus, PPML represents a promising procedure to process complex estimations with high-dimensional covariates without renouncing to completeness of results (Correia et al., 2019). The following section titled *Results* reports the final outcomes get from the estimation of Equation [2] with ZIP and PPML.

4. Results

4.1 Main Results

The main results are reported in Table 1. In accordance with the gravity framework, these models use time as accurate measure of distance within provinces and the average population as mass variables of source and destination provinces. Besides, *Notes* report the additional variables included in the regression but not displayed in Table 1, such as law deterrence, used as a control variable for the stability of judicial enforcement at origin *i* and destination j. Besides, both models consider fixed effects of centre and southern area plus years (2010-2017). The decision to insert fixed effects grouped for macro-area permits to detect common and relevant time-invariant effects that cannot be revealed if, instead, provinces are used. To address the correlation between the error term over time, clustered-robust standard errors are used to check statistical significance of the parameters.

Column (I) uses as dependent variable, the number of prospective tertiary students, column (II) uses, instead, the number of prospective tertiary students who enrol to courses of Social Science (ERC-1), column (III) of Physical Science (ERC-2) and column (IV) of Life Science (ERC-3). Columns I to IV show-off the estimates by ZIP while columns V to VIII display estimates performed by PPML.

Corruption exhibits the expected positive sign for the origin and negative sign for destination provinces. Besides, it is strongly significant for both specifications, meaning that higher corruption at origin positively influences, on average, young skilled mobility from native places, while lower corruption at destination, attract skilled flows, ceteris paribus. Although the result of the push effect of corruption is in line with the studies of Dimant et al. (2013), Dotti et al., (2013), Nifo and

Vecchione, (2014), Cooray and Schneider (2016), the result of the pull effect of corruption is rarely considered by the recent literature (Poprawe, 2015) and this paper strives to disclose this new finding. Furthermore, this study attempts to understand if the sensitivity to corruption is homogeneous or not among prospective tertiary students: results suggest that students, who decide to enrol to courses of Social Sciences (ERC-1) and Physical Sciences (ERC-2) are more sensitive to corruption at origin (which is statistical significant at 5 percent (%) and 10 percent (%) confidence level on columns II and III, significant at 5 percent (%) and 2 percent (%) on columns VI and VII) than students who enrol to courses of Life Science (ERC-3) and for whom corruption is not a significant influencing factor (columns IV and VIII) for deciding to rest or move away. To understand the intensity of the phenomenon under examination, we interpret the magnitude of the coefficients with their standard deviations. A unit increase of standard deviation in the corruption levels of origin results in an average increase of skilled mobility between 7.8 and 10 percentage points, between 5 and 6.8 percentage points for students of Social Science, between 8 and 16 percentage points for students of Physical Science and between 2 and 4.9 percentage points for students of Life Science. This novel result can be explained in two ways: first, students who enrol to courses of Social Science are, on average, more lawful-oriented than those who enrol to courses of Life Sciences. Hence, students of Social Sciences are more sensitive to meritocracy and they are prone to condemn the misuse of legal powers. Then, a second explanation relies on the fact that sensitivity to corruption reflects the existence of heterogeneous conditions of the job market for these three categories. In fact, in Italy, the employment rate for those who get a graduation in the fields of Social Science and Physical Science is lower than the employment rate for those who get graduation in the field of Life Science[30]. Hence, in the first scenario, where the job mismatch between the labour demand and supply is very pronounced, the competition among participants, after they graduated, to get a job arises and, in turn, events of

[30] According to Almalurea, in 2017, the average employment rate for those who get graduation after 1 year in studies of Social Sciences (ERC-1) is 49.7% while it is 57.2% in studies of Physical Science (ERC-2) against 69.5% in studies of Life Science (ERC-3). Computations are made by own elaboration based on data available at: Condizione occupazionale dei laureati (almalaurea.it).

corruption, such as bribery, are likely to occur. In such scenario, skilled individuals tend to be more sensible to corruption, rather than skilled persons who are going to work in the second scenario. This motivation seems to prevail over the fact that, in Italy, those who graduate in Medicine are more likely to work in the public sector, where events of corruption occur usually, than those who get graduation in Economics, Engineering and Law, who are likely to work in the private sector[31].

Then, time and the average population of origin and destinations are statistically significant and have the expected signs: time exhibits negative sign, meanwhile, the average population of source and destinations has positive sign. Signs and magnitude of these variables are consistent with the predictions of gravity model. In fact, greater mass means that the city is large enough to offer services and entertainment activities that attract skilled people to join, while higher time necessary to travel between far-distanced provinces, does not incentivize migration due monetary and non-monetary costs of leaving home. In addition, per capita real GDP has the expected positive sign for origin and negative for destination. In fact, positive sign represents high-income families who can afford high educational costs for their young students once they decide to enrol to universities placed far-away from their homeplace. This result is in line to Ciriaci and Palma, 2008 and Ciriaci, 2013. However, for ZIP, per capita real GDP is not statistically significant neither for origin nor for destination. For PPML, it is statistically meaningful at origin (5 percent (%) and 10 percent (%) confidence levels on columns V VI and VII) and destination (10 percent (%) on column VII). Besides, for ZIP and PPML, employment rate reveals the expected negative sign at origin and positive sign for destination. It is statistically meaningful for origin, while is statistically significant for destination for PPML only (on columns V, VI and VII). Intuitively, students make their migration choices by comparing job opportunities offered by native and destination labour markets and choose the one that offers higher and better chances of employment (Dotti et al., 2013). Then, size of university has the expected negative sign for origin and positive sign for destination. Size of university is statistically significant

[31] According to Almalurea, in 2017, the average of graduates in Medicine (ERC-3) who work in the public sector is 25.6% against 14.0% of those who are graduated in Law (ERC-1), 5.7% in Economics (ERC-1) and 5.1% in Engineer (ERC-2). Data are available at: Condizione occupazionale dei laureati (almalaurea.it).

for origin and destination for PPML (1 percent (%) and 10 percent (%) confidence level on columns V, VI, VII and VIII). Thus, if size of university of origin is large, the number of resident students who move decreases because they prefer to attend universities that offer many didactic and job-partnered courses near their home. Besides, the increase of enrolments permits to large universities to become even larger because they acquire additional resources, depleting them from small universities, that, in turn, become even smaller (Ciriaci, 2013). Also, the average of the standardized values for quality of university is inserted. As expected, the sign of quality of university is negative for origin and positive for destination. Quality of university is statistically significant for origin (1% confidence level on columns V, VI and VIII) and seldom significant for destination (5% and 10% on columns VII and VIII). This suggests that high quality of university at origin tends to incentivize skilled individuals to remain to their local university if its educational quality is satisfactory. This result is in line with the main findings achieved by Ciriaci (2013), who recognizes the role of university as a key driver of economic development, through its role in knowledge, production and attraction pole for talents. Then, we add the variable of quality of life. The sign of this variable is negative for origin and positive for destination, with small exceptions. Although it is seldom significant (on columns III and VII) for origin and destination, higher quality of life at origin is associated, on average, with lower skilled mobility to different places. In fact, students prefer to live in communities with efficient services for their safety and security (Beine et al, 2014; Nifo and Vecchione, 2014; Dotti et al., 2013). Furthermore, dummies for airport, port and high-speed railway stations are added to control whether their presence ease the transfers within provinces. Airport displays the expected positive sign for origin. It is seldom significant, but its presence allows us to control for the possibility to travel in fewer hours than needed using cars. High-speed railway and ports present similar patterns. Port is an essential logistic infrastructure needed to connect islands to mainland, preventing from isolation. In addition, it facilitates transport by car and by train and does not discourage the discontinuous mobility. In sum, PPML and ZIP report estimates that have same signs and similar statistical significance with some exceptions, even if PPML presents more meaningful results, on average. For sake of completeness, the following subsections titled *Robustness Check* and *Endogeneity* report additional analyses that corroborate the validity of the main results presented so far.

Table 1. *Main Results with ZIP and PPML*

	ZIP	**ZIP**	**ZIP**	**ZIP**	**PPML**	**PPML**	**PPML**	**PPML**
	I	*II*	*III*	*IV*	*V*	*VI*	*VII*	*VIII*
	Enrolled	ERC-1	ERC-2	ERC-3	Enrolled	ERC-1	ERC-2	ERC-3
time	-.02225***	-.02284***	-.01729***	-.0151***	-.02673***	-.02846***	-.02593***	-.02423***
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
population	2.58e-07**	3.46e-07***	3.46e-07***	7.54e-08	3.03e-07***	3.77e-07***	2.65e-07**	1.79e-07
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
population_j	3.64e-07***	2.52e-07***	2.95e-07**	5.01e-07***	2.83e-07***	1.88e-07**	3.47e-07***	4.10e-07***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
corruption	**.001469****	**.0009438***	**.001603****	**.0005472**	**.001951*****	**.001288****	**.003353*****	**.00101**
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
corruption_j	**-.00311*****	**-.002182*****	**-.003786*****	**-.002017*****	**-.003373*****	**-.00231*****	**-.0055*****	**-.002443*****
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
real GDP per capita	.0000138	.0000127	-7.66e-06	4.90e-06	.0000214**	.0000196*	.0000225*	.0000205
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
real GDP per capita_j	-8.19e-06	3.11e-06	1.10e-06	-.0000114	-.0000104	3.82e-06	-.0000232*	-.0000254
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
employment	-.0469***	-.03719***	-.03909***	-.03518**	-.05837***	-.05432***	-.05377***	-.07205***
	{0.013}	{0.013}	{0.014}	{0.014}	{0.013}	{0.013}	{0.015}	{0.014}
employment_j	.02083	.006165	.009782	.01051	.03291**	.02658*	.02968	.0511***
	{0.014}	{0.015}	{0.016}	{0.015}	{0.014}	{0.015}	{0.018}	{0.016}
size university	-.1436*	-.1179	-.05357	.002883	-.2933***	-.2512***	-.3805***	-.2128*
	{0.086}	{0.084}	{0.105}	{0.108}	{0.081}	{0.081}	{0.099}	{0.115}
size university_j	.3751***	.2002**	.5945***	.2171*	.5308***	.3506***	.8872***	.458***
	{0.095}	{0.091}	{0.124}	{0.121}	{0.091}	{0.088}	{0.112}	{0.137}
quality university	-.3936**	-.3704**	-.263	-.5743***	-.4515***	-.5002***	-.256	-.6431***
	{0.164}	{0.164}	{0.214}	{0.192}	{0.157}	{0.168}	{0.201}	{0.234}
quality university_j	-.04433	-.01318	-.4454*	.267	.09124	.2046	-.4224*	.5262**

	{0.173}	{0.172}	{0.256}	{0.217}	{0.154}	{0.168}	{0.216}	{0.219}
quality life	-.421	-.329	-.6991**	-.2478	-.3295	-.1113	-.7565**	-.2235
	{0.279}	{0.267}	{0.305}	{0.357}	{0.277}	{0.262}	{0.310}	{0.416}
quality life_j	.2607	-.01667	.5656**	.1987	.2077	-.241	.8157***	.4393
	{0.240}	{0.262}	{0.272}	{0.311}	{0.235}	{0.258}	{0.265}	{0.341}
Dairport	.045	.03806	.04933	.1911	.04778	.05861	.04842	.03189
	{0.116}	{0.107}	{0.136}	{0.153}	{0.113}	{0.114}	{0.135}	{0.158}
Dairport_j	.1044	.1167	-.008307	.3003*	.08623	.05885	-.05277	.3503*
	{0.131}	{0.119}	{0.166}	{0.154}	{0.130}	{0.126}	{0.157}	{0.182}
DTAV	-.0616	-.1039	.04328	.1975	-.2519	-.2952*	-.3534	-.03559
	{0.192}	{0.185}	{0.232}	{0.200}	{0.172}	{0.162}	{0.220}	{0.198}
DTAV_j	.1386	.2066	-.01834	-.2797	.4581***	.5152***	.5659***	.1758
	{0.180}	{0.174}	{0.232}	{0.232}	{0.151}	{0.146}	{0.187}	{0.195}
Dport	.283**	.2893**	.2047	.1712	.3582***	.403***	.2298	.4739***
	{0.124}	{0.140}	{0.154}	{0.160}	{0.121}	{0.138}	{0.143}	{0.161}
Dport_j	-.04648	-.09002	.1137	-.118	-.08843	-.173	.2069	-.325
	{0.147}	{0.161}	{0.194}	{0.193}	{0.151}	{0.166}	{0.190}	{0.206}
N.	20808	20808	20808	20808	20808	20808	20808	20808
Wald Chi Square	545.044	597.845	367.115	202.422	364.188	375.918	242.792	236.564
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo-R2					0.8725	0.8883	0.8305	0.8067

Notes: For both model's specifications, we inserted law deterrence variables for origin and destination provinces as control values. In addition, fixed effects of dummies for macro-areas of North, Centre and South of origin and destination are included with interaction with year (2010-2017 period). Standard errors account for clustering of provinces. ***, ** and * denote coefficients that are statistically significant at 1%, 5% and 10%, respectively. Results are in **b/se***

4.2 Robustness Check

This subsection reports two robustness checks that consists of i) the addition of the interaction term of distance and transport infrastructures to consider the effective distance to travel from origin to destinations, and ii) the introduction of the constraint for long-distances skilled movements from the Centre-South to the North of Italy. Results are shown in Tables 1 and 2 of *Appendix B* respectively.

Table B.1 demonstrates that the sign of corruption is preserved although loses, in certain cases, statistical significance. At the same time, the sensibility to corruption of those enrolled to courses of different study-fields remain unchanged and in line with the main results previously achieved. Then, Table B.1 reports the interaction of transport infrastructures with distance, expressed in kilometres (km). Interestingly, values are, on average, statistically significant and indicate that their presence reduce the travelling distance (km) between provinces, as its negative sign mainly suggests. In fact, provinces with airports render long-distances achievable in less time. Same consideration is valid for high-speed train stations. For sake of completeness, ports are included in the estimated regression[32]. For the remaining variables, even though part of these of become unstable (for example, per capita real GDP loses significance in all cases for origin and destination provinces, size of university in three cases for origin but not for destination provinces and standardized quality of university in sixth cases for origin and destination provinces), the sign of all the estimated coefficients is preserved mainly.

Furthermore, Table B.2 reports results on corruption that maintains both the positive sign and statistical significance for origin as well as the negative sign and statistical significance for destinations. Besides, the sensibility to corruption for students enrolled in different studies fields remain unchanged even when long-distance moments are considered, further confirming its validity. Then, Table B.2 contains the specification of movements to non-adjacent macro-area. To evaluate the long-distance movements, we group the Italian provinces into three macro-area, namely North,

[32] The interaction term of distance and ports presents positive sign for origin and negative sign for destinations. In fact, connections by ports are not fast as those provided by airports and trains and time necessary to achieve long-distances is double than time spent by airplanes and/or trains. Hence, cities with ports exercise low attractiveness to fast mobility.

Centre and South. This categorical variable, designed for origin and destination, assumes the values of 1 for identifying the North, of 2 for the Centre and of 3 for the South. For all regressions (columns I to VIII), we insert the condition of skilled movements by using as benchmark the value of the Centre (if *macro-area > 2* and *macro-area_j< 2*) for skilled flows from the Centre-South to the North. For ZIP and PPML, time and population preserve their expected signs and are statistically meaningful. For the remaining variables, even if part of these one become unstable via ZIP, the results presented by PPML are more solid because the signs and statistical significance at 10 percent (%) and 5 percent (%) of the estimated coefficients are preserved. In sum, we assess that higher corruption in centre-southern provinces encourages skilled mobility to the North of Italy, because northern destinations exhibit, on average, lower level of corruption, ceteris paribus.

4.3 Endogeneity

A critical concern in empirical analysis is endogeneity which causes biased and inconsistent results. Thus, this study controls for the potential reverse causality between corruption and brain migration by mixing traditional strategies with novel procedures. In addition, it controls for possible bias determined by the network effect. The methodology adopted is similar to the one proposed by Drivas et al., 2020[33]. The instruments for corruption and network are their respective one-year lagged values. For the first relationship, we apply a two-stage residual estimation that is equivalent to a two-stage least square (2SLS) for count data. In the first stage, we regress the endogenous variable of corruption (with dual specification *i* and *j*), with its one-year lag instrument, upon the exogenous variables. Once we recover the predicted residuals (with dual specification *i* and *j*) of this estimation, we plug them into the original models (first, ZIP then PPML) at the second stage. The inference is based on bootstrapping over all the two-step procedure with 200 replications. Results are shown in Table 3, with ZIP in the second stage, and in Table 4, with PPML in the second stage, of *Appendix B*. Both tables present similar results: as expected, the sign of the coefficient of corruption at origin is positive

[33] For more details, see **Drivas et al. 2020**

while for corruption at destination is negative. However, the coefficient for corruption at origin is not statistically significant while it is statistically meaningful for corruption at destination. However, the bootstrap standard errors are relatively low and the estimated residuals for corruption at origin and destination are not statistically significant at 5 percent (%) significance level. Thus, there is weak evidence of endogeneity of corruption not as push but pull factor influencing brain drain once the model corrects for endogeneity. Then, we consider the effects of network over skilled mobility. Network is itself endogenous because past decisions tend to influence current decisions to move (Beine et al., 2014). Hence, one-year lag of the dependent variable of enrolled students is used as instrument for network because it avoids the omitted variable bias and it provides the idea of continuity trend in mobility from origins to destinations. The approach used is the same two-stage procedure described yet. The results are presented in Table 5 of *Appendix B*[34]. All the estimated coefficients have signs as expected. Besides, corruption at origin and network are not statistically significant while the coefficient for corruption at destination is statistically meaningful. However, the bootstrap standard errors are relatively low and the estimated residuals for network, corruption at origin and destination are not statistically significant at the 5 percent (%) significance level. Thus, although there is weak evidence of endogeneity for corruption not as push but pull influencing factor[35] over skilled mobility, network is not a determinant factor over the decisions of skilled individuals to move to places where native communities are deep-seated, contrary to the conclusions achieved by Beine et al., 2014[36]. Again, this result proves that endogeneity is not a severe problem and the results obtained are quite robust[37]. Thus, the trade-off between robustness and completeness in a gravity framework can be ruled out if models are correctly implemented.

[34] We have also used ZIP in the second stage but problem of convergencies arise. Thus, PPML results to be an ideal model to account for endogeneity bias with the two-stage procedure suggested by Drivas et al, (2020) for gravity models

[35] However, one limit can be represented by the number of replications for the bootstrap procedure that is not sufficient (200).

[36] Disclaim for the usage of the instrument for network: one-year lag of the dependent variable of enrolled student may be replaced by other valid instruments that could confirm or not bias of the network effects over young skilled mobility

5. Conclusions

This paper is aimed at expanding the knowledge of the size and magnitude of corruption on young brain drain from origin to destination Italian provinces. The results suggest that corruption has noticeable influence over young skilled mobility. This evidence is robust and persistent throughout the usage of ZIP and PPML, that return similar and significant results. Additive estimates confirm results that do not suffer from severe biases and inconsistency. Thus, this study overrides the trade-off between robustness and completeness, proving that complex models, if correctly implemented, shall ensure the coexistence of both features in the empirical analysis. Evidence suggests that high corruption at origins acts as push factor that incentivizes prospective tertiary students to move away while low corruption at destinations acts as pull factor that attracts skilled individuals to destinations, ceteris paribus. Interestingly, these models exploit full information and add breakthroughs to the main results. In fact, this study finds that sensitivity to corruption of prospective tertiary students varies according to the field they choose for their studies: results suggests that, on average, students of Social and Physical Sciences tend to be more susceptible to corruption than those of Life Sciences. Also, corruption and brain drain partly explains one amongst many possible causes of the socio-economic dualism between North and South of Italy: high corruption in the southern provinces tend to increase the number of skilled individuals who move from the Centre-South to the North of the country. Thus, resources are not equally distributed and determine negative consequences on the growth path of Italy, that runs fast and slow for the North and the South, respectively. Thus, few considerations on policies to reduce both phenomena can be drawn. First, policymakers should invest resources on higher education to promote meritocracy and to build-up lawful-oriented minds of students who are going to be the tomorrow class of workers. To this end, they should increase investments on didactic programs and research for universities because these are gateways for skilled mobility. In fact, universities should be able not only to attract but also to retain talents. Policymakers should ease their structural rigidity, due to excess of bureaucratic norms, and incentive transparency of public competitions and availability of grants that guarantee the right to study for all students. Also, universities should readdress the (job) insecurity suffered by students and alumni by enacting more traineeships and scholarship programs partnered by the career-offices. In doing so, talents are encouraged to remain to their local university. Then, policymakers should regulate skilled mobility and intervene when skilled outflows are greater than skilled inflows. Besides, they should contemplate norms that regulate agreements between SMEs and universities to ease talents-jobs matches on the local job market. Also, local active policies should be reinforced to eliminate disparities among underprivileged skilled minorities (women). These step-by-step corrections would lead to a virtuous circle of retaining talented flows from origin places.

Future research could therefore be directed toward conducting an empirical analysis that investigates the effects of remittances from native residences on the level of corruption at origin.[38] Another challenging task of this study consists of refining a complete subjective-objective measure for corruption, by constructing an index that encompass variables at micro, meso and macro-levels.

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[38] It is presumed that places that receive remittances from abroad are affected by economic and social issues. For more details, see Rapoport and Docquier, 2006

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Appendix A

***Table A.1**. Source of Main Variables*

Variables	*Notes*	*Source*
enrolled	number of resident students who enrol from origin province, with one local university, to university of destination provinces	MIUR
enrol erc1	number of resident students who enrol to courses of Social Science	MIUR
enrol erc2	number of resident students who enrol to courses of Physical Science	MIUR
enrol erc3	number of resident students who enrol to courses of Life Science	MIUR
time	time expressed in minutes to travel by car from origin to destination	ISTAT
pop/pop_j	average annual population of origin/destination	ISTAT
corruption/corruption_j	corruption of origin/destination vs PA (art 314-322 Italian penal law)	RE.GE ISTAT
rgdppc/rgdppc_j	per capita real GDP origin/destination, base GDP year 2010	ISTAT
employment/employment_j	employment rate of origin/destination	ISTAT
uni size/uni_size_j	number of enrolled =1 small, =2 medium, =3 large origin/destination	CENSIS
zquniv/zquniv_j	standardized value of quality of university of origin/destination	AlmaLaurea
zqlife/zqlife_j	standardized value of quality of life for origin/destination	ISTAT
Dairport/Dairport_j	dummy for airport, D=1 airport presence, D=0 otherwise	ISTAT
DTAV/DTAV_j	dummy for high-speed train, D=1 HST presence, D=0 otherwise	Ferrovie Stato
Dport/Dport_j	dummy for port, D=1 port presence, D=0 otherwise	ISTAT
Dnorth/Dnorth_j	dummy for North macro area origin/destination	ISTAT
Dcentre/Dcentre_j	dummy for Centre macro area origin/destination	ISTAT
Dsouth/Dsouth_j	dummy for South macro area origin/destination	ISTAT
disccrim/disccrim_j	variable indicator of law enforcement of origin/destination	ISTAT
probofconv/probofconv_j	variable indicator of law enforcement of origin/destination	ISTAT

Table A.2. *Descriptive Statistics*

Variable	***Observations***	***Mean***	***Std. Dev.***	***Min***	***Max***
enrolledp1	20.808	67.76812	629.636	0	21007
enrol_erc1	20.808	35.98678	349.8259	0	11929
enrol_erc2	20.808	20.06695	191.2988	0	6649
enrol_erc3	20.808	11.71631	94.28154	0	2725
time	20.808	390.6581	244.3646	0	1026.9
pop	20.808	806643.1	783995.2	126202	4355725
pop_j	20.808	806643.1	783995.2	126202	4355725
corr_tot	20.808	41.3848	53.14326	1	413
corr_tot_j	20.808	41.3848	53.14326	1	413
rgdppc	20.808	26699.84	7906.145	12831.49	54500.27
rgdppc_j	20.808	26699.84	7906.145	12831.48	54500.27
employment	20.808	56.67339	10.4165	3.623.432	72.9
employment_j	20.808	56.67339	10.4165	3.623.432	72.9
uni_size	20.808	2.098039	.7209889	1	3
uni_size_j	20.808	2.098039	.7209889	1	3
zquniv	20.808	-1.04e-09	.3973304	-.7653301	183.594
zquniv_j	20.808	2.85e-10	.3568086	-.7678611	1.829
zqlife	20.808	.0026567	.2734514	-.7520893	1.398.549
zqlife_j	20.808	-1.71e-09	.3245846	-.843572	.9806968
disccrim	20.808	21.42328	5.567764	10.2	39.2
disccrim_j	20.808	21.42328	5.567764	10.2	39.2
probofconv	20.808	.2744877	.0990663	.042898	.6575092
probofconv_j	20.808	.2744877	.0990663	.042898	.6575091
Dairport	20.808	.5196078	.4996274	0	1
Dairport_j	20.808	.5196078	.4996274	0	1
DTAV	20.808	.1372549	.3441245	0	1
DTAV_j	20.808	.1372549	.3441245	0	1
Dport	20.808	.254902	.4358166	0	1
Dport_j	20.808	.254902	.4358166	0	1
Dnorth	20.808	.3921569	.4882431	0	1
Dnorth_j	20.808	.3921569	.4882431	0	1
Dcentre	20.808	.1960784	.3970381	0	1
Dcentre_j	20.808	.1960784	.3970381	0	1
Dsouth	20.808	.4117647	.4921648	0	1
Dsouth_j	20.808	.4117647	.4921648	0	1
macro-area	20.808	2.019608	.8964239	1	3
macro-area_j	20.808	2.019608	.8964239	1	3

Table A.3 *Italian Provinces, Regions and Macro-area of origin and destinations*[39]

Province/Province_j	***Region/Region_j***	***Macroarea/Macroarea_j***
Torino	Piedmont	North
Vercelli	Piedmont	North
Novara	Piedmont	North
Cuneo	Piedmont	North
Asti	Piedmont	North
Alessandria	Piedmont	North
Biella	Piedmont	North
Verbania	Piedmont	North
Aosta	Aosta Valley	North
Imperia	Ligury	North
Savona	Ligury	North
Genova	Ligury	North
La Spezia	Ligury	North
Varese	Lombardy	North
Como	Lombardy	North
Sondrio	Lombardy	North
Milano	Lombardy	North
Bergamo	Lombardy	North
Brescia	Lombardy	North
Pavia	Lombardy	North
Cremona	Lombardy	North
Mantova	Lombardy	North
Lecco	Lombardy	North
Lodi	Lombardy	North
Monza	Lombardy	North
Bolzano	Trentino-Alto Adige	North
Trento	Trentino-Alto Adige	North
Verona	Veneto	North
Vicenza	Veneto	North
Belluno	Veneto	North
Treviso	Veneto	North
Venezia	Veneto	North
Padova	Veneto	North
Rovigo	Veneto	North
Udine	Friuli-Venezia Giulia	North
Gorizia	Friuli-Venezia Giulia	North
Trieste	Friuli-Venezia Giulia	North
Pordenone	Friuli-Venezia Giulia	North
Piacenza	Emilia-Romagna	North
Parma	Emilia-Romagna	North

[39] Data source is provided by ISTAT

Reggio nell'Emilia	Emilia-Romagna	North
Modena	Emilia-Romagna	North
Bologna	Emilia-Romagna	North
Ferrara	Emilia-Romagna	North
Ravenna	Emilia-Romagna	North
Forlì-Cesena	Emilia-Romagna	North
Rimini	Emilia-Romagna	North
Pesaro	Marche	Centre
Ancona	Marche	Centre
Macerata	Marche	Centre
Fermo	Marche	Centre
Ascoli Piceno	Marche	Centre
Massa Carrara	Tuscany	Centre
Lucca	Tuscany	Centre
Pistoia	Tuscany	Centre
Firenze	Tuscany	Centre
Livorno	Tuscany	Centre
Pisa	Tuscany	Centre
Arezzo	Tuscany	Centre
Siena	Tuscany	Centre
Grosseto	Tuscany	Centre
Prato	Tuscany	Centre
Perugia	Umbria	Centre
Terni	Umbria	Centre
Viterbo	Lazio	Centre
Rieti	Lazio	Centre
Roma	Lazio	Centre
Latina	Lazio	Centre
Frosinone	Lazio	Centre
Caserta	Campania	South
Benevento	Campania	South
Napoli	Campania	South
Avellino	Campania	South
Salerno	Campania	South
L'Aquila	Abruzzo	South
Teramo	Abruzzo	South
Pescara	Abruzzo	South
Chieti	Abruzzo	South
Campobasso	Molise	South
Isernia	Molise	South
Foggia	Puglia	South
Bari	Puglia	South
Taranto	Puglia	South
Brindisi	Puglia	South

Lecce	Puglia	South
Trani	Puglia	South
Potenza	Basilicata	South
Matera	Basilicata	South
Cosenza	Calabria	South
Crotone	Calabria	South
Vibo Valentia	Calabria	South
Catanzaro	Calabria	South
Reggio di Calabria	Calabria	South
Trapani	Sicily	South
Palermo	Sicily	South
Messina	Sicily	South
Agrigento	Sicily	South
Caltanissetta	Sicily	South
Enna	Sicily	South
Catania	Sicily	South
Ragusa	Sicily	South
Siracusa	Sicily	South
Sassari	Sardinia	South
Nuoro	Sardinia	South
Cagliari	Sardinia	South
Oristano	Sardinia	South
Olbia-Tempio	Sardinia	South
Ogliastra	Sardinia	South
Medio Campidano	Sardinia	South
Carbonia Iglesias	Sardinia	South

Notes to Table A.3

- The nomenclature used for identifying the Italian Provinces follows the one provided by ISTAT. Specifically, this work uses the nomenclature of the edition 2016, where, the new province of Sud Sardinia, ante 2016, results to be divided into four provinces of Olbia-Tempio, Ogliastra, Medio Campidano and Carbonia Iglesias.
- For year 2017, we continue to use the divided provinces of Sud Sardinia by diving the number of enrolled students of Sud Sardinia by four and giving higher weights (in terms of number of students) to provinces with higher population density rate: Carbonia-Iglesias presented the highest rate while Ogliastra had the lowest one.

Table A.4 *Italian Provinces for origin and destination with university*[40]

Province/Province_j	***University***	***Type of University***
Torino	Università degli Studi di Torino	Public
Torino	Politecnico di Torino	Public
Torino	Bra Scienze Gastronomiche	Public
Torino	Università degli Studi del Piemonte Orientale	Public
Aosta	Università degli Studi di Aosta	Public
Genova	Università degli Studi di Genova	Public
Milano	Castellanza LIUC	Private
Milano	Università degli Studi di Milano	Public
Milano	Politecnico di Milano	Public
Milano	Università Bocconi	Private
Milano	Università Cattolica	Private
Milano	IULM	Private
Milano	Università degli Studi di Milano Bicocca	Public
Milano	Università Humanitas Rozzano	Private
Brescia	Università degli Studi di Brescia	Public
Bergamo	Università degli Studi di Bergamo	Public
Pavia	Università degli Studi di Pavia	Public
Trento	Università degli Studi di Trento	Public
Verona	Università degli Studi di Verona	Public
Venezia	Cà Foscari	Public
Venezia	Iuav- Tolentini	Public
Padova	Università degli Studi di Padova	Public
Udine	Università degli Studi di Udine	Public
Trieste	Università degli Studi di Trieste	Public
Parma	Università degli Studi di Parma	Public
Modena	Università degli Studi di Modena e Reggio Emilia	Public
Reggio nell'Emilia	Università degli Studi di Modena e Reggio Emilia	Public
Bologna	Alma Mater Studiorum -Università di Bologna	Public
Ferrara	Università degli Studi di Ferrara	Public
Pesaro	Università degli Studi di Urbino	Public
Urbino	Università degli Studi di Urbino	Public
Ancona	Università degli Studi delle Marche	Public
Macerata	Università degli Studi di Macerata	Public
Ascoli Piceno	Università di Camerino	Public
Firenze	Università degli Studi di Firenze	Public
Pisa	Università degli Studi di Pisa	Public
Siena	Università degli Studi di Siena	Public
Siena	Università per Stranieri di Siena	Public
Perugia	Università degli Studi di Perugia	Public

[40] Data source is provided by M.I.U.R

Perugia	Università per Stranieri di Perugia	Public
Viterbo	Università degli Studi della Tuscia	Public
Roma	Università Roma "La Sapienza"	Public
Roma	Università Roma "Tor Vergata"	Public
Roma	Libera Università SS. Maria Assunta - LUMSA	Private
Roma	Libera Università degli Studi Sociali - LUISS Guido Carli	Private
Roma	Università degli Studi di Roma Foro Italico	Public
Roma	Università degli Studi "Roma Tre"	Public
Roma	Università Campus Bio Medico di Roma	Private
Roma	Università degli Studi Internazionali di Roma - UNINT	Private
Roma	UER - Università Europea di Roma	Private
Frosinone	Università degli Studi di Cassino	Public
Benevento	Università degli Studi del Sannio	Public
Napoli	Università "Federico II" di Napoli	Public
Napoli	Università Parthenope di Napoli	Public
Napoli	Università degli Studi di Napoli "L'Orientale"	Public
Napoli	Università Suor Orsola Benincasa	Private
Napoli	Università degli Studi della Campania "L. Vanvitelli"	Public
Salerno	Università degli Studi di Salerno	Public
L'Aquila	Università degli Studi dell'Aquila	Public
Teramo	Università degli Studi di Teramo	Public
Chieti	Università degli Studi di Chieti e Pescara	Public
Pescara	Università degli Studi di Chieti e Pescara	Public
Molise	Università degli Studi del Molise	Public
Foggia	Università degli Studi di Foggia	Public
Bari	Università degli Studi di Bari	Public
Bari	Politecnico di Bari	Public
Bari	Università LUM Jean Monnet	Private
Lecce	Università del Salento	Public
Potenza	Università degli Studi della Basilicata	Public
Cosenza	Università della Calabria	Public
Catanzaro	Università degli Studi di Catanzaro "Magna Graecia"	Public
Reggio di Calabria	Università degli Studi Mediterranea di Reggio Calabria	Public
Reggio di Calabria	Università per Stranieri "Dante Alighieri"	Private
Palermo	Università degli Studi di Palermo	Public
Messina	Università degli Studi di Messina	Public
Enna	Università KORE di Enna	Public
Catania	Università degli Studi di Catania	Public
Sassari	Università degli Studi di Sassari	Public
Cagliari	Università degli Studi di Cagliari	Public

Notes to Table A.4

1. The provinces reported with university are 51 for origin
2. Adjustments for "Modena and Reggio nell'Emilia" and "Chieti and Pescara" have been made. The campus of such universities is placed in both cities, and we divide them respectively. Hence, the study divides the number of enrolled students by half, giving more weight (in terms of number of students) to the province that presents the highest population density rate (for example, higher number of enrolled students is attributed to Modena because its population density rate is higher than the one present by Reggio nell'Emilia. Also, higher number of enrolled students is given to Pescara because its population density rate is higher than the one presented by Chieti)
3. The analysis does not consider Telematic Universities, Schools of Superior Specialization and/or Schools of Excellence
4. The Academic Years evaluated starts from 2010-2011 to 2017-2018
5. This study reports a single-year format for the Academic Year, beginning with 2010 for the A.Y. 2010-2011 and ends with 2017 for the A.Y. 2017-2018

Table A.5 *Specification for ERC – Study Fields*[41]

ERC	*Denomination*	*Disciplines*
1	*Social Sciences* (**SH**)	Economics, Finance, Management, Sociology, Social Anthropology, Political Science, Law, Communication, Psychology and Human Behaviour
2	*Physical Sciences* (**PE**)	Mathematics, Physics, Chemistry, Computer Sciences and Informatics, Systems and Communication Engineering, Product and Processes Engineering, Universe Sciences and Astrophysics, Climatology, Ecology, Biogeochemistry
3	*Life Sciences* (**LS**)	Molecular and Structural Biology and Biochemistry, Genetics and Genomics, Cellular and Developmental Biology, Physiology, Pathophysiology and Endocrinology, Neurosciences and Neural Disorders, Immunity and Infection, Aetiology, Tropical Medicine, Public Health, Epidemiology, Pharmacology, Toxicology, Regenerative Medicine, Medical Ethics, Biodiversity, Biogeography, Marine Biology, Eco-toxicology, Microbial ecology, Population Biology, Biotechnology, Genetic Engineering, Synthetic and Chemical Biology, Industrial Biosciences, Environmental Biotechnology

[41] Data source is provided by M.I.U.R

Appendix B

Table B.1 *Robustness check with the interaction term of distance and infrastructures*

	ZIP I **Enrolled**	**ZIP** II **ERC-1**	**ZIP** III **ERC-2**	**ZIP** IV **ERC-3**	**PPML** V **Enrolled**	**PPML** VI **ERC-1**	**PPML** VII **ERC-2**	**PPML** VIII **ERC-3**
time	-.04807***	-.04631***	-.04019***	-.04538***	-.04739***	-.04522***	-.04314***	-.0523***
	{0.006}	{0.006}	{0.010}	{0.006}	{0.006}	{0.006}	{0.011}	{0.007}
population	2.96e-07***	4.19e-07***	3.18e-07***	1.52e-07	3.09e-07***	4.55e-07***	1.58e-07	1.78e-07
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
population_j	2.30e-07***	1.01e-07	2.00e-07**	3.74e-07***	2.36e-07***	8.35e-08	3.76e-07***	3.79e-07***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
corruption	.0004787	.0000645	.0006148	-.0001855	.001133*	.0004493	.002511***	.0005969
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
corruption_j	-.001822***	-.001111**	-.002444***	-.001049	-.002345***	-.001291**	-.004413***	-.001719**
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
per capita real GDP	-.0000117	-.0000119	-.0000219*	-.0000191	-.0000117	-.0000182	-3.94e-06	-.0000122
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
per capita real GDP_j	.0000148	.0000255**	.0000161	5.90e-06	.0000175	.0000367***	-1.04e-06	1.69e-07
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
employment	-.02789**	-.0207	-.0169	-.01051	-.03515***	-.02854**	-.03443**	-.04897***
	{0.013}	{0.013}	{0.014}	{0.015}	{0.013}	{0.013}	{0.014}	{0.017}
employment_j	.006193	-.00674	-.006875	-.005997	.0136	.003827	.01241	.03414*
	{0.013}	{0.013}	{0.016}	{0.016}	{0.013}	{0.014}	{0.017}	{0.018}
size university	-.1986**	-.1655*	-.2351***	-.03884	-.3281***	-.2756***	-.4881***	-.1888
	{0.090}	{0.091}	{0.090}	{0.111}	{0.085}	{0.088}	{0.090}	{0.133}
size university_j	.3901***	.2182**	.6791***	.1894	.5242***	.3428***	.9566***	.3812**
	{0.100}	{0.096}	{0.112}	{0.125}	{0.099}	{0.097}	{0.116}	{0.158}
standardized quality university	-.5734**	-.5638**	-.3478	-.6193**	-.6981***	-.7616***	-.4729*	-.8689***
	{0.230}	{0.222}	{0.282}	{0.242}	{0.211}	{0.210}	{0.263}	{0.291}
standardized quality university_j	.06558	.1266	-.343	.2868	.2472	.386*	-.269	.6246**
	{0.225}	{0.216}	{0.301}	{0.258}	{0.194}	{0.201}	{0.256}	{0.260}
standardized quality life	-.4633*	-.3041	-.7904***	-.2572	-.4385	-.1699	-.9315***	-.3655
	{0.279}	{0.282}	{0.296}	{0.342}	{0.276}	{0.278}	{0.310}	{0.410}
standardized quality life_j	.3069	-.05663	.6693**	.2851	.3226	-.1733	.9733***	.6201*
	{0.253}	{0.285}	{0.268}	{0.315}	{0.250}	{0.282}	{0.272}	{0.368}
1.Dairport#c.dist	-.002864***	-.002638***	-.002057***	-.002624***	-.003034***	-.002775***	-.002864***	-.003528***
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
1.Dairport_j#c.dist	.002299*	.001325	.003318***	-.0001714	.002382*	.001418	.005683***	.0001322
	{0.001}	{0.002}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.002}
1.DTAV#c.dist	-.007416***	-.007973***	-.00646***	-.004531**	-.008064***	-.008791***	-.008332***	-.006684***
	{0.002}	{0.002}	{0.001}	{0.002}	{0.002}	{0.002}	{0.002}	{0.002}
1.DTAV_j#c.dist	.001957*	.003265**	.0006851	.0008236	.00516***	.007292***	.003464***	.004213***
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
1.Dport#c.dist	.004399***	.004536***	.003453***	.002825***	.005443***	.005883***	.005302***	.004756***
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
1.Dport_j#c.dist	-.005315***	-.004289**	-.008261***	-.002481*	-.004747***	-.003487**	-.00959***	-.002258
	{0.002}	{0.002}	{0.002}	{0.001}	{0.002}	{0.002}	{0.002}	{0.001}
N.obs	20808	20808	20808	20808	20808	20808	20808	20808
Wald chi2 test	1110.97	10866.70	8692.09	6128.40	6224.91	6895.78	3952.55	4292.53
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo-R2					0.9102	0.9207	0.8833	0.8396

Notes: For both model's specifications, we inserted law deterrence variables for origin and destination provinces as control values. In addition, fixed effects of dummies for macro-areas of North, Centre and South of origin and destination are included with interaction with year (2010-2017 period). Standard errors account for clustering of provinces. ***, ** and * denote coefficients that are statistically significant at 1%, 5% and 10%, respectively. Results are in **b/se***

Table B.2 *Robustness check with long distance skilled movements from Centre-South to North*

	ZIP	**ZIP**	**ZIP**	**ZIP**	**PPML**	**PPML**	**PPML**	**PPML**
	I	II	III	IV	V	VI	VII	VIII
	Enrolled	**ERC-1**	**ERC-2**	**ERC-3**	**Enrolled**	**ERC-1**	**ERC-2**	**ERC-3**
time	-.01109***	-.01196***	-.007201***	-.006969***	-.01519***	-.01787***	-.0134***	-.01401***
	{0.002}	{0.002}	{0.002}	{0.002}	{0.002}	{0.002}	{0.002}	{0.002}
population	4.45e-08	-2.23e-09	1.78e-07	6.15e-08	2.17e-08	-1.80e-08	7.86e-08	1.61e-07
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
population_j	6.59e-07**	5.59e-07**	5.21e-07**	7.53e-07***	8.63e-07***	7.15e-07***	9.84e-07***	8.70e-07***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
corruption	.002295**	.002142*	.002016*	.001052	.002933***	.002663**	.003606***	.000986
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
corruption_j	-.002598**	-.0004577	-.00346***	-.002794**	-.004281***	-.001389*	-.007296***	-.002392**
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}
per capita real GDP	.0000512	.000068	2.40e-06	-.0000169	.0000644	.0000705	.0000877	.0000196
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
per capita real GDP_j	-.0000366	-2.95e-06	-.0000483*	-.0000325	-.000018	.0000468*	-.0001072***	.0000505
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
employment	-.05295**	-.06446**	-.03964	.005224	-.06342**	-.07905***	-.05653*	-.05437*
	{0.026}	{0.026}	{0.027}	{0.022}	{0.028}	{0.028}	{0.031}	{0.029}
employment_j	.06794	.0618	.02415	.05548	.06271	.0729*	.04156	.07148*
	{0.046}	{0.042}	{0.035}	{0.040}	{0.040}	{0.041}	{0.044}	{0.038}
size university	-.1471	-.09926	.1235	.0003323	-.4015**	-.3617*	-.5229**	-.2718
	{0.198}	{0.211}	{0.189}	{0.169}	{0.189}	{0.201}	{0.204}	{0.174}
size university_j	.1024	-.102	.2694	-.1101	.3091	.008161	.7892***	-.004971
	{0.239}	{0.231}	{0.262}	{0.251}	{0.226}	{0.220}	{0.235}	{0.230}
standardized quality university	-.4872	-.2808	-.2667	-1.114***	-.5163	-.5007	-.2516	-1.128**
	{0.404}	{0.445}	{0.368}	{0.346}	{0.416}	{0.450}	{0.433}	{0.454}
standardized quality university_j	-.03791	-.09394	-.9129*	-.6405	.6538*	.9994**	.3474	.4144
	{0.492}	{0.492}	{0.491}	{0.461}	{0.361}	{0.420}	{0.345}	{0.354}
standardized quality life	-.7992	-.4636	-.8644	-.4922	-.8757	-.4774	-1.412**	-.3702
	{0.614}	{0.584}	{0.608}	{0.551}	{0.535}	{0.518}	{0.579}	{0.561}
standardized quality life_j	.7041	.0855	.707	1.506***	.3916	-.1663	.8206**	1.527***
	{0.430}	{0.444}	{0.456}	{0.422}	{0.339}	{0.380}	{0.371}	{0.342}
Dairport	.04641	.01021	.2715	.5028	.05664	.05363	.05942	-.01651
	{0.314}	{0.310}	{0.277}	{0.311}	{0.314}	{0.310}	{0.336}	{0.324}
Dairport_j	.4811	.1882	.6754*	-.05106	.907***	.4923	1.574***	.7017**
	{0.354}	{0.377}	{0.357}	{0.343}	{0.330}	{0.344}	{0.344}	{0.321}
DTAV	-.4774	-.5029	-.3614	.1536	-.6425	-.6914	-.7786	-.4617
	{0.570}	{0.510}	{0.588}	{0.456}	{0.591}	{0.509}	{0.733}	{0.636}
DTAV_j	.4008	.3239	.5708	.06311	.4189	.3958	.6328	-.1617
	{0.576}	{0.543}	{0.629}	{0.541}	{0.470}	{0.467}	{0.496}	{0.582}
Dport	.3218	.5675*	-.005406	-.3724	.7208**	1.014***	.4679	.5285
	{0.331}	{0.337}	{0.327}	{0.322}	{0.342}	{0.350}	{0.418}	{0.385}
Dport_j	-.4123	-.9637**	.08335	.2207	-1.153***	-1.688***	-.7224*	-1.097**
	{0.406}	{0.377}	{0.393}	{0.425}	{0.418}	{0.421}	{0.385}	{0.441}
N	7440	7440	7440	7440	7440	7440	7440	7440
Wald Chi Square Test	314.527	395.558	245.512	210.900	853.81	743.15	781.21	693.74
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo-R2					0.7947	0.8252	0.7397	0.7408

Notes: For both model's specifications, we inserted law deterrence variables for origin and destination provinces as control values. In addition, fixed effects of dummies for macro-areas of North, Centre and South of origin and destination are included with interaction with year (2010-2017 period). Standard errors account for clustering of provinces. The constraint South-Centre to the North is added as (macroarea≥ 2 & macroarea_j ≤2) ***, ** and * denote coefficients that are statistically significant at 1%, 5% and 10%, respectively. Results are in **b/se***.

Table B.3 *Bootstrap Results with ZIP in the 2nd stage*

	Obs Coef.	Bootstrap Std. Err.	Z	P>|z|	Normal Based [95% Conf. Interval]	
r(b_corruption)	0.0015866	0.0019282	0.80	0.411	-0.0021925	0.0053658
r(b_corruption_j)	-0.0047955	0.0015685	-3.06	0.002	-0.0078698	-0.0017213
r(b_corr_res)	-0.00004	0.0015124	-0.03	0.979	-0.0030042	0.0029242
r(b_corr_res_j)	0.002326	0.0012418	1.87	0.061	-0.0001078	0.0047598

N. observations: 18.207; N. of Replications: 200 based on 2.601 cluster in panelid

Table B.4 *Bootstrap Results with PPML in the 2nd stage*

	Obs Coef.	Bootstrap Std. Err.	z	P>|z|	Normal Based [95% Conf. Interval]	
r(b_corruption)	0.0016962	0.0018408	0.92	0.357	-0.0019118	0.0053042
r(b_corruption_j)	0.0053151	0.0016113	-3.30	0.001	-0.0084731	-0.002157
r(b_corr_res)	0.0005872	0.0014817	0.40	0.692	-0.0023169	0.0034913
r(b_corr_res_j)	0.0024111	0.0013222	1.82	0.068	-0.0001803	0.0050025

N. observations: 18.207; N. of Replications: 200 based on 2.601 cluster in panelid

Table B.5 *Bootstrap Results with PPMLHDFE in the 2nd stage*

	Obs Coef.	Bootstrap Std. Err.	z	P>|z|	Normal Based [95% Conf. Interval]	
r(b_corruption)	0.0009282	0.0020431	0.45	0.650	-0.0030762	0.0049326
r(b_corruption_j)	-0.0053502	0.0016848	-3.18	0.001	-0.0086523	-0.002048
r(b_network)	0.000737	0.000147	0.50	0.616	-0.0002144	0.0003617
r(b_corr_res)	0.0007244	0.0016077	0.45	0.652	-0.0024267	0.0038755
r(b_corr_res_j)	0.0027396	0.0014912	1.84	0.066	-0.0001831	0.0056623
r(b_network_res)	0.0001788	0.0002561	0.70	0.485	-0.0003231	0.0006807

N. observations: 15.606; N. of Replications: 200 based on 2.601 cluster in panelid

Appendix C

C.1 Additive Notes

Theoretical Framework

Bilateral net skilled migration can be theorized with the utility maximization framework combined with the gravity set-up. Assumed that skilled students are rational, they are free to enrol to universities that belong to different provinces and their decision to move will be based on the comparison between the expected utilities of origin (*i*) and destination (*j*). Besides, individual utility is a function that encompasses socio-economic and quality of life variables plus the costs of moving, which are represented by distance between origin (*i*) and destination (*j*). Thus, the utility function for the skilled individual (*s*) at origin (*i*) province can be expressed as:

$$U_i^s = u(E_i, L_i) + \varepsilon_i^s \quad [1]$$

While the utility function for the skilled individual (*s*) at destination (*j*) is expressed as:

$$U_j^s = u\left(E_j, L_j\right) + \varepsilon_j^s \quad [2]$$

where the total utility U includes a deterministic part *u* and a stochastic part ε_i^s and ε_j^s The deterministic part *u* is a function of a vector of a wide range of economic (E) and quality of life (L) variables. Students will decide to move from location *i* to location *j* if the expected utility of the destination is greater than the expected utility for the origin plus the costs of relocating (which are expressed as function of distance):

$$E\left[U_j^s\right] \geqq E[U_i^s] + C(d_{ij}) \quad [3]$$

Hence, rewriting the above conditions according to the gravity model specification, we get:

$$Enrolled_{ij} = f(E_{ij} L_{ij} D_{ij}) \quad [4]$$

Where i= 1, 2, ..., 51 represents origin provinces with one local university, j= 1, 2, …, 51 represents destination provinces with one local university (with i ≠ j), E is a vector of socio-economic characteristics for origin and destination, L is a vector of quality-of-life characteristics for origin and destination and D_{ij} represents the distance between origin *i* and destination *j*.

C.2 Additive Notes

Methods used to build-up Quality of University and Quality of Life

The method used to derive quality of university and quality of life variables is a two-steps procedure that consists of taking the average of the standardized values related to the quality of university and quality of life. All variables are aggregated at Italian provincial level from 2010 to 2017.

The values used for creating quality of university are provided by ALMALAUREA and are age, grade, expected income per capita, expected time to find a job. In particular, age indicates how much old are the students when they take the bachelor's degree (3-years course program), grades indicates the final grade that the students achieve once they get graduated, expected income per capita returns an estimate of the income they would earn with their bachelor's degree and the expected time to find a job indicates how much time is needed to find a job once the students get their bachelor degree. All these variables reflect the quality of university from students' perspective: in fact, according to students, the quality of university is the highest if they learn skills that are required to graduate early, to find a job easily and to earn a pleasantly income.

In addition, the values used for creating quality of life variable are taken by ISTAT and are mortality rate, working formation, gender difference in employment, the presence of green urban areas, childcare and eldercare. Mortality rate indicates the incidence of deaths over the Italian population. It is used as proxy for quality of life because it identifies the health status of the designed population. Besides, working formation indicates the incidence of those who participate to working formation programs over the Italian population. It is used as proxy for quality because it represents the alphabetization and technological progresses needed to work in firms. In addition, gender difference in employment indicates how many women works respect to men. This value is used as proxy for indicating the existence of the equality condition within the Italian labour context. Then, green urban area indicates the presence of parks in the urbanized area. This value is exploited as proxy for quality of life because the presence of green area permits to follow good health-habits (breathing unpolluted air, walking, jogging, running, playing etc.) that positively affects individuals' lives. Finally, childcare and elderly care are primary services that cannot be overlooked in civilized societies. These are used as proxies for quality of life and states that high assistance offered to the public is associated with high quality of life where these services operate.

Once these variables are selected and collected, we standardized each of them to make an easier comparison among scores measured on different scales.

The standardization process consists of rescaling variables using the z-score, as expressed in the following formula:

$$z = \frac{X - \mu}{\sigma} \quad [1]$$

The z-score is obtained by i) subtracting the mean, from the value to be converted, X and ii) dividing the numerator by the standard deviation of the denominator. Hence, the standardized values obtained have the mean of 0 and the standard deviation of 1.

Then, we take the arithmetic average of all the z-scores get from Equation (1) for creating the variables of quality of university and quality of life, by using the following formula:

$$Average\ for\ Quality\ of\ University = \frac{1}{n}\sum_{i=1}^{n} z_i = \frac{z_1 + z_2 + \ldots + z_n}{n}$$

$$Average\ for\ Quality\ of\ Life = \frac{1}{n}\sum_{i=1}^{n} z_i = \frac{z_1 + z_2 + \ldots + z_n}{n}$$

where z_1, z_2 ... z_n represent the standardized values selected and used for creating the variables of quality of university and quality of life, while *n* indicates the number of values inserted for creating the already cited two variables.

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