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BRAIN DRAIN ON THE FAST TRAIN: HIGH-SPEED CONNECTIONS AND STUDENT MOBILITY

by Edoardo Frattola*, Elena Lazzaro**, Ilaria Lopresti*** and Mario Tartaglia****

Abstract

This paper examines the effects of improved connectivity on internal student mobility, focusing on the staggered expansion of Italy's high-speed trains (HST) network between 2010 and 2019. Using administrative data on university enrollments and a difference-in-differences design that accounts for variation in treatment timing, we find that the introduction of an HST stop leads to a significant increase in student outflows from treated provinces, with no corresponding rise in inflows. The effect is concentrated in Southern regions and driven by long-distance relocations, particularly toward larger urban centers. These findings suggest that extending high-speed train service may contribute to the spatial reallocation of human capital away from the newly connected, more peripheral areas, reinforcing existing regional disparities in talent distribution.

JEL Classification: I23, R40, O18, R11.

Keywords: high-speed rail, student mobility, higher education, regional inequality, human capital, infrastructure.

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1 Introduction[1]

The availability of human capital plays a crucial role in shaping long-run regional development. In this context, student mobility, defined as the decision to enroll in a university outside one's place of origin, can be a major driver of the spatial concentration of talent. In Italy, this phenomenon has become increasingly salient: over the past two decades, while the aggregate enrollment rate has remained relatively stable (ANVUR, 2023), internal student migration has intensified, with significant and persistent flows from less developed Southern regions to universities in the Center and North of the country (Columbu et al., 2021; Bacci and Bertaccini, 2021; Attanasio and Enea, 2019; Accetturo et al., 2022; Mariani and Torrini, 2022). Since the vast majority of students enter the labor market in the same region where they graduate, this one-way mobility exacerbates the long-lasting income gap between the South and the Center-North (Etzo et al., 2025).[2]

Despite the magnitude of this trend, relatively little is known about the role that transportation infrastructure plays in shaping student mobility patterns. This paper investigates whether and to what extent the opening of a high-speed train (HST) stop affects student inflows and outflows at the local level.[3] By reducing travel times, HST lowers both the economic and psychological costs of moving. Knowing that they can more easily return to their families whenever they want, students may be more willing to consider universities far from home, leading to an increase in student mobility (Cattaneo et al., 2016; Gibbons and Vignoles, 2012). However, the direction of this mobility is not obvious, as the introduction of an HST stop in a given area can trigger two competing mechanisms: a potential "brain gain" of outsiders due to increased accessibility, and a "brain drain" of local residents to more attractive destinations. The net effect of HST on a province's human capital stock is, therefore, theoretically ambiguous and likely to be asymmetric: areas with a lower inherent value are expected to experience a net outflow of students, while major urban centers with a higher inherent value are positioned to face a net inflow.

To empirically address this question, we use administrative data on university enrollments

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[2]According to Almalaurea data, five years after graduation, over 60% of individuals are working in the same region where they studied and almost 90% of those who graduated in the Center-North are working there.

[3]We use the terminology "high-speed train" as our focus is on the transportation service itself, which can operate on both dedicated high-speed and conventional rail lines, as better explained in Section 3.1. Other papers consider instead the "high-speed rail," which typically refers more narrowly to the underlying track infrastructure.

and exploit the staggered opening of HST stops in Italy from 2010 to 2019. The Italian high-speed rail network has expanded rapidly over the past two decades, connecting major cities across the country and significantly reducing travel times. However, not all provinces benefited equally from this expansion: some gained a direct stop, while others remained disconnected or had to rely on secondary links.[4] We exploit this variation in a staggered difference-in-differences design using the estimator proposed by Callaway and Sant'Anna (2021), which accounts for variation in treatment timing and allows us to isolate the effect of acquiring an HST stop on local enrollment dynamics.

Our analysis reveals three key findings. First, introducing an HST stop triggers a significant and growing *outflow* of students, with the effect emerging one year after treatment and growing over time. Treated provinces experience, on average, an 8% increase in the number of students leaving to attend university elsewhere. This effect is one-sided: we find no corresponding rise in student inflows. This asymmetry challenges the assumption that improved connectivity is always beneficial for newly accessible areas, as it can primarily facilitate the departure of students rather than attract human capital, at least in the short to medium term.

Second, the increase in outflows is driven by long-distance moves. The effect of HST on student mobility is statistically insignificant for short-haul journeys but increases monotonically with distance. This pattern is consistent with the idea that time-saving advantages are most pronounced on longer routes, and that faster and more comfortable connections can help overcome the psychological barrier of leaving one's home province for distant locations.

Third, the impact is geographically concentrated, with the rise in student outflows occurring exclusively in Southern provinces. In these areas, improved connectivity facilitates student departures, mostly toward the largest hub of the area (the city of Naples) and the Center-North (in particular to Rome). Conversely, new HST services in the Center-North produce no such effect. This suggests that, in the absence of parallel investments in local universities and job markets, major infrastructure projects in less-developed regions risk exacerbating, rather than correcting, existing imbalances in educational migration and accelerating the loss of human capital.

These findings should be interpreted in light of the scope of our estimand. Our research design identifies the average treatment effect on the treated (ATT), specifically for later-

[4] In Italy, there are 108 provinces (the main focus of this study), which correspond to NUTS-3 level units, and 20 regions, which correspond to NUTS-2 level units. 12 of them (Piedmont, Aosta Valley, Liguria, Lombardy, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Tuscany, Umbria, Marche, and Lazio) belong to the Center-North macroarea, and the remaining 8 (Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, and Sardinia) to the South.

adopting and relatively peripheral provinces that received an HST stop between 2010 and 2019. The estimates, therefore, measure the marginal effect of integrating these areas into an existing network, rather than the aggregate impact of the national high-speed system. As a result, the net outflows we document are distributional—at the national level, inflows and outflows offset each other—and primarily reflect relocations to hubs that were already connected before our study window.

This work contributes to several strands of literature. First, we complement critical debates on accessibility and regional inequality. Infrastructure is often promoted as a tool for convergence, yet its effects can be a double-edged sword, potentially reinforcing core-periphery dynamics instead of mitigating them (Krugman, 1991; Puga, 2002). The risk of inadvertently facilitating a "brain drain" has long been a concern with major transportation projects (Vickerman, 1995; Rietveld and Nijkamp, 1992). Our findings on the asymmetric effects of HST on human capital flows provide direct empirical support for this critical perspective (Monzón et al., 2013; Wang and Duan, 2018) and highlight the need for greater attention to the potential unintended consequences of infrastructure-led development strategies in lagging areas.

Second, we contribute to research on how transportation costs shape higher education choices. Previous studies have documented that distance is a key determinant of enrollment decisions (Skinner, 2019; Sá et al., 2006; Rizzica, 2013; Kelchtermans and Verboven, 2010; Drewes and Michael, 2006), and that transport innovations, such as low-cost flights, can alter student behavior (Cattaneo et al., 2016). We extend this line of inquiry by examining a different mode of infrastructure and by disentangling the effects on outflows versus inflows.

Third, our study engages with the extensive literature on the socioeconomic consequences of high-speed rail.[5] Previous studies have documented its positive effects on local economic output (Ahlfeldt and Feddersen, 2018), the number of firms and labor productivity (Carbo et al., 2019), scientific co-authorship and collaboration for innovation (Dong et al., 2020; Hanley et al., 2022), or tourism demand (Lopresti and Tartaglia, 2023). Other work has shown how high-speed rail reshapes labor markets by increasing passenger flows, employment, and complex commuting patterns (Lin, 2017; Heuermann and Schmieder, 2019). More recently, this literature has begun to explore how it facilitates a sorting of talent, finding that improved accessibility helps high-quality firms attract better directors, potentially at the expense of lower-quality firms (Baltrunaite and Karmaziene, 2024). Despite this rich body of work, the role of high-speed rail in shaping educational choices has remained unexamined. Our results complement this literature by showing that, for peripheral provinces

[5] For a partial review, see also Blanquart and Koning (2017).

that gain access to an already existing network, high-speed trains may also have drawbacks by functioning primarily as a facilitator of student outmigration rather than as a pull factor.

Finally, our research contributes to a growing body of work on internal student mobility in Italy, particularly the persistent South-to-North flows that risk draining peripheral areas of educated youth (Bacci and Bertaccini, 2021; Attanasio and Enea, 2019; Accetturo et al., 2022). By leveraging longitudinal data and plausibly exogenous variation in accessibility, we move beyond descriptive accounts to identify one causal driver of these dynamics.

The remainder of the paper is structured as follows. Section 2 develops a simple theoretical framework to understand the potential effect of HST on students' mobility choices. In Section 3, we describe the institutional setting, the data, and the estimation sample. Section 4 outlines our empirical strategy. Section 5 presents and discusses the results. Finally, Section 6 concludes.

2 Theoretical framework

To formalize the mechanisms driving student mobility, we adopt a random utility model, a standard framework for analyzing discrete choice behavior in economics (McFadden, 1974). This approach allows us to model a student's decision on where to enroll as a choice that maximizes their perceived utility, while acknowledging that some factors influencing this choice are unobservable to the researcher.

Consider a student from a home province i choosing among a set of J university locations. The utility, U_{ij}, that this student derives from choosing location j is composed of a deterministic component, v_{ij}, and a random, idiosyncratic error term, ϵ_{ij}:

$$U_{ij} = v_{ij} + \epsilon_{ij}$$

The deterministic part, v_{ij}, captures the observable characteristics of the choice. We specify it as a function of the inherent benefits of a location minus the costs of choosing it. Specifically, the utility of moving away to province $j \neq i$ is $v_{ij} = V_j - \delta\tau_{ij}$, while the utility of staying local in province i is $v_{ii} = V_i + H$. Here, V_j represents the inherent value of location j, a general term for the aggregate benefits of its university and city (e.g., academic prestige, economic opportunities, social amenities). The cost of moving away is the "travel friction," given by $\delta\tau_{ij}$, where $\delta > 0$ is a parameter capturing sensitivity to distance and τ_{ij} is the "generalized cost of travel," a concept that includes not only the monetary costs but also, and most importantly, the value of travel time, alongside other non-monetary factors like comfort and reliability (De Rus, 2008; Balcombe et al., 2004). While presented here as a single parameter, δ can be interpreted as the average sensitivity within the population; in principle, it could vary across individuals to reflect heterogeneous preferences regarding travel (e.g., by gender, academic ability, or family income). When staying local, the student avoids this friction and instead receives a utility bonus, $H > 0$, which we term the "home premium."

A student chooses the location j that offers the highest utility. Because of the random component ϵ_{ij}, we model the probability of a particular choice. Assuming the error terms follow a Type I Extreme Value distribution (a standard assumption in the literature), the probability of a student from i choosing location j from a set of J alternatives takes the multinomial logit form (McFadden, 1974):

$$P_{ij} = \frac{\exp(v_{ij})}{\sum_{k=1}^{J} \exp(v_{ik})}$$

Let us analyze the binary choice between staying local (in province i) and moving to a single alternative destination (province j). A student will migrate if the utility of moving is greater than the utility of staying:

$$U_{ij} > U_{ii} \iff v_{ij} + \epsilon_{ij} > v_{ii} + \epsilon_{ii}$$

Substituting the definitions for the deterministic utilities and isolating the unobserved terms, the condition becomes:

$$\epsilon_{ii} - \epsilon_{ij} < (V_j - V_i) - H - \delta\tau_{ij}$$

The term on the right-hand side represents the total deterministic gain from moving. The difference of the two error terms, $\epsilon_{ii} - \epsilon_{ij}$, follows a logistic distribution. The probability of moving is therefore given by the logistic cumulative distribution function:

$$P_{ij} = \Pr(U_{ij} > U_{ii}) = \frac{1}{1 + \exp(-(v_{ij} - v_{ii}))}$$

which is algebraically equivalent to:

$$P_{ij} = \frac{\exp(v_{ij})}{\exp(v_{ii}) + \exp(v_{ij})} = \frac{\exp(V_j - \delta\tau_{ij})}{\exp(V_i + H) + \exp(V_j - \delta\tau_{ij})}$$

This approach is conceptually linked to the broader human capital theory of migration, which frames mobility as an investment decision where individuals weigh the costs and returns of moving (Sjaastad, 1962).

2.1 The effect of an HST shock

The introduction of HST can be seen as a shock that reduces the generalized cost of travel, τ_{ij}.[6] To formally analyze its impact, we take the partial derivative of the choice probability P_{ij} with respect to the generalized cost of travel τ_{ij}:

$$\begin{aligned}\frac{\partial P_{ij}}{\partial \tau_{ij}} &= \frac{\partial}{\partial \tau_{ij}}\left(\frac{\exp(V_j - \delta\tau_{ij})}{\exp(V_i + H) + \exp(V_j - \delta\tau_{ij})}\right)\\ &= -\frac{\delta \cdot \exp(V_j - \delta\tau_{ij}) \cdot \exp(V_i + H)}{[\exp(V_i + H) + \exp(V_j - \delta\tau_{ij})]^2}\end{aligned}$$

Since all exponential terms are strictly positive and the parameter δ is positive by definition, the entire expression is strictly negative:

$$\frac{\partial P_{ij}}{\partial \tau_{ij}} < 0$$

In other words, a decrease in the generalized cost of travel (the HST shock) unambiguously increases the probability of a student moving to a connected location, all else being equal. This general effect is visualized in Figure 1.

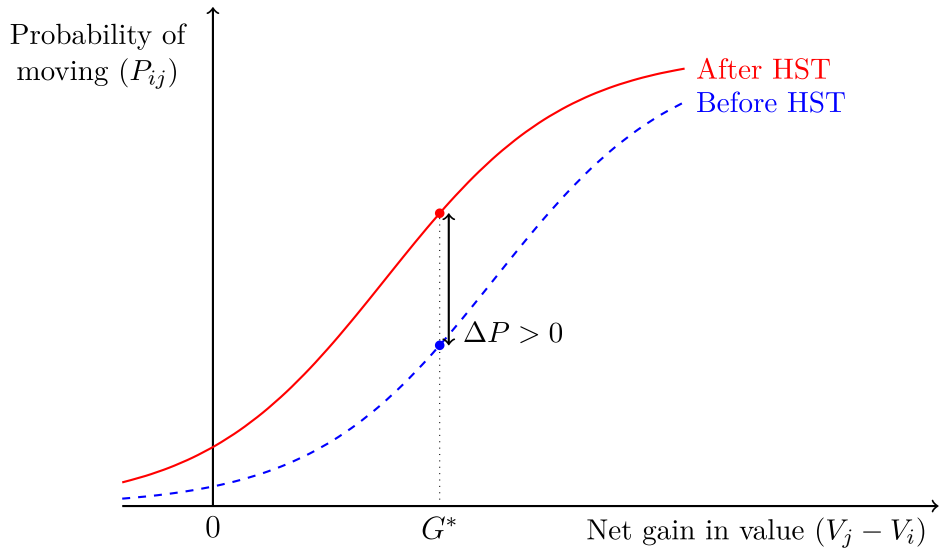
2.2 The role of pre-existing choice probabilities

While a transport improvement always makes a connected destination more attractive, the magnitude of the resulting change in student flows is not uniform. The model can explain this heterogeneity. The key insight is that the impact of a utility change depends on the baseline probability of that choice.

The effect of an HST shock is a change in the generalized cost of travel, $\Delta\tau_{ij}$. To see how this affects the probability of moving, we can use the chain rule. The change in probability with respect to the generalized cost of travel is the product of how probability changes with

[6] It is worth noting that transport infrastructure can also have general equilibrium effects, potentially increasing the inherent value (V_j) of a connected location through agglomeration economies. In this framework, we focus exclusively on the direct effect of HST as a reduction in the generalized cost of travel, treating V_j as fixed. This simplification allows for a clear and tractable analysis of the primary mechanism influencing student choice. We argue this is a reasonable assumption in our context because such agglomeration effects, while important, typically materialize over a much longer time horizon than the student enrollment decision period we analyze. Furthermore, incorporating this second channel would complicate the model without altering its core intuition regarding the role of mobility costs and pre-existing conditions.

Figure 1: **The positive effect of HST on the probability of student mobility**



Notes: The introduction of HST reduces the total friction of moving ($H + \delta\tau$). This shifts the probability curve to the left (from dashed blue to solid red), meaning that for any given net gain in value ($G^* = V_j - V_i$), the probability of a student choosing to move increases.

utility, and how utility changes with the generalized cost of travel:

$$\frac{\partial P_{ij}}{\partial \tau_{ij}} = \frac{\partial P_{ij}}{\partial v_{ij}} \cdot \frac{\partial v_{ij}}{\partial \tau_{ij}}$$

From our utility specification, we know that $\frac{\partial v_{ij}}{\partial \tau_{ij}} = -\delta$. The crucial term is the first one, i.e., the sensitivity of the choice probability to a change in its own utility. For the multinomial logit model, this has a well-known form:

$$\frac{\partial P_{ij}}{\partial v_{ij}} = P_{ij}(1 - P_{ij})$$

Substituting this back into the chain rule gives us the marginal effect of the generalized cost of travel on the probability of choosing destination j:

$$\frac{\partial P_{ij}}{\partial \tau_{ij}} = -\delta \cdot P_{ij}(1 - P_{ij})$$

This equation provides a powerful economic intuition. The magnitude of the effect of a reduction in the generalized cost of travel is governed by the term $P_{ij}(1-P_{ij})$. This function is an inverted U-shape, maximized when the probability $P_{ij} = 0.5$, and approaching zero as P_{ij} approaches either 0 or 1. This leads to three distinct scenarios for the impact of an HST shock:

1. High impact (marginal choices): The effect is strongest for destinations where the choice was initially highly contested (i.e., P_{ij} is far from 0 and 1). In our binary choice context, this corresponds to students who were "on the margin"—for whom the costs almost perfectly offset the perceived value of moving to province j. Formally, this is when $(V_j - V_i) \approx H + \delta\tau_{ij}$. For these students, the reduction in τ_{ij} from HST is a powerful nudge that can decisively tip the scales in favor of moving.

2. Low impact (dominated choices): If a destination j is significantly less attractive than staying home (i.e., $V_j \ll V_i$), the initial probability of moving, P_{ij}, will be close to zero. The sensitivity term $P_{ij}(1 - P_{ij})$ will therefore also be close to zero. Even a large reduction in the generalized cost of travel will not be enough to make the destination viable, resulting in a negligible change in student flows. The choice to move is "dominated."

3. Low impact (dominant choices): Conversely, if a destination j is so vastly superior to staying home that nearly everyone already chooses to move there ($P_{ij} \to 1$), a further reduction in the generalized cost of travel will have little additional effect. There is a ceiling effect, as most of the potential movers have already been captured.

Therefore, the model predicts that the impact of HST will be greatest not on the destinations with the highest absolute values, but on those that were previously "competitive but costly" alternatives. Figure 2 illustrates this formal result.

2.3 Implications for net student flows

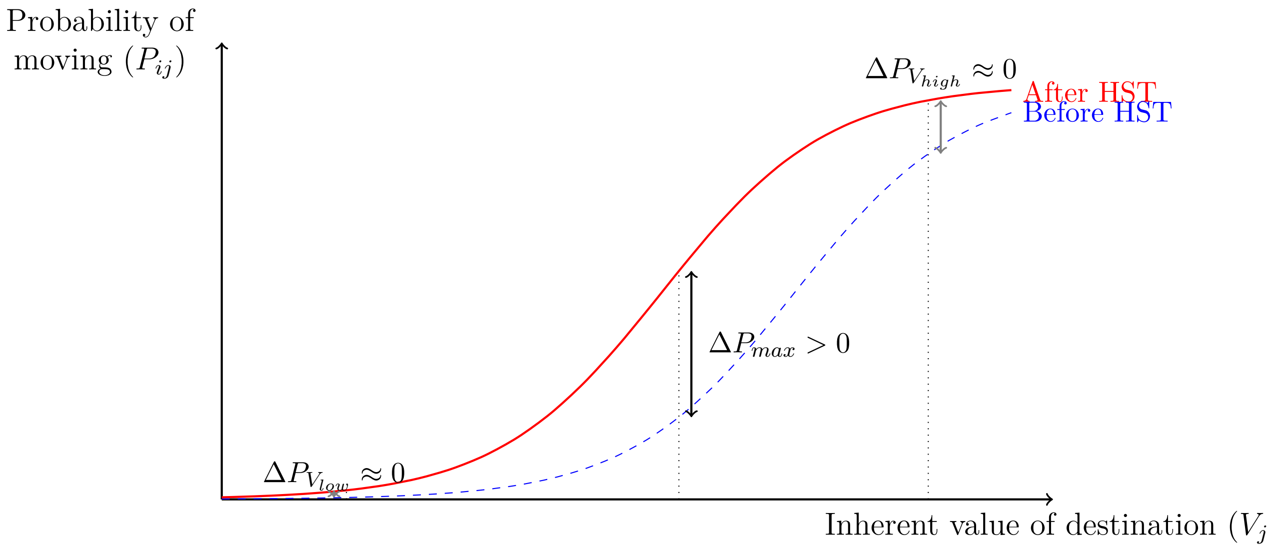
This theoretical framework provides a clear lens through which to analyze the net effects of an infrastructure shock such as HST on a province's student population. Any given province i is simultaneously an origin for its own students and a potential destination for students from all other provinces k. The introduction of HST alters this competitive landscape.

A province's net change in student enrollment is the difference between the change in inflows and the change in outflows:

$$\Delta(\text{Net Flow})_i = \sum_{k \neq i} \Delta(\text{Inflow from } k \text{ to } i) - \sum_{j \neq i} \Delta(\text{Outflow from } i \text{ to } j)$$

Our model predicts that the magnitudes of these changes are determined by the pre-existing distribution of inherent value across all provinces. Provinces with a relatively low inherent value (V_i) that gain an HST connection to provinces with a high inherent value (V_j) will

Figure 2: **The asymmetric effect of HST based on destination value**



Notes: The magnitude of the increase in mobility probability (ΔP) is heterogeneous: it is negligible for low-value destinations (V_{low}, where the choice is dominated) and for very high-value destinations (V_{high}, due to a ceiling effect), but is maximized for "marginal" destinations where the choice was initially most uncertain.

experience a strong outflow effect (ΔP_{ij} will be large) and a weak inflow effect (ΔP_{ji} will be small). This will result in a net loss of students (a "brain drain"). Conversely, provinces with a high inherent value (V_i) that gain an HST connection to provinces with lower inherent value (V_k) will experience a strong inflow effect and a weak outflow effect, resulting in a net gain of students (a "brain gain").

This general framework formally shows that the introduction of HST creates both outflow and inflow pressures for any given province. However, the magnitude of these pressures is conditioned by the spatial distribution of inherent value. A province's net change in student population depends on the balance between the outflow of its local students to more attractive regions and the inflow of students from less attractive ones.

Our simple model, therefore, predicts that the effects of HST will not be uniform. In cases where a province with a relatively low V_i becomes connected to provinces with much higher V_j, the outflow effect will be strong and the inflow effect weak, leading to a net loss of human capital. Conversely, the framework predicts that established hubs with high intrinsic value would experience a net human capital gain when connected to less attractive provinces. This heterogeneity in the predicted treatment effect, conditional on the province's initial characteristics, is central to the interpretation of our empirical results, which focus on the effect for a specific subset of provinces that gained HST access more recently.

3 Background and data

3.1 High-speed trains in Italy

The introduction of high-speed rail has fundamentally transformed long-distance mobility in Italy, altering the travel habits of millions of citizens. Following the inauguration of the first *Direttissima* line from Florence to Rome in 1992, the development of the high-speed network accelerated sharply between 2005 and 2009 with the completion of the first strategic corridor from Turin to Salerno (passing through Milan, Bologna, Florence, Rome, and Naples). However, the most widespread expansion of the service occurred in the following decade, with the number of kilometers served by high-speed trains growing at a 12% compound annual rate from 2010 to 2018 (Capurso and Tartaglia, 2023). While 35 stations (in 25 provinces) were served in 2010, this number increased to 104 (in 57 provinces) by the end of 2019, extending the benefits of high-speed travel to an ever-growing number of locations. In particular, several Southern provinces became better connected, thanks to the Tyrrhenian corridor towards Reggio Calabria and the Adriatic corridor towards Lecce.

This dramatic rise in connections was also facilitated by the market liberalization process in the rail transport sector, which the European Commission has promoted since the 1990s to enhance efficiency, promote competition, and foster innovation. The Italian national railway operator, Ferrovie dello Stato (FS), was transformed into a holding company controlling the infrastructure manager, Rete Ferroviaria Italiana, which maintained the natural monopoly on rail infrastructure, and the passenger operator, Trenitalia. Initially, the high-speed rail service was operated only by the incumbent Trenitalia, first with its Eurostar Italia trains and, from 2009 onwards, with the Frecciarossa (maximum speed of 300km/h) and Frecciargento (maximum speed of 250km/h) trains. In 2012, a new competitor, Nuovo Trasporto Viaggiatori (NTV), entered the market with the train brand Italo, and gradually expanded its service, now reaching almost 60 stations.[7] As argued by Capurso and Tartaglia (2023), this competition led to a decrease in prices, an increase in service supply, changes in long-haul travel demand, and improved accessibility.

A fundamental characteristic of the Italian system is its adoption of a "mixed model" (Campos and De Rus, 2009), in which high-speed trains are designed to operate on both new, dedicated high-speed rail (HSR) lines and on conventional tracks. This technological

[7] Only four of them are currently served only by NTV (Aversa, Molfetta, Bisceglie, Trani). In our empirical analysis, we focus exclusively on Trenitalia's high-speed service because the time a given location was first served by an HST almost always depended on the expansion strategy of the incumbent, while NTV has typically acted as a follower in this duopolistic market.

flexibility enables the decoupling of the concept of physical infrastructure (the rail) from that of the transport service (the train). The construction of HSR infrastructure is a multi-year process, announced long in advance and subject to extensive planning horizons. In contrast, activating an HST service at a given station is a more flexible and rapid operational decision made by the train operators. Service modifications, including the addition of new stops, are implemented in conjunction with the biannual updates to the national railway timetable in June and December (the "summer" and "winter" timetables, respectively). These new services are typically announced to the public only a few weeks prior to their implementation. This difference in timing is essential for our empirical strategy: while the opening of a physical line is an event anticipated for years, the activation of an HST service at a station represents a sharper and less foreseeable shock to a province's accessibility.

3.2 The Italian university system and student mobility

The Italian university system comprises 99 universities, including 68 public and 31 private institutions (ANVUR, 2023). Universities are spread throughout the country, with 67 located in the Center-North and 32 in the South. They offer three types of degree programs: three-year bachelor's degrees, five-to-six-year single-cycle degrees, and two-year master's degrees.[8] The number of enrolled students declined from 1.77 million in 2011 to 1.68 million in 2015, before recovering to 1.95 million in 2021, mostly benefiting from the relevant growth of online universities.

Over the same period, student mobility has become an increasingly salient phenomenon. According to data from the Ministry of University and Research, in 2021, 52% of students who enrolled in the first year of a bachelor's or single-cycle program did so outside their province of residence, up from an already high 47% in 2011; in particular, 23% of students moved to a different region and 9% to a different macroarea. Previous research has shown that the probability of moving is higher for males, natives, students with a better family background, coming from an academic high school, with better school performance, and who reside in smaller municipalities and areas where the quantity and quality of offered degree programs is lower (De Angelis et al., 2016; Tosi et al., 2019; Ballarino et al., 2022); in terms of destination characteristics, mobility is positively associated with the quality of research and teaching and with the job prospects offered by hosting universities (De Angelis et al., 2017).

[8] In the academic year 2020-21, Italian universities were offering over 5,000 programs: 48% were bachelor's degrees, 45% master's, and the remaining 7% single-cycle.

A distinguishing feature of student mobility in Italy is its strong geographical asymmetry. Aggregate figures are the result of significant and persistent one-sided flows of students from the South to the Center-North of the country (Columbu et al., 2021; Bacci and Bertaccini, 2021; Attanasio and Enea, 2019; Accetturo et al., 2022; Mariani and Torrini, 2022; De Angelis et al., 2017; D'Agostino et al., 2019). For instance, in 2021, over 22% of students who reside in the South enrolled in a degree program offered in the Center-North (2 percentage points more than in 2011), while only 1% moved in the opposite direction. As a consequence, around 62% of students reside in the Center-North, but universities located there account for 71% of enrolled students.

3.3 Data and sample selection

To perform our empirical analysis, we combine for the first time administrative microdata on Italian university students, provided by the Ministry of University and Research, with official information on high-speed train stops, as recorded by Ferrovie dello Stato (FS).

In particular, the *Anagrafe Nazionale degli Studenti* is a panel dataset that contains individual characteristics of all students who enrolled in Italian universities since 2010. Our focus is on students enrolling in the first year of a bachelor's or single-cycle degree program.[9] The main variables of interest for this study are the student's province of residence and province of enrollment. When these two locations do not coincide, we define the student as out-of-province. For each province, we then compute the inflow and outflow of out-of-province students: the former measures the number of out-of-province students who enroll in that specific province in a given year, while the latter measures the number of out-of-province students who reside in the province but enroll elsewhere. In addition, to study potential heterogeneities in students' responses to the opening of an HST stop, we also compute inflows and outflows for some relevant subgroups of out-of-province students, defined by gender and quartile of high-school performance.[10] Our period of analysis runs until 2019, to avoid dealing with enrollment decisions taken during the COVID-19 pandemic.

The second source of information is the dataset on HST stops collected by FS. For each province, we know whether at least one Trenitalia HST (either a Frecciarossa or a Freccia-

[9]Given that our data only cover students who entered the Italian university system since 2010, in the analysis we do not consider enrollments in master's degree programs, which would not be consistently available before 2013 (i.e., before any student could have completed a three-year bachelor's degree).

[10]To measure school performance, for each year of enrollment t, we consider the distribution of the grade of diploma (*voto di maturità*) within each high school for the subpopulation of students who then enrolled in a bachelor's or single-cycle degree program in t, and assign students to their corresponding quartile of the distribution.

rgento) stopped at a train station located within the provincial boundaries, for each year between 2010 and 2019.

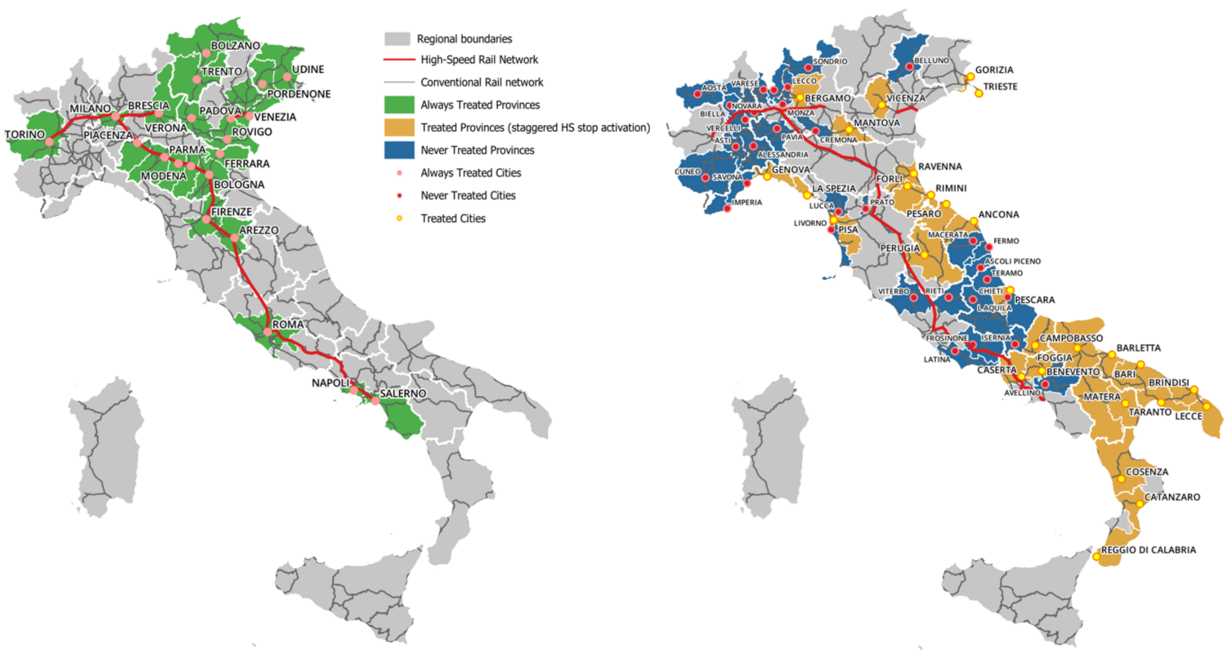
Our population of interest consists of all Italian provinces that host at least one university campus offering a bachelor's or single-cycle degree program, and that (in principle) could be connected through a high-speed train system. Out of the 108 Italian provinces, we therefore exclude from our sample: (a) 15 provinces located in the islands of Sicily and Sardinia, which could not be reached by direct trains from mainland Italy; (b) 7 provinces without a university campus in our period of analysis, for which we could only measure the outflow but not the inflow of students.[11] Moreover, since the empirical strategy outlined in Section 4 requires the treatment to be an absorbing state, we also exclude the provinces of Siena and Terni, where the HST stop was deactivated in 2012.[12]

Our final sample thus includes 84 provinces, each of which was observed within the ten-year window between 2010 and 2019. Based on the time when an HST stop was first introduced, these provinces can be grouped into three categories (Figure 3 and Table A1). Following the terminology of Callaway and Sant'Anna (2021), the group of the "always treated" consists of 23 provinces that already had an HST stop in 2010 (and therefore will not be part of our empirical analysis); the group of "eventually treated" includes 29 provinces where the HST stop was activated between 2011 and 2019; while the 32 "never treated" provinces are those without an HST stop at the end of our period of analysis. Table A2 shows descriptive statistics for the three categories. Always treated provinces, more likely to be located in the North of the country, were larger and in better economic conditions, offered more degree programs, and had more students enrolled, including those coming from elsewhere. Compared to never treated units, which were smaller, eventually treated provinces were typically medium-sized, with around half a million inhabitants; they showed worse economic indicators (as measured, for instance, by the unemployment rate and the value added per capita), a larger presence in the South of Italy, and a higher number of university students and degree programs.

[11]These seven provinces are Crotone, Grosseto, Lodi, Massa-Carrara, Pistoia, Verbano-Cusio-Ossola, and Vibo Valentia.

[12]Given that these 24 provinces are not part of our analysis, we do not even include students living or studying there when computing the inflow and outflow of out-of-province students for the remaining 84 provinces. In other words, we consider Italy *as if* it were composed of 84 instead of 108 provinces, and students' mobility can only occur within this area.

Figure 3: **Italian provinces by treatment status**



Notes: The maps show the 84 Italian provinces included in our sample, divided into "always treated" (green, left panel), "eventually treated" (yellow, right panel), and "never treated" (blue, right panel).

4 Empirical strategy

To estimate the causal effect of HST connections on the inflow and outflow of university students, we exploit the staggered introduction of our treatment, i.e., the opening of an HST stop at the provincial level. We adopt a dynamic difference-in-differences (DiD) design, comparing the evolution of outcomes in provinces where an HST stop was activated between 2010 and 2019 (the "eventually treated" group) with the evolution in provinces without HST connections (the "never treated" group). To account for potentially heterogeneous treatment effects over time and across adoption cohorts, we follow the methodology proposed by Callaway and Sant'Anna (2021). Specifically, our two-way fixed effects model is given by:

$$Y_{pt} = \alpha_p + \lambda_t + \sum_{j=-4}^{6} \beta_j \mathbb{1}[E_{pt} = j] + \epsilon_{pt} \tag{1}$$

where Y_{pt} is the inflow (or outflow) of out-of-province students coming to (or departing from) province p in year t, α_p are province fixed effects, λ_t are year fixed effects, and $E_{pt} = t - G_p$ is the time relative to treatment adoption (with G_p denoting the cohort province p belongs to, i.e., the first year in which it was treated). As discussed in Section 2, in this setting the treatment should be interpreted as a reduction in the "generalized cost of travel"

(De Rus, 2008; Balcombe et al., 2004), that is, an HST-induced change in a bundle of travel characteristics including travel times but also comfort and reliability of the service.

Our main parameters of interest are β_j's for $j \geq 0$, which capture the average treatment effect on the treated (ATT) j years after the opening of the HST stop. In this context, the ATT identifies the causal effect on the subpopulation of latecomers, i.e., provinces that eventually received the treatment during our period of analysis. This estimand is likely to differ from the average treatment effect (ATE), which would capture the impact of HST across the entire population of Italian provinces, including those already treated by 2010. This difference is a direct prediction of our theoretical framework (Section 2), which posits that the effect of an HST connection depends on a province's initial attractiveness. The "always treated" provinces, which include primary economic and academic hubs, differ systematically from the "eventually treated" provinces, which constitute our treatment group (see Table A2). Consequently, our results should not be interpreted as an estimate of the net, nationwide impact of the high-speed rail network per se. Rather, they aim to quantify the effect on a specific and policy-relevant margin, the integration of smaller, more peripheral, and later-adopting provinces into the existing network.

As usual in these settings, we have two underlying identification assumptions (Roth et al. (2023)) for the ATT.[13] The first one is that in the absence of HST connections, the average outcome for the treated and untreated groups would have evolved in parallel (parallel trends assumption). Although we cannot directly test this assumption, we can examine whether the trends in inflows and outflows were similar between treated and controls in the pre-treatment periods by looking at the estimates of β_j's for $j < 0$. The second assumption requires that prospective university students did not change their enrollment behavior before the opening of the HST stop in anticipation of the future treatment adoption (no-anticipation assumption). As highlighted in Section 3.1, high-speed service modifications were typically announced to the public only a few weeks before they took effect, thereby making it unlikely to correctly anticipate the opening of a new stop in a given location. Under these two assumptions, we can identify and estimate cohort-time average treatment effects and then aggregate them at the event-time level to obtain event-study estimates $\hat{\beta}_j$ or an average estimated effect for the post-treatment period $\hat{\beta}_{post}$.[14]

[13] Difference-in-differences settings always implicitly encode also the stable unit treatment value assumption (SUTVA), i.e. that province p's outcomes do not depend on the treatment status of province $q \neq p$, which rules out spillover and general equilibrium effects.

[14] In particular, we estimate each cohort-time average treatment effect using the outcome regression DiD estimator based on ordinary least squares, which is the default option in the STATA `csdid` command when no covariates are specified. Event-study estimates are then computed as a weighted average of treatment effects j periods after adoption across different adoption cohorts, with weights proportional to the relative

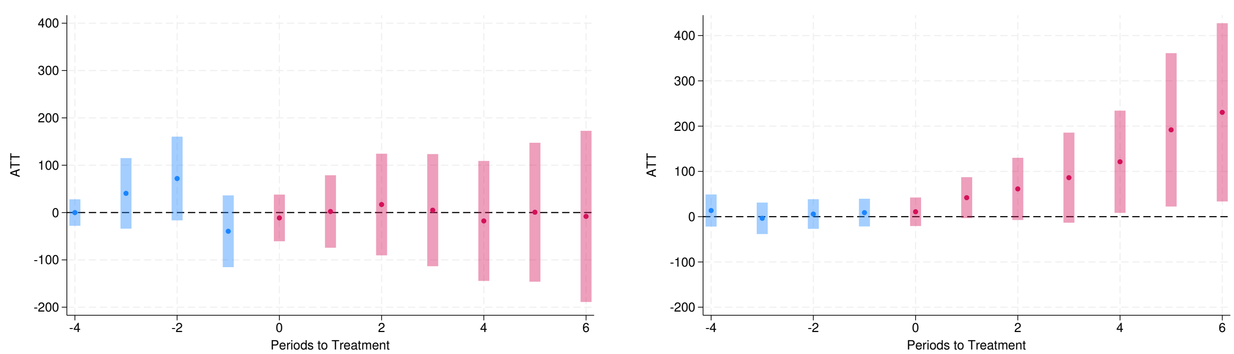
5 Results

5.1 The effect of HST on student mobility flows

We begin by examining the overall impact of the opening of a high-speed train stop on student mobility, distinguishing between outflows (students leaving the province for university) and inflows (students entering the province). As discussed in Section 2, a reduction in the generalized cost of travel τ should unambiguously increase the probability of moving to a connected destination. However, the net effect on a province's student population, which balances inflows and outflows, is theoretically ambiguous and depends on local conditions. Figure 4 presents the event-study estimates $\hat{\beta}_j$ from Equation (1).

Figure 4: **Inflow and outflow of out-of-province students**

(a) Inflow (b) Outflow



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the overall inflow (or outflow) of out-of-province students. Standard errors are clustered at the province level.

Our findings reveal a clear and statistically significant increase in student outflows following the introduction of an HST stop. The effect becomes evident starting one year after the treatment and grows in magnitude over the medium term. This result is consistent with the model's core prediction: by reducing the generalized cost of travel τ_{ij}, HST lowers the total friction of moving, making previously costly destinations viable alternatives and thus increasing the probability of departure P_{ij}. On average, after the treatment, a province loses around 100 students, or an additional 8% relative to the pre-treatment mean (Table A3, column 2). In contrast, we find no statistically significant effect on student inflows, with point estimates very close to zero (Table A3, column 1). Within our theoretical framework, the null effect on inflows for the average treated province is consistent with a scenario where its

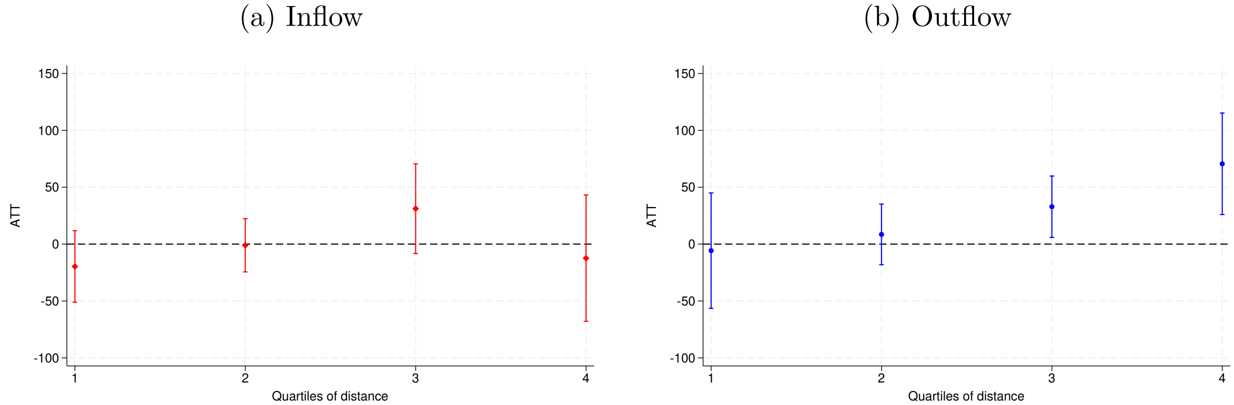
frequency of each cohort in the treated population.

initial inherent value is insufficient to make it a competitive destination, even with reduced travel friction. The result is an asymmetric effect: HST access facilitates student departures from these provinces without inducing a corresponding inflow. It is important to note, however, that this finding represents only one side of a broader human capital reallocation. The same theoretical logic implies a corresponding brain gain for the high-value destination hubs, which are predominantly in the always-treated group (and therefore outside of our regressions). Our analysis, by design, isolates and quantifies the consequences only for the newly connected areas, whereas a comprehensive ATE would aggregate both sides of this process.

To better understand these mobility changes, we disaggregate out-of-province inflows and outflows by geographic patterns. Our baseline definition of mobility across provinces encompasses three distinct types of movement: within the same region, across regions within the same macroarea (Center-North or South), and across macroareas. For student inflows, the analysis confirms the absence of any significant effect across all geographic categories (Figure A1 and Table A3, columns 3-5). The opening of an HST stop does not lead to an increase in incoming students, whether from nearby provinces or from another region or macroarea. On the other hand, the results on outflow reveal important heterogeneity (Figure A2). The positive effect observed on aggregate is entirely driven by increased student migration to provinces located in a different macroarea, while we find no evidence of higher mobility within the same region or macroarea (Table A3, columns 6-8). On average, around three-quarters of the overall effect on the outflow is due to the former type of mobility, which increased by 21% relative to the pre-treatment mean. Point estimates of the effect on the outflow to provinces in the same region or macroarea are instead much lower (both about 3% relative to the mean) and not significant at conventional levels. This picture is confirmed when looking at inflows and outflows over different distances (Figure 5 and Table A4): on the one hand, once again, we do not find any significant change in the inflow of students, regardless of the distance group; on the other, the effect of HST on outward mobility is monotonically increasing in distance and statistically different from zero only above the median of the distribution (i.e., for origin-to-destination distances larger than 92 km). The HST shock, $\Delta\tau$, is substantially larger for long-distance connections. Since the change in utility is proportional to this shock ($\Delta v = -\delta\Delta\tau$), our theoretical model predicts that the largest behavioral responses should occur precisely for these long-haul relocations, where the reduction in mobility costs is most significant.

Taken together, these findings suggest that for the provinces treated in our sample, the effects of improved HST connectivity were not neutral. The dominant effect was to enable

Figure 5: **Inflow and outflow by distance**



Notes: The graphs show point estimates and 95% confidence intervals for the ATT in the six-year post-treatment period (β_{post}) from Equation (1), where the outcome variable is the inflow (panel a) or outflow (panel b) of out-of-province students, by quartile of origin-to-destination distance. In particular, the first quartile includes distances from 2.6 to 51.7 km, the second from 51.8 to 92.2 km, the third from 92.3 to 232.1 km, and the fourth from 232.2 to 1446.6 km. Standard errors are clustered at the province level.

long-distance departures from these areas, without fostering a symmetric inflow of students.

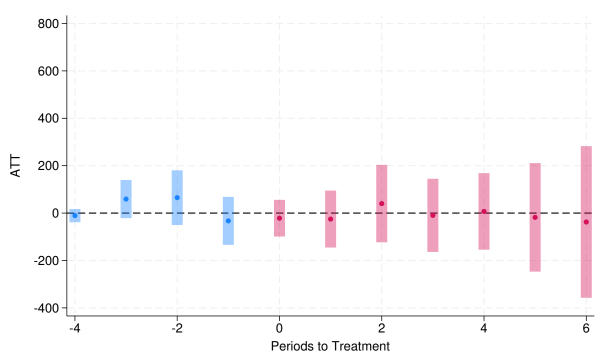
5.2 Geographical heterogeneity

As highlighted in Section 3.2, student mobility in Italy has increasingly taken place along the South-to-North axis. In this context, it is relevant to understand whether the higher accessibility due to HST has favored movements in that specific direction. To test this hypothesis, we separately consider the effect of HST for treated provinces located in the Center-North and in the South of the country (Figure 6). Results reveal a strong geographical heterogeneity. On the one hand, in the Center-North, the opening of an HST stop did not affect either the inflow or outflow of out-of-province students. As argued in Section 2, when provinces are characterized by high and similar inherent values ($V_i \approx V_j$), the strong home premium makes the initial probability of moving between them very low ($P_{ij} \approx 0$). The system is therefore insensitive to mobility shocks because students are not "on the margin," and the HST is insufficient to alter decisions that are already consolidated. On the other hand, Southern provinces that became more connected experienced a non-significant increase in the inflow, but a large, increasing over time, and highly significant effect on the outflow of students. On average, in the six years after the first HST connection, the number of students leaving the treated provinces in the South increased by 170, or 11% on top of the pretreatment mean (Table A5). The overall effect on outflow shown in Figure 4b is therefore entirely driven by departures from this area. This finding supports the "brain drain hypothesis": locations with a relatively lower V_i (our treated provinces in the South) connected to destinations with a higher V_j (provinces in the Center-North or major hubs) should experience a strong outflow effect, as the HST removes a key barrier for students who were already on the margin to move.

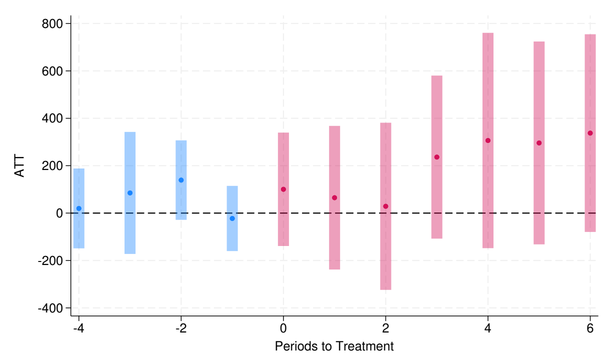
From a regional inequality perspective, it is important to determine whether this pattern reflects a "brain drain" from the South toward the Center-North, or if part of this outflow benefits other non-treated provinces in the same area. In Figures A3 and A4, we look at mobility flows happening within each macroarea and across macroareas, respectively. Out of the 170 additional students leaving on average a treated province in the South, around three-fifths decided to study in another province of the same macroarea (a 12% increase relative to the pretreatment mean; Table A6), while the remaining two-fifths moved outside (+11%).

Figure 6: **Heterogeneity of inflow and outflow by macroarea**

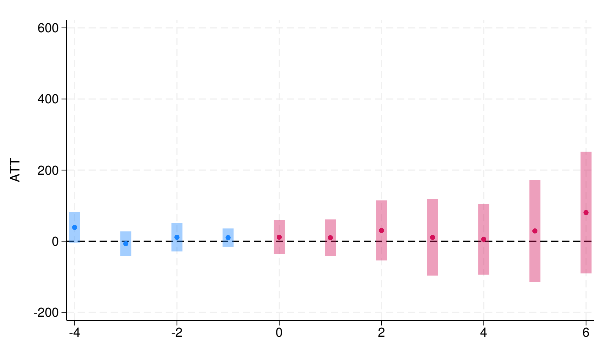
(a) Center-North, Inflow



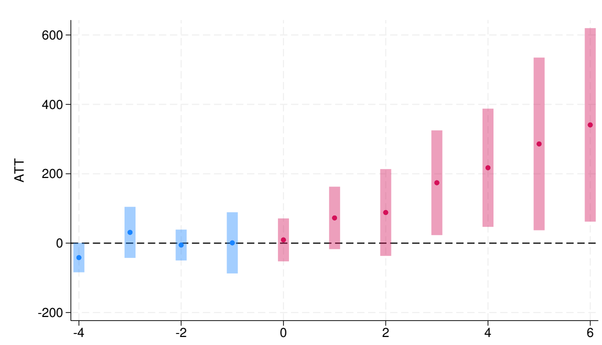
(b) South, Inflow



(c) Center-North, Outflow



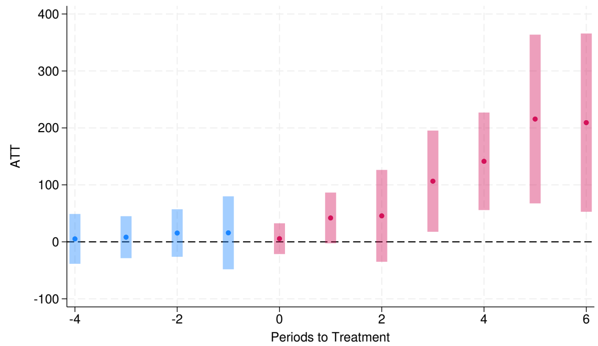
(d) South, Outflow



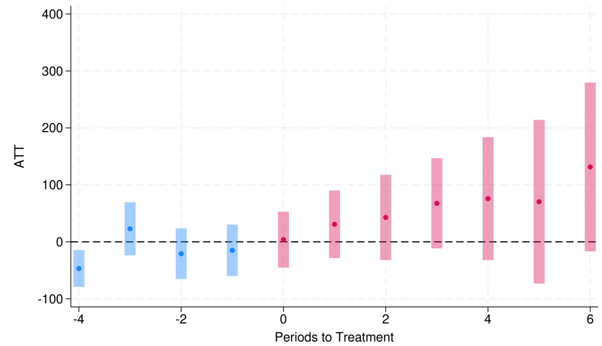
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the overall inflow (or outflow) of out-of-province students in the subsample of provinces located in the Center-North (left panels) or in the South (right panels). Standard errors are clustered at the province level.

Figure 7: **Outflow from the South: main destinations**

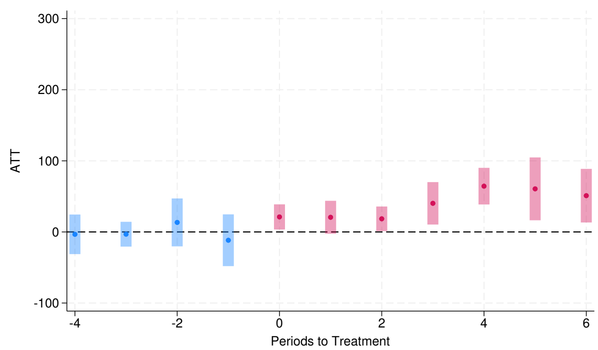
(a) Major cities



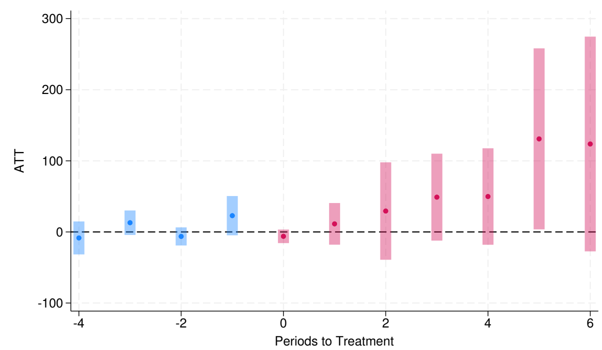
(b) Other cities



(c) Rome



(d) Naples



Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the outflow of out-of-province students from provinces located in the South to different destinations. "Major cities" refer to Turin, Milan, Bologna, Florence, Rome, and Naples, while "Other cities" refer to the remaining 78 provinces in our sample. Standard errors are clustered at the province level.

To further explore where out-migrating students from the South were directed, we separately consider two groups of destinations: the six largest cities already served by HST before the beginning of our period of analysis (Turin, Milan, Bologna, Florence, Rome, and Naples), and all the other 78 provinces in the sample. Figure 7 shows that the effect on the outflow was stronger and more significant towards major urban centers, where it increased on average by 18% relative to the pretreatment mean (Table A7). This confirms that students are moving towards destinations with a higher inherent value, which is proxied by the attractiveness of these large academic and economic hubs. In particular, students from treated Southern provinces tended to choose Rome (Figure 7c) and Naples (Figure 7d) as their main destinations. One-third of the additional outflow ended up studying in Naples (55 students, a 30% increase), even if the estimated coefficient is not statistically significant at conventional levels; around one quarter opted instead for Rome (39 students, +20%), while the point estimates for the other major cities are much lower in magnitude and not statistically different from zero (Figure A5).

This picture is consistent with the idea that high-speed trains can amplify centripetal forces toward large academic and economic hubs. The opening of an HST stop in our medium-sized southern provinces led to a significant outflow of students, who, in most cases, decided to study either in the main city of the area (Naples) or in the closest big city of the Center-North (Rome). While these results may be interpreted as an improvement in students' choice sets and mobility freedom, they also raise some concerns about the long-term implications for local human capital retention and territorial equity. The South as a whole lost some students to the benefit of Rome in particular. However, the main redistribution of human capital took place within the South itself, with Naples gaining at the expense of smaller Southern provinces, which are the main "net losers" in our setting.

5.3 Heterogeneity by students' characteristics

Finally, we explore whether the observed increase in outflows from Southern provinces following the introduction of an HST stop differs by individual characteristics. We focus on two relevant dimensions: gender and school performance of students.[15] Understanding whether infrastructure-driven mobility disproportionately affects specific subgroups is important for assessing potential implications for inequality and selection.

From a theoretical perspective, we might expect treatment effects to differ along these dimensions. Specifically, our model accommodates such heterogeneity through the δ parameter, which captures the sensitivity to travel costs and can vary across individuals. Gender differences may arise due to varying preferences or constraints regarding geographic mobility, with previous literature documenting higher mobility costs for women, often attributed to family responsibilities or social expectations (Mincer, 1978; Dustmann, 2004; Grossbard, 2003; Bielby and Bielby, 1989; Tanturri and Mencarini, 2008; Esping-Andersen, 1999). Similarly, students with higher academic standing have been shown to be more mobile (Ballarino et al., 2022; Faggian et al., 2007; Gibbons and Vignoles, 2012). However, it is unclear whether new mobility opportunities would benefit this group more or, instead, lower-performing students, who are typically less inclined or less encouraged to study elsewhere.

In our context, we find no strong evidence of systematic heterogeneity. The estimated effects of the treatment on student outflows from the South are remarkably similar across

[15]Performance is measured as the quartiles of the distribution of high school graduation grades within each student's high school. Results are robust to using quartiles computed within the region of residence.

genders (Figure A6 and Table A8). Both male and female students exhibit positive and statistically significant responses to the treatment, with overlapping confidence intervals across all categories of destinations (any other province or mobility within or across macroareas). Likewise, when we disaggregate by school performance, we observe positive and often statistically significant effects across all quartiles, with no meaningful differences (Figure A7 and Table A9).

The absence of heterogeneity implies that all groups of students living in the South were equally affected by the opening of an HST stop, with a higher fraction of them deciding to study outside their province of residence, regardless of gender or school achievement. This empirical finding suggests that, within our theoretical framework, the sensitivity to travel costs does not differ systematically across these observed characteristics in our sample. The reduction in mobility frictions appears to be a universally valued benefit for all types of students in the South who were considering moving.

6 Conclusion

Improved connectivity through infrastructure investments is often seen as beneficial for local development and promoted as a tool for economic convergence. We contribute to this debate by examining how the staggered opening of high-speed train (HST) stops affected university student mobility in Italy between 2010 and 2019. In particular, we ask whether provinces benefit from the access to HST in terms of attracting more students to their local universities, a relevant dimension of long-run regional growth.

Our analysis reveals a clear pattern for the specific subpopulation of smaller and more peripheral provinces that were linked to the already existing high-speed network during our period of analysis. For these areas, rather than enhancing their local attractiveness, improved connectivity primarily facilitated student departures. Treated provinces experienced a significant rise in *outflows* of students attending university elsewhere, beginning one year after HST access and intensifying over time. On average, the number of students leaving increased by approximately 8%. Crucially, this effect was not offset by a corresponding rise in inflows, suggesting that in our setting, high-speed trains served more as a channel for exit than as a mechanism for attracting talent. The effects are especially pronounced for long-distance moves and are geographically concentrated in Southern Italy. In these regions, the increase in student outmigration was particularly directed toward large urban centers, such as Naples and Rome. By contrast, we find no significant effect on student flows in provinces located in the Center-North, highlighting the role of regional context in shaping the impact of transport shocks.

This asymmetric response in student mobility has broader implications for regional inequality and the dynamics of human capital. The increased ease of mobility brought about by HST appears to amplify existing territorial imbalances in the distribution of higher education opportunities. While our findings confirm the persistence of the long-standing "brain drain" from southern to northern Italy, they also highlight a second and equally important pattern: the growing attractiveness of larger urban centers relative to smaller provincial cities. In this sense, the observed imbalances are not only between macroareas but also within them, reflecting strong centripetal forces that draw students toward metropolitan hubs. The result might lead to a dual polarization, both inter-regional and intra-regional, in the geography of university enrollment.

As students increasingly concentrate in a limited number of large cities, smaller and peripheral provinces risk being left behind—not only in terms of population, but also in terms of skills, innovation potential, and future labor market competitiveness. Since university years are often decisive in shaping long-term career trajectories and regional attachment, this early stage of mobility can trigger cumulative processes of divergence. Areas that lose students today may struggle to attract skilled workers tomorrow, creating a feedback loop of educational and economic disadvantage. The extent to which these dynamics translate into a permanent reshaping of the local human capital stock ultimately depends on post-graduation mobility patterns, and in particular on the intensity of return migration.[16] As noted in Section 1, aggregate evidence for Italy suggests that most students begin their careers in the region where they graduate, while return rates to the South remain modest. A direct analysis of whether improved HST connectivity affects these longer-term decisions is beyond the scope of this paper, but represents a promising avenue for future research to better assess the long-run impact on the spatial distribution of talent.

Taken together, our findings suggest that major transport infrastructure investments can also have some drawbacks on newly connected locations, particularly those in lagging regions, at least in the medium term considered here. In contexts marked by high regional disparities, such as Italy, and for the cohort of latecomer provinces that joined the existing network in a subsequent phase, improved physical connectivity does not, on its own, translate into greater

[16] In addition to return migration, the medium- to long-run effect of HST on local human capital also depends on post-graduation retention patterns, which may differ by city size and geography. In smaller and more peripheral provinces, particularly in the South, graduate out-migration may already be substantial, even in the absence of new HST connections. Where this is the case, an HST-induced increase in study-related mobility may not proportionally worsen local human capital losses, although it can still further marginalize local universities. Unfortunately, we lack detailed data to verify whether job-related post-graduation migration rates from our treated provinces were already high prior to the treatment.

attractiveness for local educational institutions. When other pull factors, such as university reputation, job opportunities, or social amenities, are concentrated elsewhere, connectivity appears to facilitate outward reallocation toward metropolitan hubs, with the risk of amplifying human capital losses in economically weaker areas. Understanding and addressing the unintended consequences of infrastructure investments is essential for promoting inclusive growth.

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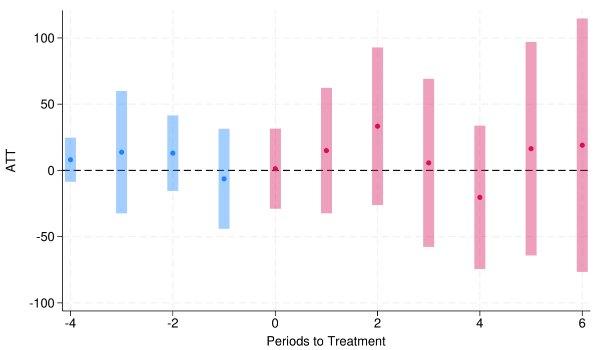
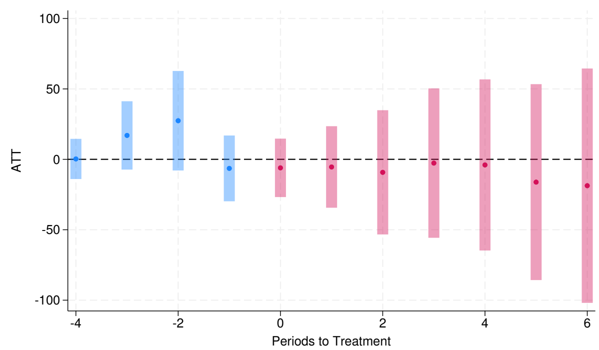
Additional Figures and Tables

Figure A1: **Inflow of out-of-province students from different origins**

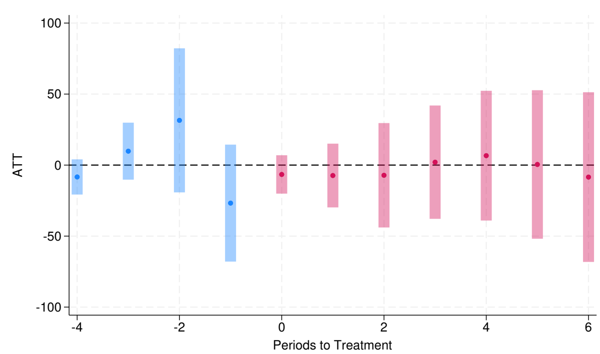
(a) Same region



(b) Other region, same macroarea



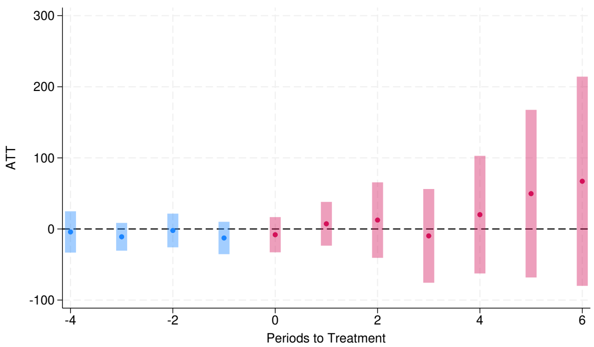
(c) Other macroarea



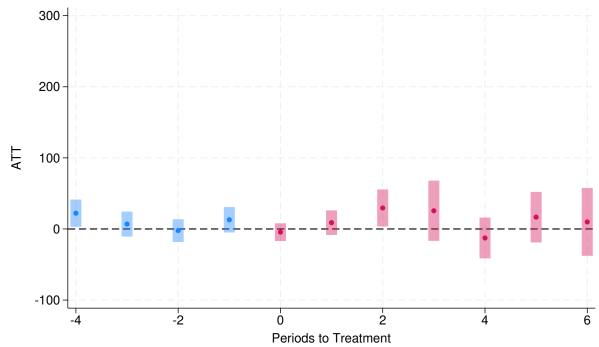
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the inflow of out-of-province students from different origins. Standard errors are clustered at the province level.

Figure A2: **Outflow of out-of-province students to different destinations**

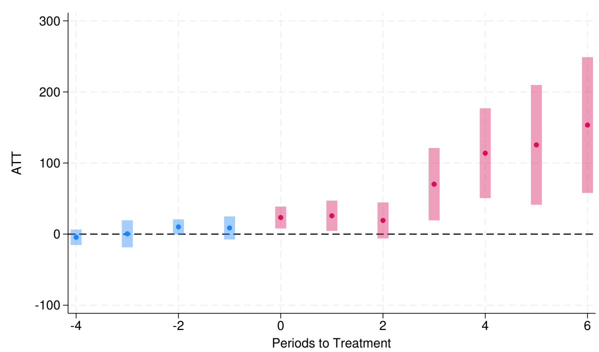
(a) Same region



(b) Other region, same macroarea



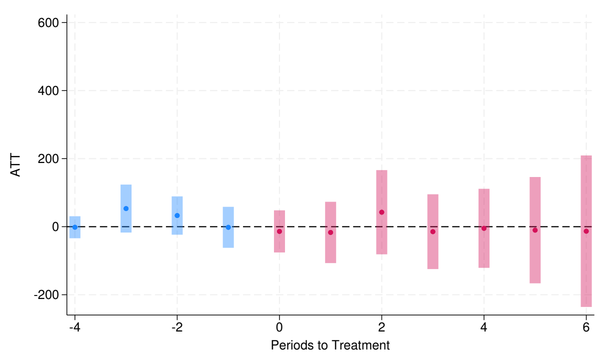
(c) Other macroarea



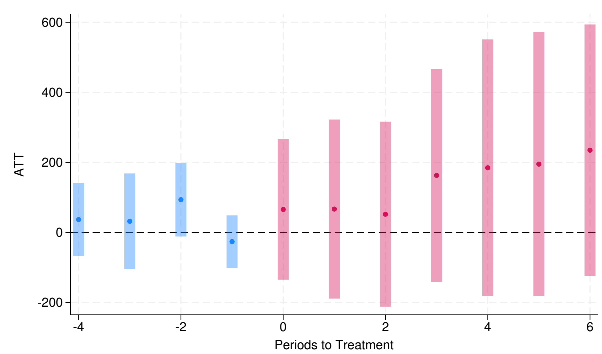
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the outflow of out-of-province students to different destinations. Standard errors are clustered at the province level.

Figure A3: **Geographical heterogeneity: mobility within macroareas**

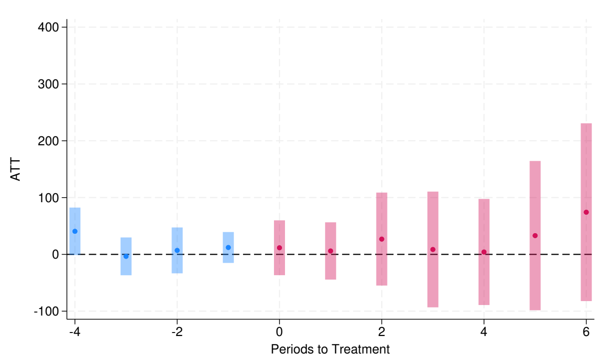
(a) Center-North, Inflow (same macroarea)



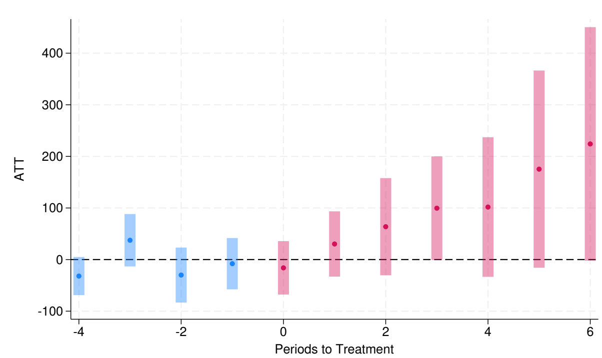
(b) South, Inflow (same macroarea)



(c) Center-North, Outflow (same macroarea)



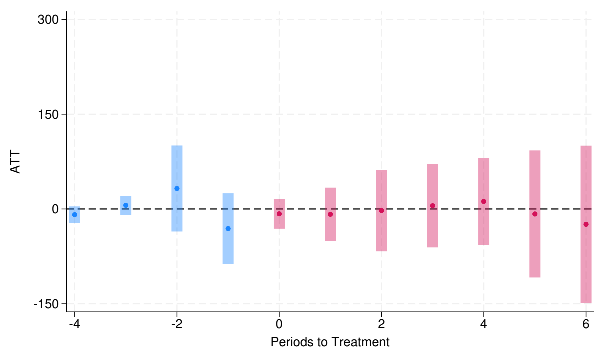
(d) South, Outflow (same macroarea)



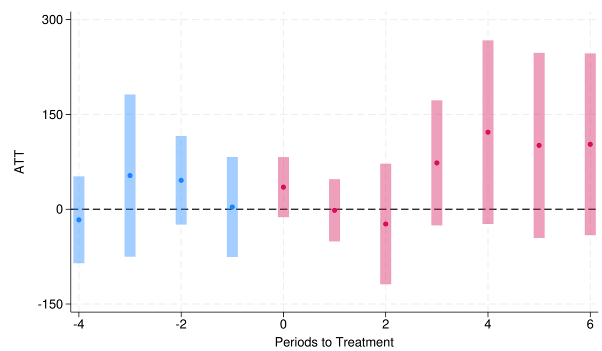
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the overall inflow (or outflow) of out-of-province students who move within the same macroarea in the subsample of provinces located in the Center-North (left panels) or in the South (right panels). Standard errors are clustered at the province level.

Figure A4: **Geographical heterogeneity: mobility across macroareas**

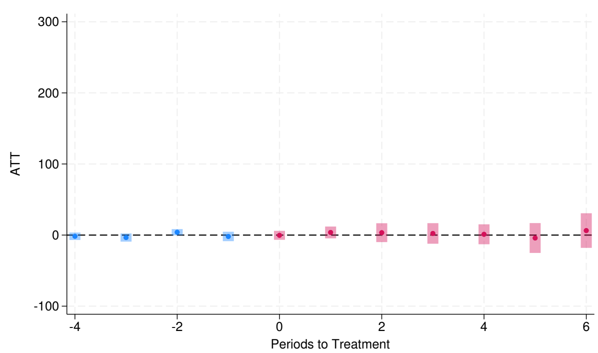
(a) Center-North, Inflow (other macroarea)



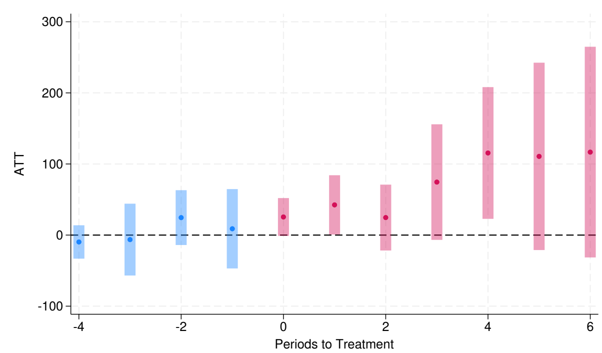
(b) South, Inflow (other macroarea)



(c) Center-North, Outflow (other macroarea)

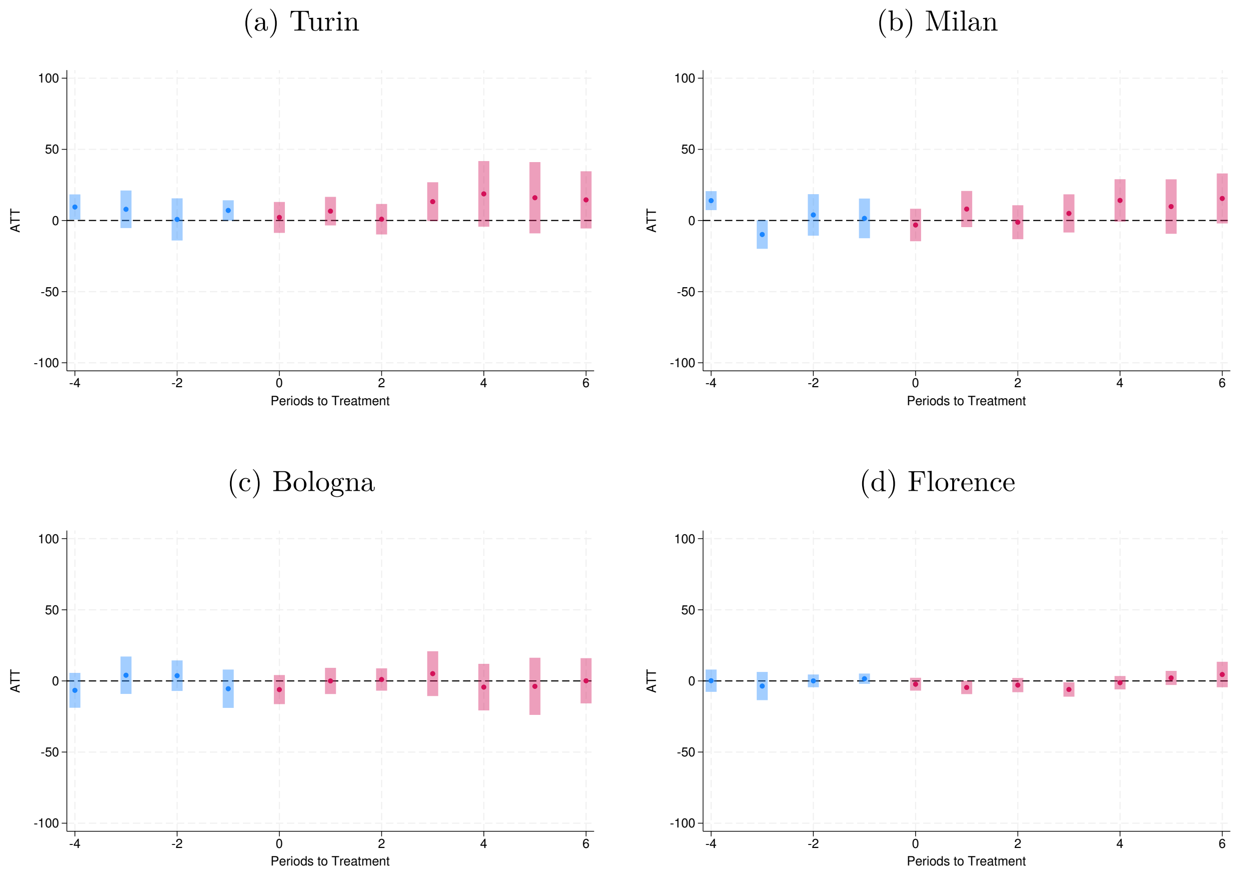


(d) South, Outflow (other macroarea)



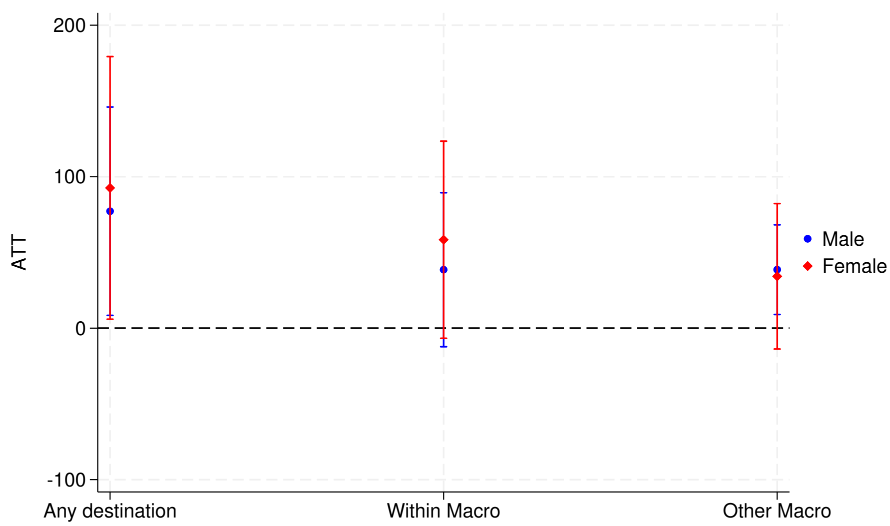
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the overall inflow (or outflow) of out-of-province students who move across macroareas in the subsample of provinces located in the Center-North (left panels) or in the South (right panels). Standard errors are clustered at the province level.

Figure A5: **Outflow from the South: other major cities**



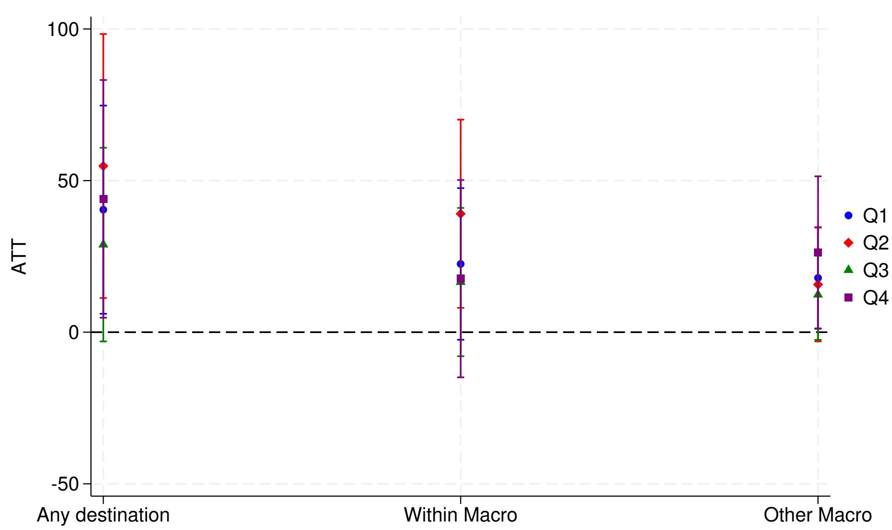
Notes: The graphs show point estimates and 95% confidence intervals for the parameters β_j from Equation (1), where the outcome variable is the outflow of out-of-province students from provinces located in the South to different destinations. Standard errors are clustered at the province level.

Figure A6: **Outflow from the South by gender**



Notes: The graphs show point estimates and 95% confidence intervals for the ATT in the six-year post-treatment period (β_{post}) from Equation (1), where the outcome variable is the outflow of out-of-province male or female students, from provinces located in the South to different destinations. Standard errors are clustered at the province level.

Figure A7: **Outflow from the South by quartile of school performance**



Notes: The graphs show point estimates and 95% confidence intervals for the ATT in the six-year post-treatment period (β_{post}) from Equation (1), where the outcome variable is the outflow of out-of-province students with different quartiles of school performance, from provinces located in the South to different destinations. Standard errors are clustered at the province level.

Table A1: **High-speed train stops by year of activation**

HST stop	Year of activation	Provinces	Group
Yes	2008-2010	Arezzo, Bologna, Bozen, Brescia, Ferrara, Florence, Milan, Modena, Naples, Padua, Parma, Piacenza, Pordenone, Reggio Emilia, Rome, Rovigo, Salerno, Trento, Treviso, Turin, Udine, Venice, Verona	Always treated
	2011	Bari, Barletta-Andria-Trani, Benevento, Brindisi, Caserta, Catanzaro, Cosenza, Foggia, Lecce, Reggio Calabria	Eventually treated
	2013	Ancona, Forli-Cesena, Pesaro-Urbino, Rimini	
	2014	Trieste	
	2015	Pescara	
	2016	Campobasso, Gorizia, Mantova, Vicenza	
	2017	Bergamo, Genoa, Matera, Pisa, Potenza, La Spezia, Taranto	
	2018	Perugia	
	2019	Ravenna	
No	/	Alessandria, Aosta, Ascoli Piceno, Asti, Avellino, Belluno, Biella, Chieti, Como, Cremona, Cuneo, Fermo, Frosinone, Imperia, Isernia, L'Aquila, Latina, Lecco, Livorno, Lucca, Monza-Brianza, Macerata, Novara, Pavia, Prato, Rieti, Savona, Sondrio, Teramo, Varese, Vercelli, Viterbo	Never treated

Notes: The sample does not include 15 provinces located in Sicily and Sardinia, 7 provinces (Crotone, Grosseto, Lodi, Massa-Carrara, Pistoia, Verbano-Cusio-Ossola, and Vibo Valentia) without university campuses, and 2 provinces (Siena and Terni) where an HST stop was deactivated within our period of analysis. Source: FS Research Centre.

Table A2: **Descriptive statistics**

	(1) Always treated Mean	(2) Eventually treated Mean	(3) Never treated Mean	(4) Difference (2) - (3)
Population	1,085,072.00	512,570.50	351,031.20	161,539.30***
Population aged 14-18	50,773.91	26,033.62	15,803.56	10,230.06***
Unemployment rate (%)	6.48	9.06	7.08	1.99***
Value added per capita (euros)	27,840.20	20,558.93	22,704.22	-2,145.29*
North	0.78	0.34	0.53	-0.19
Center	0.13	0.14	0.31	-0.17
South	0.09	0.52	0.16	0.36***
N. degree programs	78.04	29.90	16.38	13.52***
N. students	6,745.52	2,056.72	781.56	1,275.16***
Inflow of students	2,766.00	766.72	417.19	349.54*
Outflow of students	1,240.44	1,209.66	1,112.28	97.37
N	23	29	32	61

Notes: All variables are measured in 2010. "N. students" is the number of students who enrolled in the first year of a bachelor's or single-cycle degree program offered by a university located within the province. Inflow and outflow of students refer to movements across provinces. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%. Sources: Ministry of University and Research, *Anagrafe Nazionale degli Studenti*; FS Research Centre; ISTAT.

Table A3: **Inflow and outflow of out-of-province students**

	(1) Inflow Any origin	(2) Outflow Any destination	(3) Inflow Same region	(4) Inflow Same macro	(5) Inflow Other macro	(6) Outflow Same region	(7) Outflow Same macro	(8) Outflow Other macro
β_{pre}	18.22	6.21	7.12	9.55	1.55	-7.49	9.94*	3.76
	(16.39)	(8.93)	(10.60)	(6.85)	(4.52)	(6.08)	(5.56)	(5.45)
β_{post}	-1.75	106.29**	10.06	-8.90	-2.91	19.85	10.50	75.95***
	(52.80)	(48.19)	(27.22)	(24.26)	(18.21)	(35.12)	(11.86)	(23.53)
β_{-4}	-0.03	13.62	8.06	0.27	-8.35	-4.17	22.19**	-4.39
	(14.27)	(18.07)	(8.51)	(7.28)	(6.32)	(14.83)	(9.78)	(5.54)
β_{-3}	40.54	-3.61	13.75	16.97	9.81	-10.99	6.89	0.48
	(38.02)	(17.74)	(23.56)	(12.38)	(10.24)	(9.98)	(8.98)	(9.70)
β_{-2}	71.93	5.79	13.02	27.40	31.51	-2.13	-2.27	10.19*
	(45.11)	(16.69)	(14.57)	(18.02)	(25.89)	(12.08)	(8.15)	(5.41)
β_{-1}	-39.56	9.03	-6.35	-6.44	-26.77	-12.66	12.95	8.74
	(38.68)	(15.59)	(19.27)	(11.91)	(21.01)	(11.62)	(9.14)	(8.28)
β_0	-11.35	10.86	1.30	-6.06	-6.58	-8.07	-4.48	23.41***
	(25.18)	(16.08)	(15.43)	(10.58)	(6.89)	(12.63)	(6.35)	(7.84)
β_1	2.19	42.00*	14.96	-5.43	-7.35	7.29	8.88	25.84**
	(39.07)	(23.11)	(24.16)	(14.77)	(11.46)	(15.71)	(8.81)	(10.88)
β_2	16.96	61.38*	33.36	-9.24	-7.17	12.50	29.56**	19.31
	(54.79)	(35.05)	(30.35)	(22.50)	(18.75)	(27.09)	(13.29)	(12.93)
β_3	5.08	86.21*	5.70	-2.68	2.06	-9.71	25.65	70.27***
	(60.46)	(50.77)	(32.38)	(27.06)	(20.36)	(33.63)	(21.62)	(25.94)
β_4	-17.69	121.32**	-20.35	-3.99	6.65	20.14	-12.69	113.87***
	(64.66)	(57.62)	(27.63)	(30.99)	(23.31)	(42.20)	(14.62)	(32.23)
β_5	0.68	191.81**	16.41	-16.19	0.45	49.67	16.61	125.53***
	(74.89)	(86.44)	(41.12)	(35.48)	(26.68)	(60.14)	(18.15)	(42.97)
β_6	-8.12	230.49**	19.03	-18.72	-8.44	67.11	9.96	153.42***
	(92.25)	(100.44)	(48.81)	(42.45)	(30.49)	(75.05)	(24.36)	(48.71)
$\bar{Y}_{g-1}$	857.86	1350.38	557.90	213.10	86.86	630.48	353.34	366.55
N	610	610	610	610	610	610	610	610

Notes: Column 1 considers as the outcome variable the inflow of students from any origin; column 2 the outflow to any destination; columns 3-5 (6-8) the inflow from (outflow to) the same region, a different region in the same macroarea, and a different macroarea, respectively. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A4: **Inflow and outflow of out-of-province students by distance**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inflow by distance quartile				Outflow by distance quartile			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
β_{pre}	6.05	1.43	4.74	6.03	-4.62	3.69	-0.62	7.78
	(6.71)	(5.06)	(4.68)	(5.77)	(3.68)	(3.78)	(3.34)	(6.59)
β_{post}	-19.63	-1.05	31.16	-12.35	-5.73	8.51	32.88**	70.61***
	(16.04)	(11.94)	(20.11)	(28.33)	(25.88)	(13.59)	(13.77)	(22.76)
β_{-4}	1.81	-0.92	6.56	-7.41	-2.12	6.39	2.26	7.09
	(6.23)	(4.67)	(8.11)	(6.25)	(6.27)	(8.85)	(10.29)	(9.72)
β_{-3}	14.38	-4.11	18.34	11.86	-3.05	-7.70	5.30	1.83
	(14.76)	(10.94)	(13.43)	(9.25)	(7.03)	(8.72)	(7.72)	(8.95)
β_{-2}	5.77	11.55*	17.97	36.71	-1.81	3.45	-2.18	6.33
	(7.23)	(6.44)	(14.50)	(30.25)	(6.84)	(9.57)	(5.85)	(5.65)
β_{-1}	2.25	-0.79	-23.89***	-17.03	-11.49*	12.63*	-7.85	15.85
	(10.04)	(8.70)	(9.05)	(25.24)	(6.15)	(7.49)	(5.54)	(11.59)
β_0	-7.50	-0.17	7.00	-10.70	-8.23	1.15	3.99	13.98*
	(8.68)	(7.03)	(11.62)	(11.78)	(7.88)	(6.14)	(6.54)	(7.34)
β_1	-4.72	-0.57	18.05	-10.73	-2.00	-1.83	22.56**	23.20**
	(14.76)	(7.94)	(14.85)	(18.58)	(9.63)	(7.95)	(10.30)	(9.47)
β_2	1.83	14.44	19.12	-18.68	0.45	4.38	23.87*	32.52***
	(18.39)	(10.45)	(17.51)	(30.91)	(20.49)	(10.38)	(13.31)	(12.52)
β_3	-20.10	-1.35	30.81	-4.49	-14.05	2.11	36.57*	61.56**
	(19.36)	(12.59)	(26.18)	(30.54)	(24.96)	(13.76)	(18.73)	(24.20)
β_4	-33.62**	-15.98	35.38	-3.38	-11.11	12.55	31.35*	88.75***
	(16.59)	(16.81)	(25.92)	(30.46)	(26.47)	(18.82)	(17.81)	(30.00)
β_5	-33.16	-7.00	49.77*	-8.98	-0.28	13.37	51.39**	127.30***
	(22.97)	(23.40)	(28.48)	(36.18)	(42.82)	(24.85)	(22.11)	(43.29)
β_6	-40.11	3.28	58.01*	-29.50	-4.89	27.86	60.42**	146.93***
	(28.09)	(23.85)	(33.53)	(49.09)	(57.07)	(27.28)	(24.36)	(50.54)
$\bar{Y}_{g-1}$	238.24	246.34	242.21	131.03	254.48	318.03	313.93	463.72
N	610	610	610	610	610	610	610	610

Notes: Columns 1-4 (5-8) consider as the outcome variable the inflow (outflow) of students from (to) provinces located in the four quartiles of origin-to-destination distance, respectively. In particular, the first quartile includes distances from 2.6 to 51.7 km, the second from 51.8 to 92.2 km, the third from 92.3 to 232.1 km, and the fourth from 232.2 to 1446.6 km. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A5: **Geographical heterogeneity: Inflow and outflow of out-of-province students**

	(1) Inflow Center-North	(2) Inflow South	(3) Outflow Center-North	(4) Outflow South
β_{pre}	20.19	55.30	13.30*	-3.74
	(19.11)	(42.45)	(7.74)	(21.05)
β_{post}	-9.23	195.71	25.31	169.83**
	(80.84)	(164.86)	(41.85)	(75.90)
β_{-4}	-10.69	19.68	38.94*	-41.60*
	(14.27)	(85.96)	(21.89)	(21.61)
β_{-3}	59.07	85.04	-6.95	31.12
	(41.05)	(131.32)	(17.65)	(37.54)
β_{-2}	65.19	139.20	11.00	-5.40
	(58.86)	(85.58)	(20.29)	(22.68)
β_{-1}	-32.80	-22.72	10.20	0.92
	(51.65)	(70.16)	(13.13)	(44.98)
β_0	-21.49	100.40	11.31	9.45
	(39.49)	(122.07)	(24.46)	(31.55)
β_1	-25.21	64.89	9.74	72.73
	(61.32)	(154.61)	(26.30)	(45.91)
β_2	40.07	28.64	30.34	88.37
	(83.35)	(179.91)	(43.09)	(63.82)
β_3	-9.55	236.27	10.93	174.13**
	(78.74)	(175.51)	(54.92)	(77.02)
β_4	7.14	306.29	5.33	217.29**
	(82.41)	(231.80)	(50.75)	(86.90)
β_5	-18.05	296.00	28.91	286.00**
	(116.83)	(218.34)	(73.04)	(126.94)
β_6	-37.52	337.50	80.61	340.80**
	(163.24)	(212.77)	(87.32)	(142.27)
$\bar{Y}_{g-1}$	1097.36	634.33	1162.29	1525.93
N	410	200	410	200

Notes: Columns 1-2 (3-4) consider as the outcome variable the inflow (outflow) of students from any origin (to any destination) for the subsamples of provinces located in the Center-North and in the South, respectively. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A6: **Geographical heterogeneity: Mobility within and across macroareas**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inflow (same macro)		Outflow (same macro)		Inflow (other macro)		Outflow (other macro)	
	Center-North	South	Center-North	South	Center-North	South	Center-North	South
β_{pre}	20.66	33.87	14.06*	-8.09	-0.47	21.43	-0.77	4.35
	(17.21)	(25.40)	(7.47)	(11.48)	(4.47)	(20.73)	(1.08)	(16.55)
β_{post}	-4.42	137.34	23.54	96.97*	-4.81	58.37	1.77	72.86*
	(54.75)	(146.98)	(38.87)	(57.36)	(34.07)	(36.11)	(6.16)	(37.46)
β_{-4}	-1.61	36.48	40.62*	-31.92*	-9.08	-16.80	-1.68	-9.68
	(16.51)	(53.17)	(21.32)	(18.83)	(6.71)	(35.08)	(2.68)	(11.97)
β_{-3}	53.30	31.80	-3.50	37.48	5.78	53.24	-3.45	-6.36
	(35.96)	(69.67)	(16.98)	(25.90)	(7.65)	(65.49)	(2.95)	(25.76)
β_{-2}	32.79	93.48*	6.99	-29.96	32.40	45.72	4.01*	24.56
	(28.74)	(53.68)	(20.60)	(27.18)	(34.71)	(35.77)	(2.24)	(19.67)
β_{-1}	-1.83	-26.28	12.14	-7.96	-30.97	3.56	-1.94	8.88
	(30.72)	(38.22)	(13.87)	(25.37)	(28.46)	(40.34)	(3.37)	(28.47)
β_0	-13.82	65.52	11.65	-16.01	-7.67	34.88	-0.34	25.47*
	(31.59)	(102.32)	(24.63)	(26.40)	(12.01)	(24.25)	(3.22)	(13.57)
β_1	-16.89	66.65	6.03	30.24	-8.32	-1.76	3.72	42.49**
	(45.96)	(130.44)	(25.72)	(32.28)	(21.48)	(25.13)	(4.24)	(21.27)
β_2	42.57	52.03	26.94	63.75	-2.50	-23.39	3.40	24.63
	(63.12)	(134.81)	(41.76)	(48.06)	(32.93)	(48.72)	(6.77)	(23.63)
β_3	-14.62	162.97	8.63	99.60*	5.07	73.30	2.30	74.53*
	(56.08)	(155.08)	(51.98)	(51.20)	(33.60)	(50.49)	(7.38)	(41.48)
β_4	-4.77	184.44	4.22	101.82	11.91	121.85	1.11	115.47**
	(59.24)	(187.11)	(47.65)	(69.05)	(35.21)	(74.16)	(7.16)	(47.26)
β_5	-10.19	195.00	33.03	175.30*	-7.87	101.00	-4.12	110.70*
	(79.69)	(192.45)	(67.03)	(97.52)	(51.28)	(74.70)	(10.71)	(67.22)
β_6	-13.24	234.80	74.25	224.10*	-24.28	102.70	6.36	116.70
	(113.58)	(183.17)	(79.85)	(115.46)	(63.52)	(73.39)	(12.42)	(75.60)
$\bar{Y}_{g-1}$	934.57	618.33	1145.07	833.33	162.79	16.00	17.21	692.60
N	410	200	410	200	410	200	410	200

Notes: Columns 1-2 (3-4) consider as the outcome variable the inflow (outflow) of students from (to) the same macroarea for the subsamples of provinces located in the Center-North and in the South, respectively, while columns 5-6 (7-8) the inflow from (outflow to) a different macroarea for the subsamples of provinces located in the Center-North and in the South, respectively. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A7: **Outflow from the South: Main destinations**

	(1) Big cities	(2) Other cities	(3) Rome	(4) Naples	(5) Turin	(6) Milan	(7) Bologna	(8) Florence
β_{pre}	11.18	-14.92	-1.21	5.27	6.30**	2.38	-1.10	-0.46
	(14.98)	(9.13)	(6.17)	(4.72)	(3.15)	(1.48)	(1.58)	(1.54)
β_{post}	109.42***	60.41	39.49***	55.41	10.30	6.87	-1.15	-1.50
	(40.34)	(44.15)	(10.89)	(35.93)	(7.25)	(5.65)	(5.90)	(1.72)
β_{-4}	5.20	-46.80***	-3.36	-8.44	9.48**	13.96***	-6.60	0.16
	(22.32)	(16.49)	(14.21)	(11.83)	(4.52)	(3.40)	(6.25)	(3.99)
β_{-3}	8.20	22.92	-3.20	12.96	7.88	-9.84*	4.00	-3.60
	(18.79)	(23.79)	(8.90)	(8.78)	(6.73)	(5.13)	(6.70)	(5.06)
β_{-2}	15.48	-20.88	13.40	-6.32	0.76	3.92	3.68	0.04
	(21.27)	(22.71)	(17.20)	(6.50)	(7.56)	(7.44)	(5.48)	(2.29)
β_{-1}	15.84	-14.92	-11.68	22.88	7.08*	1.48	-5.48	1.56
	(32.67)	(23.04)	(18.58)	(14.09)	(3.63)	(7.11)	(6.87)	(1.85)
β_0	5.55	3.91	21.13**	-6.19	2.16	-3.16	-6.09	-2.31
	(13.77)	(25.05)	(9.03)	(4.86)	(5.54)	(5.83)	(5.22)	(2.30)
β_1	41.96*	30.77	20.60*	11.35	6.57	8.05	-0.01	-4.60*
	(22.74)	(30.27)	(11.83)	(14.95)	(5.12)	(6.49)	(4.70)	(2.38)
β_2	45.63	42.75	18.47**	29.39	0.91	-1.21	1.00	-2.92
	(41.14)	(38.17)	(8.82)	(34.96)	(5.47)	(6.09)	(4.00)	(2.56)
β_3	106.50**	67.63*	40.25***	48.92	13.25*	4.98	5.12	-6.02**
	(45.32)	(40.40)	(15.23)	(31.19)	(6.96)	(6.85)	(8.03)	(2.58)
β_4	141.40***	75.89	64.38***	49.82	18.71	14.11*	-4.36	-1.25
	(43.68)	(55.09)	(13.14)	(34.62)	(11.77)	(7.60)	(8.35)	(2.40)
β_5	215.60***	70.40	60.60***	130.90**	16.00	9.80	-3.80	2.10
	(75.58)	(73.28)	(22.55)	(64.95)	(12.78)	(9.77)	(10.25)	(2.53)
β_6	209.30***	131.50*	51.00***	123.70	14.50	15.50*	0.10	4.50
	(79.83)	(75.56)	(19.24)	(77.05)	(10.25)	(8.97)	(8.11)	(4.56)
$\bar{Y}_{g-1}$	609.93	916.00	194.47	184.80	54.87	93.93	56.93	24.93
N	200	200	200	200	200	200	200	200

Notes: Each column considers the outflow of students to a given destination as the outcome variable for the subsample of provinces located in the South. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A8: **Outflow from the South by gender**

	(1)	(2)	(3)	(4)	(5)	(6)
	Any destination		Same macro		Other macro	
	Male	Female	Male	Female	Male	Female
β_{pre}	-0.04	-3.70	-4.95	-3.14	4.91	-0.56
	(10.01)	(12.17)	(4.84)	(7.76)	(8.25)	(9.05)
β_{post}	77.22**	92.60**	38.59	58.38*	38.63**	34.22
	(35.10)	(44.24)	(25.93)	(33.20)	(15.10)	(24.50)
β_{-4}	-16.04	-25.56	-24.04**	-7.88	8.00	-17.68*
	(12.27)	(16.71)	(10.54)	(15.03)	(10.44)	(9.17)
β_{-3}	7.64	23.48	6.16	31.32	1.48	-7.84
	(10.16)	(29.81)	(8.27)	(22.31)	(11.51)	(17.29)
β_{-2}	7.04	-12.44	8.64	-38.60	-1.60	26.16
	(7.82)	(20.18)	(11.24)	(25.30)	(8.81)	(17.12)
β_{-1}	1.20	-0.28	-10.56	2.60	11.76	-2.88
	(32.29)	(18.93)	(16.21)	(14.38)	(20.64)	(13.81)
β_0	-8.71	18.16	-20.29	4.28	11.59	13.88
	(18.08)	(20.29)	(13.00)	(17.12)	(9.10)	(11.29)
β_1	35.44	37.29	4.87	25.37	30.57***	11.92
	(22.72)	(26.97)	(18.40)	(16.89)	(11.13)	(14.07)
β_2	47.04*	41.33	24.96	38.79	22.08**	2.55
	(27.15)	(39.82)	(21.11)	(29.72)	(10.45)	(15.96)
β_3	70.57**	103.57**	36.40*	63.20*	34.17*	40.37
	(33.18)	(49.00)	(21.08)	(33.04)	(19.68)	(25.53)
β_4	117.53***	99.76*	52.20*	49.62	65.33***	50.15
	(37.45)	(55.89)	(28.48)	(43.85)	(18.29)	(32.11)
β_5	126.50**	159.50**	79.20*	96.10*	47.30	63.40
	(61.42)	(73.76)	(44.02)	(56.95)	(30.07)	(42.18)
β_6	152.20**	188.60**	92.80	131.30**	59.40**	57.30
	(73.27)	(74.57)	(58.38)	(59.80)	(30.27)	(48.76)
$\bar{Y}_{g-1}$	676.40	849.53	338.67	494.67	337.73	354.87
N	200	200	200	200	200	200

Notes: Columns 1, 3, and 5 (2, 4, and 6) consider as the outcome variable the outflow of male (female) students to any destination, the same macroarea, and a different macroarea, respectively, for the subsample of provinces located in the South. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.

Table A9: **Outflow from the South by quartile of school performance**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Any destination				Same macro				Other macro			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
β_{pre}	-1.71	-4.42	4.64	-1.60	-2.23	-3.19	-0.64	-1.28	0.52	-1.23	5.28	-0.32
	(4.90)	(5.49)	(5.09)	(6.03)	(3.12)	(3.05)	(2.15)	(5.05)	(2.83)	(5.09)	(4.14)	(4.96)
β_{post}	40.41**	54.80**	28.89*	43.98**	22.52*	39.07**	16.53	17.65	17.89**	15.73	12.37	26.32**
	(17.52)	(22.21)	(16.29)	(20.00)	(12.76)	(15.83)	(12.48)	(16.60)	(8.54)	(9.57)	(7.59)	(12.80)
β_{-4}	-8.80	-16.92**	0.72	-14.56*	-9.44	-3.04	-6.64	-10.36	0.64	-13.88**	7.36	-4.20
	(6.16)	(8.62)	(7.29)	(7.98)	(6.54)	(8.30)	(5.28)	(9.04)	(6.79)	(6.73)	(5.72)	(9.89)
β_{-3}	18.80	8.64	4.28	-3.88	14.08	10.40	-0.16	9.76	4.72	-1.76	4.44	-13.64
	(13.78)	(14.07)	(15.13)	(7.39)	(10.97)	(8.59)	(5.13)	(11.77)	(6.06)	(8.58)	(11.70)	(9.41)
β_{-2}	-4.72	-4.60	-2.76	10.32*	-2.12	-10.84	-10.48	-4.32	-2.60	6.24	7.72	14.64
	(8.50)	(10.95)	(9.78)	(5.95)	(10.83)	(9.38)	(7.98)	(9.86)	(7.35)	(6.56)	(6.17)	(9.74)
β_{-1}	-12.12	-4.80	16.32	1.72	-11.44	-9.28**	14.72*	-0.20	-0.68	4.48	1.60	1.92
	(8.28)	(11.48)	(13.72)	(17.10)	(11.10)	(4.67)	(7.94)	(11.11)	(5.97)	(9.50)	(9.88)	(14.12)
β_0	8.00	22.17**	-15.15	-0.73	-1.41	14.04*	-9.60	-16.99**	9.41*	8.13*	-5.55	16.25**
	(9.15)	(9.28)	(10.12)	(9.00)	(7.33)	(7.77)	(9.99)	(7.09)	(4.87)	(4.73)	(4.72)	(6.41)
β_1	26.03**	22.83*	0.87	21.95	8.32	13.72*	0.45	6.85	17.71***	9.11	0.41	15.09**
	(12.57)	(13.26)	(11.96)	(13.48)	(10.37)	(7.52)	(8.07)	(10.42)	(5.42)	(7.74)	(5.83)	(6.20)
β_2	22.88	29.77*	11.75	16.01	13.25	27.13**	8.52	9.28	9.63	2.64	3.23	6.73
	(15.04)	(17.53)	(11.75)	(18.01)	(10.92)	(13.76)	(8.37)	(13.03)	(6.73)	(6.27)	(6.36)	(10.45)
β_3	39.60**	55.33***	39.77*	36.62*	21.75*	38.12**	20.23	17.90	17.85	17.22*	19.53*	18.72
	(19.17)	(21.37)	(20.75)	(18.76)	(11.71)	(15.80)	(13.10)	(14.55)	(11.22)	(10.24)	(10.39)	(15.13)
β_4	47.75**	72.20***	35.42*	59.89**	29.91*	42.40**	11.07	17.22	17.84	29.80**	24.35**	42.67***
	(18.89)	(27.89)	(20.83)	(23.38)	(16.44)	(19.82)	(14.40)	(20.77)	(11.31)	(14.39)	(10.99)	(15.76)
β_5	54.30*	82.30**	61.60**	88.60***	34.80	61.00**	34.80*	45.20	19.50	21.30	26.80**	43.40*
	(28.85)	(41.23)	(25.95)	(33.48)	(21.72)	(28.46)	(20.33)	(31.14)	(13.20)	(18.74)	(13.37)	(24.27)
β_6	84.30**	99.00***	68.00**	85.50**	51.00**	77.10**	50.20*	44.10	33.30*	21.90	17.80	41.40*
	(34.63)	(38.16)	(32.02)	(38.34)	(25.84)	(30.24)	(29.15)	(33.30)	(17.34)	(17.88)	(16.50)	(24.79)
$\bar{Y}_{g-1}$	303.40	371.53	375.87	459.73	179.13	212.93	212.00	225.53	124.27	158.60	163.87	234.20
N	200	200	200	200	200	200	200	200	200	200	200	200

Notes: Columns 1-4 consider as the outcome variable the outflow to any destination of students belonging to the four quartiles of school performance, respectively, for the subsample of provinces located in the South, while columns 5-8 (9-12) the corresponding outflow to the same (a different) macroarea. β_j's denote the event-study estimates of Equation (1), estimated following the methodology proposed by Callaway and Sant'Anna (2021). β_{pre} and β_{post} denote the average estimated effect for the pre-treatment and post-treatment period, respectively. Standard errors are clustered at the province level and shown in parentheses. $\bar{Y}_{g-1}$ denotes the average of the outcome variable in the eventually treated group, measured in the last year before the treatment. *** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%.