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On Track to New Jobs: High-Speed Rail and Worker Mobility in Italy

(*Verso una nuova occupazione: l'Alta Velocità ferroviaria e la mobilità dei lavoratori in Italia*)*

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Abstract

Using Italian administrative data on the population of private-sector workers from 2005 to 2022, we examine how the opening of high-speed rail (HSR) routes expands labor market opportunities. To this end, we estimate gravity-type models at a high level of spatial granularity (municipality) and implement a staggered difference-in-differences research design. We find that the development of new HSR routes induced workers to change their employment location along these routes, with heterogeneous treatment effects by gender, age, contract type, and job qualification. Moreover, such effect is found to be increasing over time, eventually generating additional job relocations of about 12,000 workers per year, and largely due to flows between large municipalities and from small to large ones. The estimation of an AKM model suggests that the connection to the HSR network induced an increase in assortative matching at municipal level.

Utilizzando dati amministrativi italiani sull'universo dei lavoratori del settore privato dal 2005 al 2022, analizziamo come l'apertura delle linee ferroviarie ad alta velocità (HSR) ampli le opportunità nel mercato del lavoro. A tal fine, stimiamo modelli di tipo gravitazionale con un elevato livello di granularità spaziale (comunale) e adottiamo un disegno di ricerca difference-in-differences con introduzione scaglionata. Mostriamo che lo sviluppo di nuove linee HSR ha indotto i lavoratori a cambiare il luogo di lavoro lungo tali direttrici, con effetti di trattamento eterogenei per genere, età, tipologia contrattuale e qualifica professionale. Inoltre, l'effetto risulta crescente nel tempo, fino a generare circa 12.000 ricollocazioni occupazionali aggiuntive all'anno, ed è dovuto in larga parte a flussi tra grandi comuni e da comuni piccoli verso comuni grandi. La stima di un modello AKM suggerisce che la connessione alla rete HSR ha determinato un miglioramento del matching tra imprese e lavoratori a livello comunale.

Keywords: labor mobility; high-speed rail; sorting; Italy
JEL codes: J61 J31 018

1 Introduction

The role of the High Speed Rail (HSR) network in the transportation systems of many countries has increased rapidly over the past two decades, at the global level from about 5,000 km in the early 2000s to about 60,000 km in 2024 (Koster and Thisse, 2025). Although this massive increase has been mostly due to China—that in about 20 years has built about 40,000 km of new lines—the HSR network continued to grow also in early adopters of this transportation mode, such as Japan and various European Union countries (like France, Italy, Germany, and Spain, among others), featuring a key role also in the transportation program of the European Commission.

The reduction in journey times[1] favored by a municipality's connection to the HSR network can significantly increase the scope of job searches by workers, thus leading to a significant enlargement of the local labor market—given that recent research has highlighted how workers' job searches appear to be highly sensitive to distance from home (Manning and Petrongolo, 2017)—ultimately enlarging workers' outside options, as in the German case (Caldwell and Danieli, 2024). Moreover, a larger local labor market due to a reduction in trip durations might improve the efficiency of the matching process between workers and firms—with possible important implications for the productivity of the worker-firm matches, as in Agrawal et al. (2024). Indeed, the enlargement of the local labor market may change the value of workers' outside options, possibly leading to higher wages and lower monopsonistic labor market power (Caldwell and Danieli, 2024; Brooks et al., 2021) for commuters, but also for non-commuters that can benefit from the increased labor demand (Caldwell and Danieli, 2024).

Against this background, in this paper we analyze, using a Difference-in-Differences (DiD) identification strategy, whether the (staggered) roll-out of the Italian HSR network[2] increased the flow of workers changing jobs between any two connected municipalities, compared to other possible pairs of municipalities that were not connected to the HSR network. In particular, we consider a dyad of two municipalities as treated if both municipalities are located within 30 km from an HSR station (Bernard et al., 2019), while we include in the control group only municipality dyads located between 30 and 60 km from an HSR station. So doing, we do not compare treated connections to dyads whose ends are located far away from an HSR station, as the latter could be different from the treated ones along many dimensions. It is worth noting that, as better explained in the Data Section, although the Italian HSR network has been largely developed between 2005 and 2020, we focus on links opened in 2009 and 2013 in order to be able to conduct a meaningful pre-trend analysis. Nevertheless, this approach still allows us to consider the finalization of the Milan-Turin link, the opening of an intermediate HSR station between Milan and Bologna (Reggio Emilia AV), and, finally, the realization of the Bologna-Florence link, which can also be considered as the completion of the main backbone of the Italian HSR network, since it has allowed passengers to start using HSR trains also for very long-distance journeys (e.g., from Salerno, in Southern Italy to Turin in Northern Italy), as can be seen in Figure 1.

The Italian HSR case is particularly interesting because, despite being designed to be also a high-capacity system (thereby allowing for the integration of passengers and freight), this capability has remained so far largely unused (Chitti and Beria, 2025). This study

[1] By way of example, Koster et al. (2022) report that travel time was cut by more than half with the Japanese Shinkansen high-speed train, while Cascetta et al. (2020) estimate, for the case of Italy, a cut in travel times between the largest connected cities of about 30%.

[2] See Beria et al. (2018) for a critical discussion of the HSR experience in Italy and interesting statistics.

therefore isolates the economic impacts of HSR by focusing exclusively on labor and passenger mobility, given that the network's influence on freight logistics has remained negligible in practice, so that changes in mobility in response to modifications in the pattern of interregional trade and local industrial specialization (Duranton et al., 2014) due to a fall in the cost of transporting goods cannot bias our results.

We measure worker flows between any two municipalities using detailed employer-employee administrative data provided by the Italian National Social Security Institute (the *Istituto Nazionale per la Previdenza Sociale*, INPS, hereafter), which contain information also on the location (at the municipality level) of all job positions between 2005 and 2021: in particular, if we see that the (main) employment location of an individual worker changes between years $t-1$ and t from municipality "o" (origin) to municipality "d" (destination), we count a flow of one for the *od* dyad, and zero otherwise.[3] This flow measure thus captures changes at a dyadic level of the municipality of the firm where a given individual works and, as such, it may capture a commuting of the worker (e.g., from municipality "o" where she also lives, to municipality "d" where she works) but also a change of residence, with the worker changing both employer and place of living. In both cases, if the identification assumptions (parallel trends and no anticipation effects) hold, we can interpret changes in these flows as caused by the connection to the HSR network: an increase in these flows can be due to a genuine enlargement of the local labor market with individuals living in one municipality and working in the other, but also to an increased attractiveness of one or both of the local economies at the two ends of the dyads (say, because of changes in the economic and sectoral specialization of the two local economies that become more integrated), with individuals changing both place of work and living. However, our gravity-type approach will help us to isolate the first effect.[4]

From an empirical point of view, the individual-level flows, as defined above, are aggregated at the level of *od* municipality pairs, and these panel data are employed to estimate gravity-type equations in a DiD setting, where the dependent variable is the flow of workers between two municipalities. We include origin-by-year and destination-by-year fixed effects in order to capture possible differential trends in origin and destination municipalities (akin to the multilateral resistance terms in the trade literature), besides dyadic fixed effects to capture time-invariant unobserved heterogeneity at the dyadic level, such as distance. We deal with the staggered roll-out of the HSR network in Italy by using the Extended Two-Way Fixed effect (ETWFE) approach proposed by Wooldridge (2025), which avoids the common pitfalls of the conventional Two-Way Fixed Effects model by allowing for differential effects of the various cohorts over time and that provides Average Treatment Effects on the Treated (ATTs) by cohort and time period identical to those of Borusyak et al. (2024).

Our results can be summarized as follows. First, the opening of an HSR connection tends to increase the average job mobility between connected municipalities by about 0.12 additional workers. While this may seem a small amount, it is not, as in many dyads the flow is zero, with an average in treated municipalities of 0.66 moves before treatment. An overall ATT of 0.12 amounts to a percentage increase of about 18% that translates to an average of 4,500 additional flows of workers per year.[5]

Second, we find that the effect was virtually absent before 2015 and began increasing

[3] While we have information on the residential address of the worker, we do not exploit it given the common practice, especially in the case of young individuals, of not formally changing their residential address even when they change the municipality where they live.

[4] This is done including in the model multilateral resistance terms.

[5] Computed by multiplying the average effect per treated dyad by the number of treated dyads.

thereafter, resulting in an additional 12,000 worker location changes in 2021. This pattern is consistent with the figures discussed in Beria et al. (2018) and Shtele and Beria (2025), who argue that demand for high-speed trains was slow to take off even in 2010 and began to ramp up only afterwards, especially following the entry in 2012 of *Italo*, the first competitor to the incumbent operator *Trenitalia*.

Third, consistently with previous empirical literature suggesting that men tend to have higher mobility than women,[6] we find a larger absolute increase in the case of males, although the difference is less pronounced in percentage terms. Moreover, when focusing on percentage effects, we see a slightly lower effect on the job mobility of top wage earners and a more substantial impact on the mobility of older workers and those on temporary contracts. Interestingly, we observe a declining relationship between the magnitude of the treatment effect and the type of occupation, with the largest positive effect for blue-collar workers, followed by white-collar workers; managers displayed, instead, a small decline in mobility.

Additional insights emerge when we disaggregate mobility by the population size of origin and destination municipalities. Most of the overall effect is driven by mobility between large municipalities (defined as those with more than 100,000 inhabitants), where worker flows increase by approximately 33%. This is followed by flows from small to large municipalities, which rise by about 22%. By contrast, mobility from large to small municipalities and mobility between small municipalities exhibit effects close to zero. These patterns suggest that HSR primarily facilitates worker movements between major urban centers, which generally offer more attractive employment opportunities. At the same time, the increased flow of workers from smaller to larger municipalities indicates that small centers may suffer employment losses.

After observing an increased mobility in dyads that got connected to the HSR network, we estimate a wage equation using the AKM empirical framework (Abowd et al., 1999), which is used to derive a set of firm and worker fixed effects (FEs). We then derive a mismatch measure defined as the absolute value of the difference between the decile ranks of the worker and firm fixed effects in their respective empirical distributions. We use this mismatch measure at the municipality level to assess whether the increased mobility brought about by the connection to the HSR has improved the efficiency of the average match; indeed, we find mild evidence that, following the HSR connection, the mismatch fell in treated municipalities (together with an increase in the average quality of the workforce), suggesting an improvement in the worker-firm matches. It is interesting to note that an increase in worker-firm assortativity is important per se, given that it corresponds to a larger wage dispersion (Agrawal et al., 2024; Card et al., 2013). To the best of our knowledge, this is the first study that provides, even tentatively, a causal estimate of the impact of the connection to the HSR network on assortative matching in the labor market.

[6] Bütikofer et al. (2024) exploit the construction of the Oresund bridge between Sweden and Denmark to analyze the impact of access to a larger labor market and find a substantial increase of commuting towards Denmark and an increase of wages of Swedes working in Denmark, particularly in the case of highly educated men, with the smallest effect among low-educated women. Interestingly, this differential effect is at least partly driven by differences in commuting propensity across genders. Le Barbanchon et al. (2020) find that women value commuting 20% more than men and therefore have a higher maximum acceptable commuting distance and that this is at the heart of the gender wage gap. See also Liu and Su (2024), who note that different commuting preferences can explain the gender wage gap only if the wage penalty for not commuting is sufficiently large, which in turn boils down to the geography of jobs.

Related literature. Our paper relates to different strands of literature. The current study belongs to the body of literature that analyzes the economic impact of transport infrastructure and, in particular, to those studies that have recently analyzed the local impact of HSR. They generally find substantial positive effects on local development and sectoral specialization (Ahlfeldt and Feddersen, 2017; Lin, 2017), firm productivity (Bernard et al., 2019), managerial organization (Charnoz et al., 2018; Gumpert et al., 2021), market potential (Zheng and Kahn, 2013), and innovation (Dong et al., 2020; Bottasso et al., 2025). Some scholars have observed significant spatial reallocation effects, with small connected intermediate cities losing out relative to (very) large centers (Koster et al., 2022) or to intermediate unconnected towns (Qin, 2016).[7] While the extant literature has mostly analyzed the ultimate economic effects of an HSR connection, ours is one of the very few papers to actually test whether the opening of an HSR connection actually alters the pattern of job mobility between connected municipalities, which is an important condition for the unfolding of the wider economic effects of HSR on the local economy that require an enlargement of the local labor market. Indeed, we exploit an uniquely rich administrative-level dataset to show that the opening of an HSR station induces an increase in job mobility between connected municipalities relative to control ones. Furthermore, our finding that the HSR connection reduces the worker-firm mismatch in connected municipalities provides a possible complementary explanation for the increase in the productivity of the local area to those based on the diffusion of knowledge, associated with the mobility of workers in the right tail of the human capital distribution (as in Dong et al., 2020), or on the growth in the number and quality of intermediate goods suppliers discussed in Bernard et al. (2019).

The studies most similar to ours are those by Baltrunaite and Karmaziene (2024) and Heuermann and Schmieder (2018). The first uses Italian firm-level data to analyze the impact of the expansion of the non-local pool of board directors associated with the roll-out of the HSR network on the quality of board members and finds an increase in the degree of assortative matching, with local high-quality firms that managed to attract higher-quality board members when they got connected to the HSR network, a result consistent with the decrease in worker-firm mismatch that we find in this study. In turn, Heuermann and Schmieder (2018) investigates the impact of the reduction in travel time brought about by the roll-out of the German HSR network and finds that when two regions are connected, journey time decreases, which in turn leads to a rise in the number of commuters. While their paper is not strictly comparable to ours (we consider job mobility rather than simply commuters; moreover, we use finer-grained geospatial data), the results of the two papers are broadly consistent.

Second, our paper speaks to the growing labor economics literature on mobility, labor market definition, outside options, monopsony power and assortative matching (Manning and Petrongolo, 2017; Caldwell and Danieli, 2024; Benmelech et al., 2022; Le Barbanchon et al., 2020; Card et al., 2013; Bertheau et al., 2023). We add to this literature by showing that a transportation infrastructure that considerably reduces travel times might favor job mobility among connected locations, which in turn also experience an increase in assortative matching.[8] Consistent with most prior literature, which finds that men are more willing to

[7] Our paper is also related to the larger literature that has investigated the effects of roads and highways on cities' skill composition (Cucu, 2025), suburbanization (Baum-Snow, 2007), trade (Duranton et al., 2014) and economic development (Duranton and Turner, 2012; Baum-Snow et al., 2020), typically finding non-negligible welfare gains (Allen and Arkolakis, 2022).

[8] Banerjee and Sequeira (2023) find, using a field experiment in the South African city of Johannesburg, that transportation subsidies can increase search intensity. See also Agrawal et al. (2024) on transportation subsidies, commuting distance and sorting for the German case.

travel longer distances, we observe a larger increase in job mobility among men; moreover, we find novel, significant heterogeneous treatment effects by contract type, age, and job qualification.

The remainder of the paper is organized as follows. In Section 2, we discuss the identification strategy, while Section 3 presents the data used in our empirical analysis. Section 4 comments on the results, and Section 5 concludes.

2 Empirical Strategy

2.1 Labor Mobility

As described in the next section, administrative individual-level worker data on year-to-year changes in workers' municipalities of work are aggregated at the origin-destination *od* dyads in order to estimate a staggered DiD gravity model (Nagengast and Yotov, 2025):

$$y_{o,d,t} = \alpha + \sum_{g \in G} \sum_{\tau=0}^{\bar{\tau}} \beta_{g,\tau} D_{o,d,g,\tau} + D_{o,t} + D_{d,t} + \epsilon_{o,d,t} \tag{1}$$

and

$$D_{o,d,g,\tau} \equiv \mathbb{1}(G_i = g)\mathbb{1}(t - g = \tau),$$

where $y_{o,d,t}$ is mobility from o towards d in period t, defined as the number of individuals that had the main job (see the Data Section) in municipality o at time $t-1$ and the main job in municipality d at time t; $D_{o,d,g,\tau}$ is a dyadic treatment for both municipality o and municipality d being located within 30 km from the closest HSR station (so as the comparison municipalities are those located between 30 km and 60 km from the closest HSR station), where g indicates a group of dyads that starts to be treated in the same year and $\bar{\tau}$ is the last post-treatment period observed in the data; $D_{o,d}$ are dyadic fixed effects, accounting for *od* time-invariant unobservables; $D_{o,t}$ and $D_{d,t}$ are origin-time and destination-time fixed effects (FEs) accounting for multilateral-resistance terms; $\epsilon_{o,d,t}$ is an idiosyncratic error term. Observations are clustered at the *od* level to account for serial correlation within dyads.

Our parameters of interest are the $\beta_{g,\tau}$, capturing the increase in the number of movers due to the opening of a new HSR route among the treated dyads (i.e., the Average Treatment Effect on the Treated, ATT), which are treatment-cohort and time specific. The model in Equation (1) includes the whole set of "lag" terms (in the event study jargon). A variant of Equation (1), including the "lead" terms, is used to investigate the parallel-trends assumption. It is important to stress that possible effects of the connection to the HSR network that are non-dyadic (e.g., the creation of new firms at the origin or destination municipalities) are captured by the multilateral resistance terms (i.e., the $D_{o,t}$ and $D_{d,t}$ fixed effects), so that our identification setting eliminates possible general equilibrium effects associated with the development of the HSR network.[9]

[9] The $D_{o,t}$ and $D_{d,t}$ fixed effects also take into account that some origin or destination municipalities were already connected to the HSR network before treatment. For example, when comparing the 2009 treated dyad Florence-Bologna (or any two municipalities close to the two HSR stations of Florence and Bologna), the $D_{o,t}$ and $D_{d,t}$ fixed effects take into account that, for instance, Bologna was already connected to, say, Milan and Florence had an already established connection with, say, Rome, via the HSR network.

We measure the flows in levels and use a linear specification of Equation (1). Non-linear models, such as Poisson Pseudo Maximum Likelihood models (PPML) are more common when one is interested in directly estimating the *percentage change* in mobility determined by the treatment and represent a better alternative to estimating the model in logarithms after adding a small constant to zero flows (Chen and Roth, 2024). However, linear and PPML specifications imply different parallel-trends assumptions. While the linear DiD specification requires parallel trends in levels (*linear parallel trends*, LPT, assumption), the assumption for PPML requires an approximation of the stability in the proportional difference in growth rates across groups, which is defined in Wooldridge (2023) as the *conditional index parallel trends* (CIPT) assumption. In case the means of the outcome variables for treated and control units are very different at baseline, like in our case where the average pre-treatment mobility was 0.26 workers in control and 0.66 workers in treated dyads (see Table 1), models in levels and PPML models can even give treatment effects of opposite signs (McConnell, 2024). Since our main interest is in the levels of mobility, we adopt a linear specification. The model is estimated using the ETWFE estimator proposed by Wooldridge (2025). The adequacy of the LPT assumption is investigated by including lead terms in Equation (1).

2.2 Worker-firm matching ("sorting")

To examine how the introduction of HSR services affects worker–firm matching patterns, this study employs the two-way fixed-effects framework developed by Abowd et al. (1999). The model decomposes individual wages into components reflecting worker heterogeneity, firm wage policies, and unobserved idiosyncratic variation, allowing us to capture the underlying structure of wage determination and matching in the labor market.

Let i denote workers, t time, and $j(i,t)$ the firm employing worker i at time t. The logarithm of wages, y_{it}, is modelled as

$$y_{i,t} = \mathbf{x}'_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta} + \phi_{j(i,t)} + \eta_i + e_{i,t}, \tag{2}$$

where $\mathbf{x}_{\mathbf{i},\mathbf{t}}$ represents a vector of observable, time-varying characteristics, $\boldsymbol{\beta}$ is a vector of coefficients to be estimated, ϕ_j is the firm fixed effect interpreted as the firm-specific wage premium, η_i is the worker fixed effect capturing unobserved, time-invariant earning ability, and $e_{i,t}$ is an idiosyncratic error term with zero mean. The model accounts for both observable and unobservable sources of heterogeneity, isolating systematic differences in pay that arise from the specific pairing of workers and firms.

Identification of the worker and firm components relies on mobility across firms. When workers change employers, the associated variation in wages provides the information necessary to disentangle the contributions of worker-specific ability and firm-specific wage policies. Estimation is performed on the largest connected set of workers and firms linked through observed job transitions, ensuring comparability of estimated firm effects within the network of employment relationships. The idiosyncratic component $e_{i,t}$ is assumed to have an expected value of zero and may follow a unit root process, allowing for persistent shocks to unobserved productivity. To ensure consistency, the model imposes a strict exogeneity condition of the form

$$E[e_{i,t} \mid x_{i,1}, \ldots, x_{i,T}, \eta_i, \phi_j] = 0 \quad \forall t, \tag{3}$$

which implies that the error term is uncorrelated with the history of observable characteristics and with the worker and firm effects. Under these assumptions, the model parameters can be consistently estimated by ordinary least squares (OLS) through the inclusion of worker and firm dummy variables.

The assumption of strict exogeneity excludes any systematic pattern of endogenous mobility driven by unobserved wage shocks.

The key question is whether the improvement in accessibility determined by the new HSR routes affects the structure of worker–firm matches. Indeed, the expansion of transport infrastructure can facilitate the reallocation of workers across regional labor markets and increase the incidence of cross-regional employment relationships. This geographical integration has the potential to reshape the composition of worker–firm matches and alter the observed correlation between estimated worker and firm effects.

To analyze these dynamics empirically, we estimate the AKM model over a sequence of rolling panels corresponding to different phases of the HSR network expansion. This approach allows us to observe how the relationship between worker and firm effects evolves as connectivity improves.

The first panel covers 2005–2008 and serves as the pre-treatment baseline, preceding any HSR openings. The second panel, 2009–2013, captures the first wave of openings, while the third panel, 2013–2016, corresponds to the second wave. The fourth subperiod, 2016–2020, represents the mature phase of the network, during which both groups of HSR routes were operational for several years. To assess longer-term adjustments, we also estimate a fifth panel spanning 2016–2022, which extends the post-treatment interval to also include the post-COVID-19 period. The baseline control variables in the AKM model include a cubic polynomial in age and experience, as well as a full set of time fixed effects.

For each panel, we estimate worker and firm fixed effects according to the AKM specification. We then rank both effects by decile and compute the absolute value of the difference between the firm and worker decile positions for each observed match, which serves as a proxy for match quality. Let $D(x) \in \{1, \dots, 10\}$ denote the decile rank of x in its empirical distributions; in practice, the mismatch measure is defined as

$$mismatch_{i,j,t} = |D(\phi_{j,t}) - D(\eta_{i,t})| \tag{4}$$

where i, j and t are worker, firm, and sub-period subscripts; $mismatch_{i,j,t}$ is an ordinal measure, being based on a difference in ranks, and does not have a cardinal interpretation.[10] For instance, both a worker in the second decile of the firm effect distribution and in the first decile of the worker effect distribution and one in the ninth decile of the firm distribution and the eighth decile of the worker distribution have $mismatch_{ijt} = 1$.

Worker fixed effects, firm fixed effects, and mismatch measures are then aggregated by municipality, sub-period (t), and treatment cohort, yielding municipality-level measures. Finally, we estimate a staggered difference-in-differences model of the form

$$y_{i,t} = \alpha + \sum_{g \in G} \sum_{\tau=0}^{\bar{\tau}} \theta_{g,\tau} D_{i,g,\tau} + \xi_i + \xi_t + \varepsilon_{i,t} \tag{5}$$

and

$$D_{i,g,\tau} \equiv \mathbb{1}(G_i = g)\mathbb{1}(t - g = \tau),$$

where $y_{i,t}$ represents the relevant outcome (firm effect, worker effect, or mismatch measure) for municipality c in subperiod t; $D_{i,g,\tau}$ is an indicator that takes value 1 if the observation is in the treatment group g on sub-period t and 0 otherwise. ξ_i and ξ_t are

[10] See, for a similar approach in measuring worker-firm mismatch, Braunschweig et al. (2024).

sets of fixed effects for municipality and sub-period, respectively. Treated municipalities are defined as those within 30 kilometers of an HSR station, while those located beyond this radius serve as controls. It is important to stress that, compared to Equation (1), the data are no longer dyadic, and treatment status is only defined according to distance from newly treated HSR stations, i.e., the stations newly connected to the HSR network or that added more connections to those already existing. Our parameters of interest are the $\theta_{g,\tau}$: $\theta_{g,\tau} < 0$ would imply a reduction, while $\theta_{g,\tau} > 0$ an increase in mismatch.

3 Data

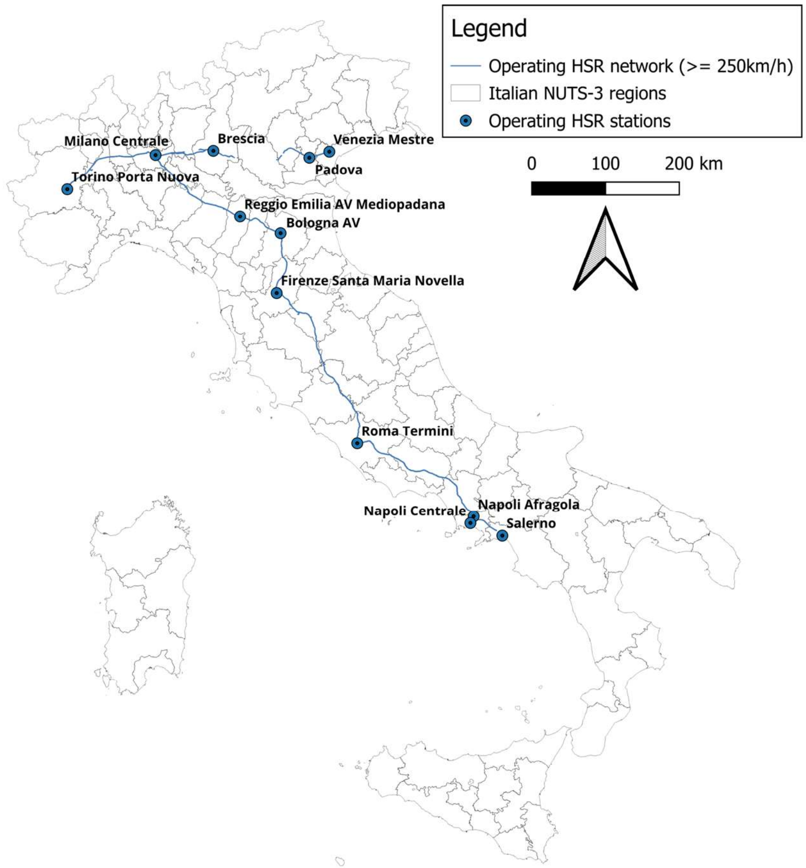
To examine the impact of HSR on worker mobility across different areas, we leverage a detailed employer–employee matched database provided by INPS. The INPS data encompass the entire population of employees in the Italian private sector, excluding agriculture, and contain detailed information on approximately 18 million workers and 1.5 million firms per year. For each employee, the dataset includes wages, days worked during the year, employment contract type, job location at the municipal level, and basic demographic characteristics such as gender and age. We focus on the period from 2005—the first year for which information on job location at the municipal level is available in the data—to 2022.

The INPS data record pays that are gross of taxes and inclusive of all cash benefits but exclude in-kind benefits. We measure earnings using the logarithm of gross weekly wages, adjusted to constant 2022 prices. Following standard practices in the literature using similar data, we take several preparatory steps. First, for employees holding multiple jobs in the same year, we select the job spell with the longest duration in months, weeks, and days worked; in the rare cases of ties, we retain the spell with the highest earnings. Second, we exclude from the sample all employment spells shorter than approximately two months (eight weeks).

We then assign to each job municipality the closest HSR station and restrict the sample to municipalities located within a 60-km radius of a high-speed rail station. This restriction implies that, out of 7,904 Italian municipalities, we retain 2,592 municipalities in our analytical sample.

Figure A1 in the Appendix presents a timeline of the chronological development of the Italian HSR infrastructure. Excluding the Rome–Florence line (the so-called *Direttissima*, completed in 1992 and therefore not considered in this analysis), the more recent expansion of the Italian HSR network unfolded in several stages during the first two decades of the 2000s. In 2005 Rome and Naples got connected, followed in 2006 by the opening of a segment of the Turin-Milan link. In 2007, Padua and Venice were connected by high-speed rail, although this section remained isolated from the rest of the network (see Figure 1). In 2008 the Milan–Bologna and Naples–Salerno links were completed and marked a major step toward the completion of the national HSR network. In 2009 the link between Milan and Turin was finally completed together with the Bologna-Florence link. A further milestone was the opening in 2013 of the Reggio Emilia AV Mediopadana station, serving a medium-sized town approximately halfway between Milan and Bologna. Finally, in 2016, the relatively short segment between Milan and Brescia was completed, which, however, is excluded because an important portion is not a real high-speed network (i.e., trains do not travel at more than 250 km/h). In terms of passengers, Beria et al. (2018) notes that traffic grew very slowly, at least until 2012, when the entry of the first alternative operator to the incumbent *Trenitalia* increased competition, leading to lower fares and higher quality

Figure 1. HSR Network Map



Notes. Map of the current HSR (speed higher than 250 km/h) network in Italy. NUTS-3 are Nomenclature of Territorial Units for Statistics level 3 units, i.e., province in Italy.

(Bergantino et al., 2015; Shtele and Beria, 2025) and, finally, to a rapid take-up in the number of passengers, which, according to figures reported by Shtele and Beria (2025), reached about 24 billion passenger-km in 2019, starting from about 17 billion passenger-km in 2012.[11]

As explained in Section 2, we analyze the effect of HSR on worker mobility using a municipality-level gravity model. For each observed job mobility spell between year $t-1$ and year t, we identify an origin and a destination municipality, constructing dyadic pairs of municipalities. Specifically, the origin municipality is the one in which the plant of worker i's firm is located in year $t-1$, while the destination municipality is the one in which the plant of the worker's new firm is located in year $t-1$. For each dyad, we compute the total volume of worker mobility, accounting for heterogeneity by individual characteristics (e.g.,

[11] Beria et al. (2018) report, for 2010, a figure of 11.6 billions passenger-km.

gender and age) and by job characteristics at year $t-1$, such as the position in the wage distribution at the firm level, occupation, and type of employment contract. The aggregated data by year and municipality dyads with positive flows consist of 2,239,066 observations covering the period from 2005 to 2021.

We are interested in evaluating how the introduction of HSR affects mobility between municipalities. Therefore, we exclude all dyads that involve the same HSR station removing 1,486,640 and keeping 752,426 observations. Since it is not possible to investigate pre-trends for the HSR routes opened before the observation window—namely the Rome–Florence route (opened in 1992) and the Milan–Bologna and Naples–Salerno routes (opened in 2008)—we remove these dyads from the sample along with the corresponding catchment areas, that is, the municipalities surrounding those dyads keeping an unbalanced panel of 597,605 observations. We thus focus on the effects of HSR openings that occurred between 2009 and 2013. Finally, to avoid results being driven by episodes of firm restructuring or relocation, we exclude municipalities with worker flows larger than 1,000 units (falling into the 0.007 percentile of the mobility distribution). This restriction leads to the removal of the following dyads: Milan-Rome, Rome-Milan, Milan-Turin, Turin-Milan, Turin-Rome, Rome-Turin, Naples-Milan, Somma Lombardo-Fiumicino.[12]

To perform the staggered difference-in-differences analysis, we rectangularize the dataset by dyad and year,[13] obtaining 2,119,152 observations. We identify treated dyads as those in which the distance to the closest HSR stations newly connected by HSR for the municipalities of origin and destination is less than 30 km, implying greater exposure to HSR openings. Dyads located more than 30 km away are considered untreated.[14] Table 1 reports descriptive statistics on worker mobility, comparing treated and untreated municipality dyads before and after the introduction of HSR. Overall, treated dyads display substantially higher levels of mobility both before and after the opening of the HSR routes. In the pre-treatment period, average total mobility in treated dyads equals 0.66 (s.e.==8.15) compared with 0.26 (s.e. =2.79) in untreated dyads. After the HSR opening, mobility rises to 0.74 (s.e.=8.73) in treated dyads and to 0.28 (s.e.=3.11) in untreated ones, suggesting a larger increase among municipalities exposed to the new HSR infrastructure.

Mobility by worker characteristics shows similar trends. Both female and male mobility rates increase after the openings, with men exhibiting higher overall levels. The pattern is consistent across different mobility thresholds: movements of workers above the 75th percentile of the within-firm wage distribution at the origin, as well as those below this cut-off, both exhibit higher intensity and slightly larger post-opening increases in treated dyads. Mobility increases more for older workers than for younger ones, although younger workers continue to exhibit higher overall mobility in all periods. Similarly, temporary workers experience a greater increase in mobility than permanent workers following the HSR expansion. These descriptive patterns suggest that municipalities connected by, or located closer to, new HSR routes exhibit greater worker reallocation over time, consistent

[12] The latter is most likely due to the relocation of a whole firm operating airport services, since Somma Lombardo is close to the Milan-Malpensa airport, and Fiumicino is where the Rome-Fiumicino airport is located.

[13] This consists of imputing zeros to dyads that are observed with at least one positive flow during the period, for the years in which the flows are missing in the data.

[14] The choice of 30 km is popular in the related literature (Bernard et al., 2019; Bottasso et al., 2023). The idea is that municipalities within a 30-km radius are easily accessible from the municipality where the HSR station is located, or that the station is easily accessible from municipalities that are not more than 30-km away. On the latter, Bratti et al. (2025), estimating a model for daily commuting flows, show that flows drop above 30 km, and become approximately zero.

with the hypothesis that improved accessibility spurs labor mobility.

4 Empirical Results

4.1 Labor mobility

Main results. The first part of the empirical analysis focuses on estimating Equation (1) to examine the impact of the opening of new HSR routes on worker mobility. Estimates of the gravity model are reported in Table 2. Column (1) shows the aggregate ATT for the full sample, which is significantly positive and equal to approximately 0.12. This estimate implies that the introduction of an HSR connection increases average job mobility between treated municipalities by about 0.12 workers per year. Given that the number of treated dyads is 38,753, this corresponds to an increase of roughly 4,500 workers per year. In percentage terms, an additional 0.12 workers represents an increase of about 18% relative to pre-treatment mobility in treated dyads. In particular, if we separately focus on ATTs at cohort level, the results reported in Column (1) suggest that mobility increased by 0.19 units in the 2013 cohort and by 0.09 units in the 2009 one.

Turning to the pattern of ATTs over time, panel (b) of Figure 2 suggests that the effect of HSR opening has been very slow to materialize, starting to be notable and statistically significant five years after treatment onset.[15] Moreover, the size of the ATT is increasing over time, except for a dip around period 10, which, however, corresponds to 2020 for the 2009 cohort and such year was characterized by a drop in mobility related to COVID-19. In the last year of our sample period, the ATT is approximately 0.31, implying an additional annual flow of about 12,000 workers among treated dyads.[16]

The time profile of the ATT estimates aligns well with the evidence reported in Beria et al. (2018) and Shtele and Beria (2025), who note that demand for HSR services was slow to take off even in 2010 and began to grow substantially only later, particularly after the first competitor to the incumbent operator entered the market in 2012.

Our findings are consistent with Caldwell and Danieli (2024), who find that the opening of an HSR station in the small German town of Montabour increased workers' outside options by providing access to more distant jobs. Similarly, Bütikofer et al. (2024) finds that the opening of the Oresund bridge connecting Denmark and Sweden significantly increased commuting of Swedes working in Denmark. Furthermore, our results align with Heuermann and Schmieder (2018), which finds that reduced travel time across regions due to HSR connections increased the number of commuters. It is worth noting that even if our results are consistent with the above contributions, they are not directly comparable since we do not distinguish between worker flows due to commuting and those associated with a change in both employer and residence. Our findings of higher worker mobility associated with connection to the HSR network are consistent with reduced travel times and increased outside options generated by an expansion of the local labor market.

To assess the validity of our identification strategy, we first estimate an event-study regression that allows us to test for the presence of anticipation effects by including in Equation (1) a full set of leads. The graphical evidence reported in panel (a) of Figure 2 suggests that the parallel-trends assumption is reasonable, as none of the leads is statistically significant

[15] For the 2013 cohort, the effect becomes positive and significant after two years.

[16] We report in the Appendix estimated ATTs specific to each cohort/year. The value 0.31 is the average of ATTs in 2021 across cohorts, weighted for the respective shares of treated dyads. In particular, in 2021 the ATT for the 2009 cohort is 0.25, while for the 2013 cohort is 0.44.

at the 10% level. Moreover, a joint test fails to reject the null hypothesis that the pre-treatment coefficients are jointly equal to zero (the p-value is 0.43). Furthermore, we probe the robustness of our results to changes in the distance threshold to the HSR station that defines treated versus control municipalities. Even if a 30-km threshold from the station seems a reasonable cut-off, given that commuting beyond 30 km is very unlikely (Manning and Petrongolo, 2017; Bratti et al., 2025), as a robustness check, we redefine the treatment group to include only municipalities located within 20 km from the nearest HSR station, while the control group consists exclusively of municipalities situated between 40 and 60 km from an HSR station. We exclude from the sample the municipalities whose centroid is between 20 and 40 km from the HSR station and whose inclusion in the treatment versus the control group may be questionable.[17] Reassuringly, results displayed in Figure A2 in the Appendix show that the magnitude and time profile of the effects are very similar. It is also important to note that, as explained in the Data Section, we have eliminated from the sample the dyads involving as both origin and destination the most important urban centers in order to avoid that results are driven by the largest worker flows. By doing this, we should also reduce the likelihood that our results are driven by endogeneity concerns related to the sequencing of link openings, which is typically biased toward the largest urban centers (Redding and Turner, 2015). However, if we let these large dyads enter the sample, results remain fully consistent.[18]

Effect heterogeneity. We extend the baseline analysis by leveraging the rich information in INPS data, which provide individual-level records on gender, age, earnings level, type of contract, and occupational classification. The estimated event-study post-treatment effects are plotted in Figures A3-A5 in the Appendix. As far as the gender composition of our main effect is concerned, our estimates suggest that the increase in worker flows of 0.12 can be decomposed into 0.086 additional males and 0.03 additional females (Table 2, Columns 2-3 respectively). In percentage terms, relative to the respective pre-treatmemt values, these results imply an increase of about 13% for women and of about 19.5% for men. This finding is in line with previous empirical evidence indicating that men generally exhibit higher mobility than women (Caldwell and Danieli, 2024; Bütikofer et al., 2024; Le Barbanchon et al., 2020).[19]

When analyzing other sources of heterogeneity, we find that the opening of the HSR stations has differentially affected workers of different ages (Table 2, Columns 4-5 respectively). Even if additional flows are equally split between younger (less than 45 y.o.) and older (above 45 y.o.) workers, the percentage increase for the latter is much higher (increase of about 11% vs. 50%). Focusing on heterogeneity by workers' earnings, Columns 6-7 of Table 2 show ATT estimates for top wage earners, which indicate a 12% increase in flows of workers belonging to the upper quartile of the wage distribution vs. a 19% increase in flows of other workers, suggesting that the increase in mobility was slightly smaller in the case of high-wage earners, who typically are also those in the upper tail of the human capital distribution.[20] Another informative sample split concerns workers' contract types, whose results are reported in Columns 8 and 9. We find that most of the additional mobility is driven

[17] Moreover, by excluding municipalities located at intermediate distances we also assess possible violations of the Stable unit Treatment Value Assumption (SUTVA).

[18] Indeed, we find a slightly larger effect, corresponding to an increase in average mobility of about 0.16 additional workers, which is in turn equivalent to about 6,000 additional workers per year.

[19] By way of contrast, Agrawal et al. (2024) shows that men and women equally react to a reform of commuting subsidies in Germany.

[20] Results are similar when we focus on the upper decile vs. the rest of the earning distribution.

by flows of workers on temporary contracts, who experience a percentage increase of about 42%, compared with 8% for workers on permanent contracts. This pattern suggests that workers in permanent positions may be more hesitant to leave their current employment for new opportunities because of higher employment protection (Bentolila and Bertola, 1990; Blanchard and Portugal, 2001), higher job security (Molloy et al., 2024), or stronger local ties (David et al., 2010).

We then turn to analyze the impact of the opening of new HSR routes on worker flows according to their job qualification (Columns 10-13). In this case, we find that the bulk of the effect is on blue-collar workers' mobility (33%), followed by white-collar workers with an increase of about 10%, albeit imprecisely estimated, while for managers we observe a weak reduction in mobility of about 3%. This finding of an inverse relationship between mobility and job qualification can be consistent with a possible increase in managers' bargaining power associated with an enlargement of their outside options generated by HSR connections, which might have allowed them to bargain for better conditions in their current job, thereby reducing mobility in equilibrium. By contrast, white-collar workers and, especially, blue-collar workers, who presumably have lower bargaining power, might have exploited their increased outside options by changing jobs.[21] On the one hand, this result is consistent with Agrawal et al. (2024), who find that commuting distance increases with the generosity of commuting subsidies in Germany, particularly for low-skilled workers. On the other hand, this finding contrasts with Caldwell and Danieli (2024), who show that the reduced travel times associated with connecting the small town of Montabour to the HSR network expanded the set of outside options, especially for workers with higher levels of education.

Finally, we split mobility flows according to the population size of the origin and destination municipalities. We define as large a municipality with more than 100,000 inhabitants (see the Data Section) and we analyze the impact of the connection to the HSR for large-to-large, large-to-small, small-to-large, and small-to-small dyads. As reported in Table A1 in the Appendix, the HSR effect is positive and statistically significant in the case of large-to-large dyads, with an increase in movements that is equivalent to a growth of about 33%, followed by movements from small to large municipalities, which increase by about 22%. The effect in the case of movements between small municipalities and from large to small municipalities is instead close to nil.[22] The post-treatment estimates by year are reported in Figure A6 in the Appendix.

Taken at face value, these results suggest that the opening of an HSR route, by reducing journey times, encourages the movements of workers towards large centers from both small and large ones. Given that large centers tend to be also more productive (Combes et al., 2012), higher flows of workers to large urban centers might improve spatial allocative efficiency by favoring sectoral specialization, agglomeration economies, and better firm-quality matches (see below). However, small centers do not experience larger inflows from large centers, i.e., they lose workers who move to larger cities following their connection to the HSR network. If this is due to more commuting, these small centers may simply be experiencing job losses (but not necessarily income losses); however, if workers change both employers and place of living, small centers might also be experiencing a net population decline but

[21] We also find an increase in mobility for the apprentices (23%); however, such sample overlaps with youngsters, and this result might be driven by an age effect rather than by job qualification.

[22] In the case of large-to-small municipalities, we find, however, a positive effect in the last years of the panel. This may suggest that an increased mobility from large to smaller municipalities may require time for the effect of the HSR connection to unfold, possibly because of the time that it is necessary for new firms to open in small towns following the opening of the HSR route.

also a loss in income, as suggested by Koster et al. (2022).

Although our results are not strictly comparable to those in Heuermann and Schmieder (2018), our result of higher mobility primarily towards large centers seems to be at odds with their finding of increased commuting mainly from large to small cities after the opening of an HSR station. This difference can be due either to the fact that we consider job mobility and not simply commuting, or to the differences in how HSR works in Italy relative to Germany. Indeed, the German model of HSR is more integrated, as it is based on many intermediate stations serving also small centers, unlike in Japan (Koster and Thisse, 2025) and Italy.[23]

4.2 Worker-firm match and "sorting"

In this Section we discuss results of the staggered DiD estimation of Equation (5), assessing how the openings of new HSR routes affected wages, firm fixed effects, worker fixed effects and the mismatch measure as estimated from Equation (4) at the municipality level. In Panel (a) of Table 3 we report estimates of the baseline specification, with data organized as four-year panel up to 2020 (i.e., 2005-2008, 2009-2012, 2013-2016, and 2017-2020). The analysis shown in Panel (b) extends the final sub-period to a six-year window (2017–2022) to account for possible longer-term adjustments, while including the post-COVID-19 period.

Table 3 shows results based on two different definitions of treatment status. In the left panel, municipalities are classified as treated based on their distance to HSR stations that were newly connected or that gained additional HSR connections. In contrast, the right panel restricts the analysis to municipalities near newly treated HSR stations only (Turin in 2009 and Reggio Emilia AV in 2013), excluding those close to stations that merely expanded existing HSR services over the sample period. We comment upon estimates for the restricted sample case and for the longer panel, given that overall findings are broadly consistent across samples.

The coefficient on average weekly wages is positive, although imprecisely estimated. Consistently with the mobility analysis, the average treatment effect grows over time: two periods after treatment begins, wages in treated municipalities rise by about 1.6%, a result that is statistically significant at the 10% level. In turn, the coefficient associated with firm fixed effects is close to zero and statistically insignificant, exhibiting no clear time trend; by contrast, and in line with the modest increase in average wages observed in treated municipalities, the coefficient on worker fixed effect is positive and increases over time. This pattern suggests that treated municipalities experienced a slight rise in the average unobserved earning ability of their workforce (amounting to approximately one-eighth of a standard deviation two periods after treatment) following their connection to the HSR network. Such evidence is consistent with a mild positive selection of more productive workers into areas that benefited from improved accessibility.

Finally, for the mismatch measure, defined as the absolute difference between firm and worker decile positions in their respective distributions, we estimate a negative and marginally statistically significant average treatment effect that grows in magnitude over time. The negative coefficient indicates a modest reduction in worker–firm mismatch; consistently with the previous findings, in the second period after treatment onset, the ATT increases in absolute value, rising from approximately -0.07 to -0.11. It is worth noting

[23] Indeed, Koster and Thisse (2025) note that the finding that small cities gains from HSR in Germany might be explained by arguing that HSR makes it easier for service-based businesses to open in smaller, mid-way stops, which in turn creates new jobs in those areas.

that the average pre-treatment mismatch in treated municipalities is approximately 3, indicating that workers were, on average, matched to firms located three deciles away from their own position in the AKM worker-effect distribution. The estimated ATT corresponds to a reduction in mismatch of about 4%, thereby suggesting an improvement in the alignment between worker and firm quality following the expansion of the HSR network.[24] The reduction in mismatch that we observe is consistent with the findings by Agrawal et al. (2024) on German data, where an increase in commuting subsidies induced workers to switch to longer commutes and generated positive assortativity in the labor market.

Overall, these findings suggest that connection to the HSR network led to modest, yet economically meaningful adjustments in local labor market conditions. Treated municipalities experienced increases in both average weekly wages and the average quality of their workforce. Moreover, the decline in the mismatch measure suggests that firms were able to leverage the expansion of their local labor market by recruiting higher-quality workers who may not have been accessible prior to the introduction of HSR services. This mechanism may, in turn, contribute to explain the observed rise in wage levels at the municipal level.

5 Concluding remarks

HSR networks, by facilitating people mobility, can reduce local mismatches between labor supply and labor demand and foster the integration of regional labor markets.

In this study, we use administrative data covering the entire population of private-sector workers in Italy to examine the pro-mobility effects of the HSR route openings in 2009 and 2013, which fall within the time span of our data. Our empirical strategy combines a staggered DiD research design with highly granular, municipality-level data in a gravity-type setting. Worker flows are measured as the number of workers who change employer location between two consecutive years.

Our analysis reveals several noteworthy findings. Municipalities affected by the new HSR routes experienced, on average, a 18% annual increase in worker flows, with larger effects for the 2013 treatment cohort (27%). At the national level, these effects account for an average of about 4,500 additional workers changing employer location each year, thanks to the new HSR routes (about equally split between the first and the second treated cohort). Mobility effects increased over time in both cohorts, so that, in 2021, the last year in our sample period, the higher mobility due to the openings of the HSR connections amounted to about 12,000 additional workers. Moreover, we find that new HSR links mainly affect mobility between large centers and from small to large municipalities, which can have significant implications for spatial allocative efficiency. At the same time, small centers connected to the HSR network may lose workers and possibly population, thus suggesting that connecting to the HSR network can have important heterogeneous effects at the spatial level.

In addition, we conduct an exploratory analysis of worker–firm matches using a staggered DiD approach applied to AKM estimates of worker and firm fixed effects computed over four four-year windows. The results suggest an improvement in worker ability, a modest increase in average wages, and a reduction in mismatch—measured as the average of the absolute value of the difference between the decile ranks of the worker and firm fixed effects in their respective empirical distributions—in municipalities served by the new HSR routes.

[24] Macis and Schivardi (2016) report a near-to-zero correlation between firm and worker fixed effects in their AKM exercise for the Italian manufacturing sector, thus suggesting that mismatch in the Italian labor market might be important.

Overall, these findings suggest that, by fostering worker mobility, connection to the HSR network can facilitate firms' access to a larger pool of higher-quality workers and increase the degree of assortativity in local labor markets. In the presence of complementarities between firm and worker productivity, greater assortativity within a local area can, in turn, lead to higher local productivity. Our results might therefore provide a complementary explanation for the HSR-induced increase in productivity with respect to those provided by Bernard et al. (2019) and Dong et al. (2020), who point towards improved access to higher quality intermediate suppliers and to increased innovation associated with the greater mobility of inventors.

Our analysis can be extended in several ways. First, our work focuses on changes in job location, which may reflect both workers' residential relocation and commuting. We adopt this approach because individuals often maintain their formal residence in their place of origin even when they change workplace municipalities and domicile (i.e., the place where they reside for job-related reasons), especially when they have family in the origin municipalities; failing to account for this could confound commuting with relocation. Future work could aim to disentangle these two phenomena more precisely. Second, our analysis on mobility focuses on short-term effects, i.e., on yearly changes in workers' job locations. However, one could look at other interesting longer-run effects of HSR, such as the evolution of workers' career paths.

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Table 1. Descriptive Statistics by Treatment Status and Period

Variable	Treated Pre		Treated Post		Untreated Pre		Untreated Post	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
Overall mobility	0.66	8.15	0.74	8.73	0.26	2.79	0.28	3.11
Male workers	0.44	4.88	0.49	5.43	0.17	1.85	0.19	1.94
Female workers	0.23	3.69	0.25	3.66	0.08	1.23	0.09	1.48
High-wage mobility (75%)	0.18	2.32	0.20	2.43	0.06	0.82	0.07	0.83
Low-wage mobility (75%)	0.49	5.99	0.55	6.42	0.20	2.08	0.21	2.40
Workers aged <45	0.55	6.49	0.56	6.48	0.21	2.17	0.21	2.23
Workers aged >45	0.12	1.90	0.19	2.57	0.05	0.75	0.07	1.08
Permanent workers	0.49	6.35	0.50	6.19	0.18	2.26	0.17	2.28
Temporary workers	0.18	2.36	0.25	3.01	0.08	0.92	0.11	1.31
Apprentices	0.03	0.35	0.03	0.49	0.01	0.19	0.01	0.16
Blue-collar workers	0.34	4.18	0.40	4.72	0.16	1.76	0.18	2.24
White-collar workers	0.28	4.55	0.30	4.34	0.08	1.42	0.09	1.28
Managers	0.01	0.26	0.01	0.18	0.00	0.08	0.00	0.11
Observations	203,324		455,477		460,972		999,379	

Notes: This table reports descriptive statistics (means and standard deviations — SD) of overall mobility, and mobility by worker characteristics, computed on INPS dyadic data (see Section 3). Statistics are reported by treatment status and pre- vs. post-treatment period. Mobility flows correspond to the number of workers changing municipality of work between two consecutive years.

Table 2. ATTs of new HSR routes on overall mobility and by sub-population

	Overall (1)	Male (2)	Female (3)	Age <45 (4)	Age >45 (5)	High (75%) (6)	Low (75%) (7)
ATT	0.1171	0.0861	0.0310	0.0582	0.0589	0.0215	0.0956
	(0.0281)	(0.0177)	(0.0140)	(0.0201)	(0.0104)	(0.0079)	(0.0213)
ATT Cohort 2009	0.0943	0.0715	0.0229	0.0430	0.0514	0.0137	0.0807
	(0.0314)	(0.0192)	(0.0166)	(0.0232)	(0.0111)	(0.0089)	(0.0238)
ATT Cohort 2013	0.1896	0.1330	0.0567	0.1065	0.0831	0.0465	0.1431
	(0.0390)	(0.0275)	(0.0144)	(0.0239)	(0.0180)	(0.0113)	(0.0293)
Adj R-squared	0.6774	0.6537	0.5552	0.7122	0.4325	0.6434	0.6540
Observations		2119152	2119152	2119152	2119152	2119152	2119152

	Permanent (8)	Temporary (9)	Apprentices (10)	Blue-collar (11)	White-collar (12)	Managers (13)
ATT	0.0398	0.0773	0.0099	0.0808	0.0283	-0.0038
	(0.0230)	(0.0115)	(0.0020)	(0.0187)	(0.0189)	(0.0013)
ATT Cohort 2009	0.0312	0.0632	0.0093	0.0808	0.0068	-0.0044
	(0.0265)	(0.0123)	(0.0022)	(0.0213)	(0.0223)	(0.0016)
ATT Cohort 2013	0.0674	0.1223	0.0117	0.0808	0.0968	-0.0017
	(0.0288)	(0.0192)	(0.0028)	(0.0234)	(0.0209)	(0.0010)
Adj R-squared	0.5825	0.6168	0.4614	0.4830	0.6255	0.3191
Observations	2119152	2119152	2119152	2119152	2119152	2119152

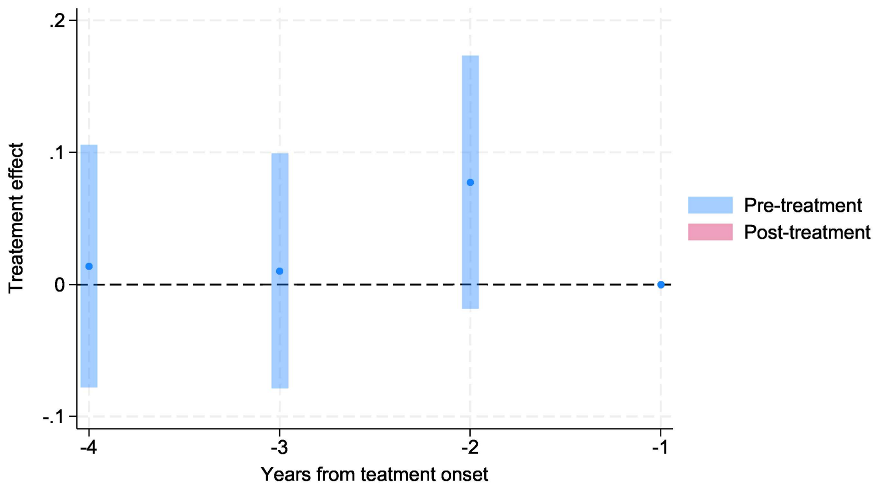
Notes: Standard errors in parentheses are clustered at the dyad level. The table reports general ATT and ATT by treatment cohort on overall mobility and mobility by subpopulations defined by specific characteristics, estimated using ETWFE (see Equation (1)). Mobility flows correspond to the number of workers changing municipality of work between two consecutive years. High and Low refer to the position in the nationwide earning distribution, e.g., High (75%) refers to the mobility of workers with earnings above the 75% percentile and Low (75%) to the mobility of workers below the 75% percentile. Permanent and Temporary refer to mobility by type of contract, and “Apprentices,” “Blue-collar,” “White-collar,” and “Managers” refer to mobility by type of occupation.

Table 3. AKM results: HSR and worker-firm mismatch at the municipality level

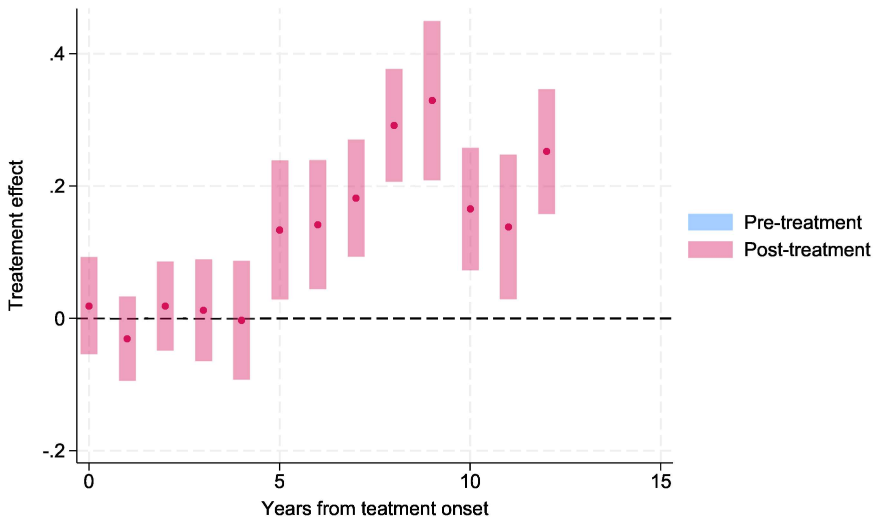
	All municipalities				Turin and Reggio Emilia AV			
	Wages (1)	Firm FE (2)	Worker FE (3)	Mismatch (4)	Wages (5)	Firm FE (6)	Worker FE (7)	Mismatch (8)
Panel (a): 2005-2020								
ATT	0.0047	-0.0060	0.0190	-0.0491	0.0088	0.0012	0.0144	-0.0721
	(0.0054)	(0.0040)	(0.0044)	(0.0288)	(0.0070)	(0.0058)	(0.0057)	(0.0425)
ATT t	-0.0028	-0.0032	-0.0021	-0.0613	0.0063	0.0062	-0.0026	-0.0690
	(0.0052)	(0.0049)	(0.0048)	(0.0417)	(0.0075)	(0.0080)	(0.0066)	(0.0587)
ATT $t+1$	0.0042	-0.0089	0.0146	-0.0543	0.0047	-0.0049	0.0102	-0.0283
	(0.0061)	(0.0047)	(0.0050)	(0.0366)	(0.0083)	(0.0067)	(0.0068)	(0.0546)
ATT $t+2$	0.0127	-0.0058	0.0445	-0.0318	0.0152	0.0022	0.0355	-0.1189
	(0.0073)	(0.0049)	(0.0070)	(0.0349)	(0.0088)	(0.0075)	(0.0089)	(0.0516)
Pre-treatment mean	6.275	-0.014	-0.011	3.062	6.287	-0.012	0.011	3.083
Adj. R^2	0.0375	0.0072	0.0238	0.0259	0.0874	0.0175	0.0625	0.0198
Observations	7,244	7,239	7,239	7,239	2,352	2,350	2,350	2,350
Panel (b): 2005-2022								
ATT	0.0047	-0.0039	0.0105	-0.0527	0.0090	0.0032	0.0070	-0.0691
	(0.0054)	(0.0040)	(0.0041)	(0.0287)	(0.0070)	(0.0058)	(0.0054)	(0.0423)
ATT t	-0.0028	-0.0032	-0.0021	-0.0613	0.0063	0.0062	-0.0026	-0.0690
	(0.0052)	(0.0049)	(0.0048)	(0.0417)	(0.0075)	(0.0080)	(0.0066)	(0.0587)
ATT $t+1$	0.0042	-0.0089	0.0146	-0.0543	0.0047	-0.0049	0.0102	-0.0283
	(0.0061)	(0.0047)	(0.0050)	(0.0366)	(0.0083)	(0.0067)	(0.0068)	(0.0546)
ATT $t+2$	0.0126	0.0006	0.0188	-0.0425	0.0159	0.0082	0.0134	-0.1099
	(0.0072)	(0.0050)	(0.0055)	(0.0318)	(0.0087)	(0.0069)	(0.0070)	(0.0478)
Pre-treatment mean	6.275	-0.014	-0.011	3.062	6.282	-0.010	0.007	3.065
Adj. R^2	0.0375	0.0081	0.0270	0.0432	0.0862	0.0204	0.0692	0.0312
Observations	7,244	7,239	7,239	7,239	2,352	2,350	2,350	2,350

Notes: Standard errors in parentheses are clustered at municipality level. The table reports average ATT and ATT by post-treatment period estimated using ETWFE (see Equation (5)). Mobility flows correspond to the number of workers changing municipality of work between two consecutive years. Column 1-4 refer to the analysis including all treated cohorts while columns 5-8 focus only on Turin and Reggion Emilia AV openings.

Figure 2. Effect of opening HSR on overall worker mobility



(a) Mobility, Event-study DiD Pre-trends



(b) Mobility, Event-Study DiD Post-Treatment Effects

Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of the lead (panel (a)) and lag (panel (b)) terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.

A Appendix

Table A1. Mobility flows by population size of the origin and destination municipalities

	Large to large (1)	Small to large (2)	Large to small (3)	Small to small (4)
ATT	13.4866	0.3237	-0.0050	0.0024
	(5.4321)	(0.1711)	(0.1903)	(0.0092)
ATT Cohort 2009	11.2137	0.3941	-0.0819	0.0012
	(6.9909)	(0.2077)	(0.2358)	(0.0099)
ATT Cohort 2013	18.4380	0.1694	0.1669	0.0067
	(5.4158)	(0.1365)	(0.1434)	(0.0149)
Pre-treatment mean	45.1705	1.519	49.08	1.908
Adj. R^2	0.7721	0.4379	0.4003	0.1800
Observations	24,735	235,416	232,050	1,626,951

Notes: Standard errors in parentheses are clustered at the dyad level. The table reports general ATT and ATT by treatment cohort on overall mobility, split by size of the origin and destination municipalities, estimated using ETWFE (see Equation (1)). Number of treated dyads: 153 large to large; 4,453 large to small; 29,753 small to small; 4,434 small to large.

Table A2. Summary Statistics First vs Last Period for the AKM model: All Municipalities vs. Turin and Reggio Emilia AV

	All Municipalities				Turin & Reggio Emilia AV			
	Wage (1)	Firm FE (2)	Worker FE (3)	Mismatch (4)	Wage (5)	Firm FE (6)	Worker FE (7)	Mismatch (8)
Panel (a): Untreated								
First Period	6.180	-0.041	-0.060	3.095	6.183	-0.037	-0.057	3.079
	(0.155)	(0.093)	(0.128)	(0.753)	(0.146)	(0.096)	(0.119)	(0.826)
Last Period (panel 2005-2020)	6.210	-0.040	-0.047	3.062	6.210	-0.045	-0.035	3.133
	(0.166)	(0.114)	(0.168)	(0.638)	(0.169)	(0.140)	(0.165)	(0.770)
Last Period (panel 2005-2022)	6.195	-0.044	-0.038	2.954	6.195	-0.048	-0.029	3.006
	(0.158)	(0.102)	(0.124)	(0.555)	(0.158)	(0.119)	(0.121)	(0.679)
Panel (b): Treated								
First Period	6.254	-0.013	-0.013	2.997	6.259	-0.011	-0.002	3.024
	(0.151)	(0.072)	(0.119)	(0.396)	(0.139)	(0.072)	(0.110)	(0.498)
Last Period (panel 2005-2020)	6.276	-0.014	-0.003	2.944	6.298	-0.012	0.033	2.941
	(0.157)	(0.086)	(0.165)	(0.444)	(0.138)	(0.100)	(0.158)	(0.617)
Last Period (panel 2005-2022)	6.260	-0.014	-0.003	2.858	6.283	-0.008	0.024	2.893
	(0.153)	(0.076)	(0.124)	(0.419)	(0.136)	(0.079)	(0.109)	(0.577)

Notes: Standard deviations in parentheses . The table report AKM decriptive statistics for the variables (or estimates) indicated in the column headings. Column 1-4 refer to the analysis including all treated cohorts while columns 5-8 focus only on Turin and Reggion Emilia AV openings. For each period, the number of observations is 1,753 for the control sample and 802 for the treated sample when considering all municipalities, and 530 and 227, respectively, for the Turin and Reggio Emilia AV subsamples.

Table A3. Summary statistics for the AKM analysis by treatment status, staggered panel

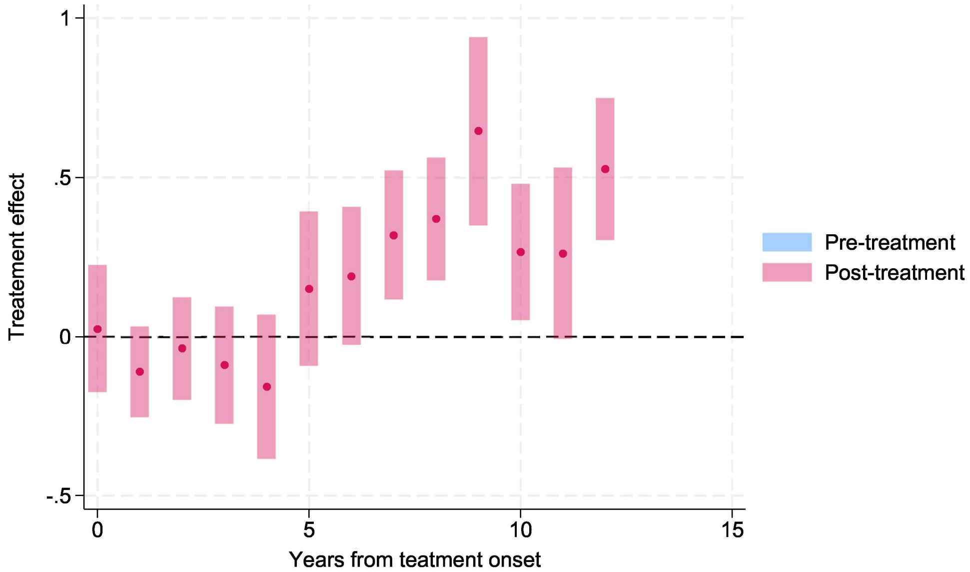
	Untreated				Treated			
	Pre		Post		Pre		Post	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
All Municipalities								
Panel (a): 2005–2020								
Wage	6.183	0.154	6.207	0.168	6.259	0.150	6.275	0.157
Firm FE	-0.040	0.092	-0.041	0.124	-0.011	0.071	-0.014	0.086
Worker FE	-0.059	0.126	-0.052	0.146	-0.009	0.117	-0.011	0.139
Mismatch	3.100	0.740	3.218	0.760	3.002	0.392	3.062	0.537
Observations	1,882		5,125		860		2,348	
Panel (b): 2005–2022								
Wage	6.183	0.154	6.202	0.166	6.259	0.150	6.269	0.156
Firm FE	-0.040	0.092	-0.042	0.121	-0.011	0.071	-0.014	0.083
Worker FE	-0.059	0.126	-0.049	0.130	-0.009	0.117	-0.011	0.124
Mismatch	3.100	0.740	3.181	0.747	3.002	0.392	3.033	0.538
Observations	1,882		5,125		860		2,348	
Turin and Reggio Emilia AV openings								
Panel (a): 2005–2020								
Wage	6.191	0.146	6.205	0.178	6.275	0.135	6.287	0.145
Firm FE	-0.035	0.093	-0.046	0.147	-0.006	0.069	-0.012	0.103
Worker FE	-0.054	0.117	-0.045	0.146	0.007	0.103	0.011	0.141
Mismacth	3.097	0.778	3.229	0.874	3.034	0.470	3.083	0.741
Observations	660		1,458		285		623	
Panel (b): 2005–2022								
Wage	6.191	0.146	6.200	0.174	6.275	0.135	6.282	0.144
Firm FE	-0.035	0.093	-0.047	0.140	-0.006	0.069	-0.010	0.096
Worker Effects	-0.054	0.117	-0.043	0.129	0.007	0.103	0.007	0.122
Mismatch	3.097	0.778	3.183	0.853	3.034	0.470	3.065	0.733
Observations	660		1,458		285		623	

Notes: The table report AKM decriptive statistics (means and standard deviations—SD) for the variables (or estimates) indicated in the column headings. Column 1-4 refer to the analysis including all treated cohorts while columns 5-8 focus only on Turin and Reggion Emilia AV openings. Pre and Post indicate the pre- and post-treatment periods, respectively.

Figure A1. Opening of HSR routes in Italy

Notes. Timeline of the completion of HSR routes in Italy since 2005. The first route (Rome-Florence) was completed in 1992. The HSR route openings considered in this study are drawn in blue. The opening of Treviglio-Brescia is not considered, as trains do not travel at high speed (above 250 km/h) while those pre-dating 2009 are not considered because of an insufficient pre-treatment period to investigate parallel trends.

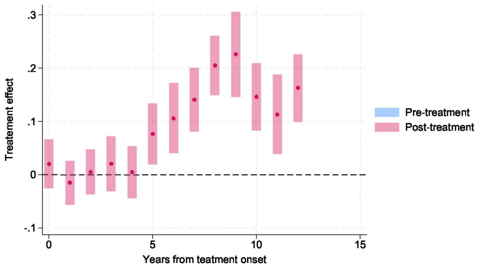
Figure A2. Post-treatment effects with different thresholds: 0-20 km treated vs. 40-60 km untreated



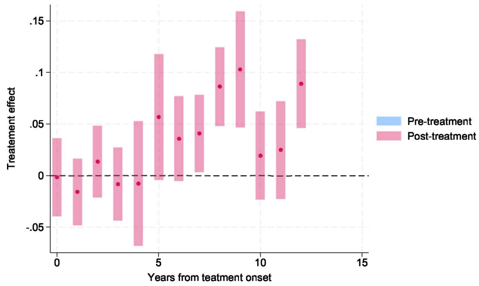
Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of lag terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.

Figure A3. Post-treatment effects by worker characteristics

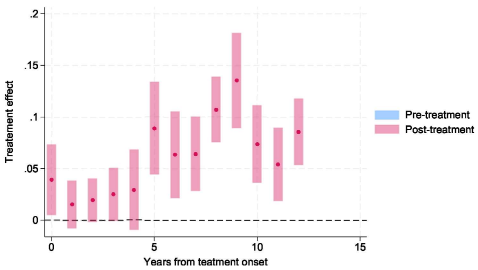
(a) Males



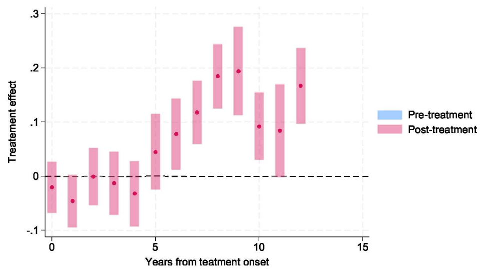
(b) Females



(c) Old Workers



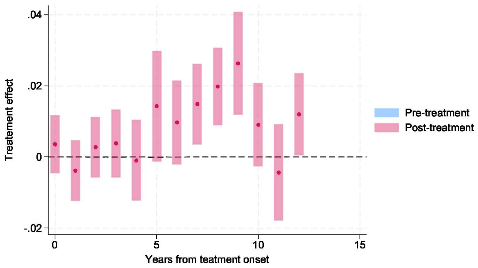
(d) Young Workers



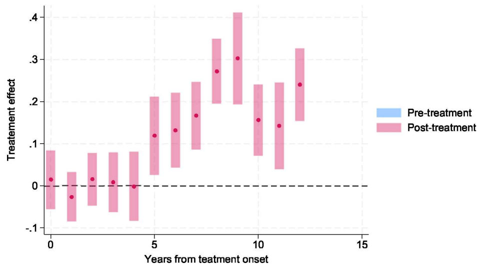
Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of the lag terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.

Figure A4. Post-treatment effects by job characteristics

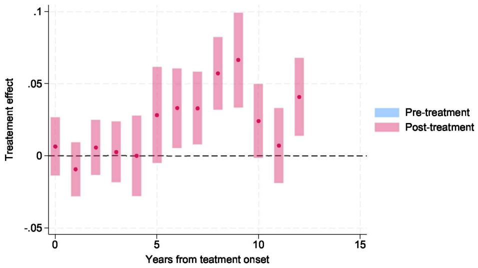
(a) Above the 90th Percentile



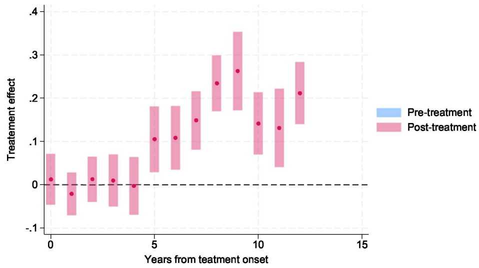
(b) Below the 90th Percentile



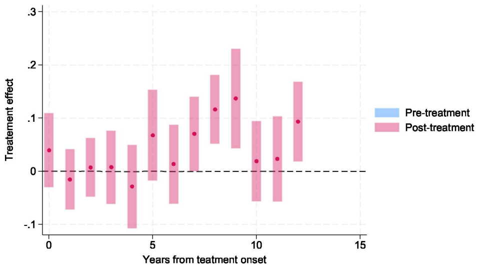
(c) Above the 75th Percentile



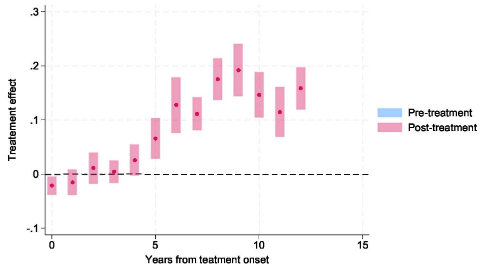
(d) Below the 75th Percentile



(e) Permanent

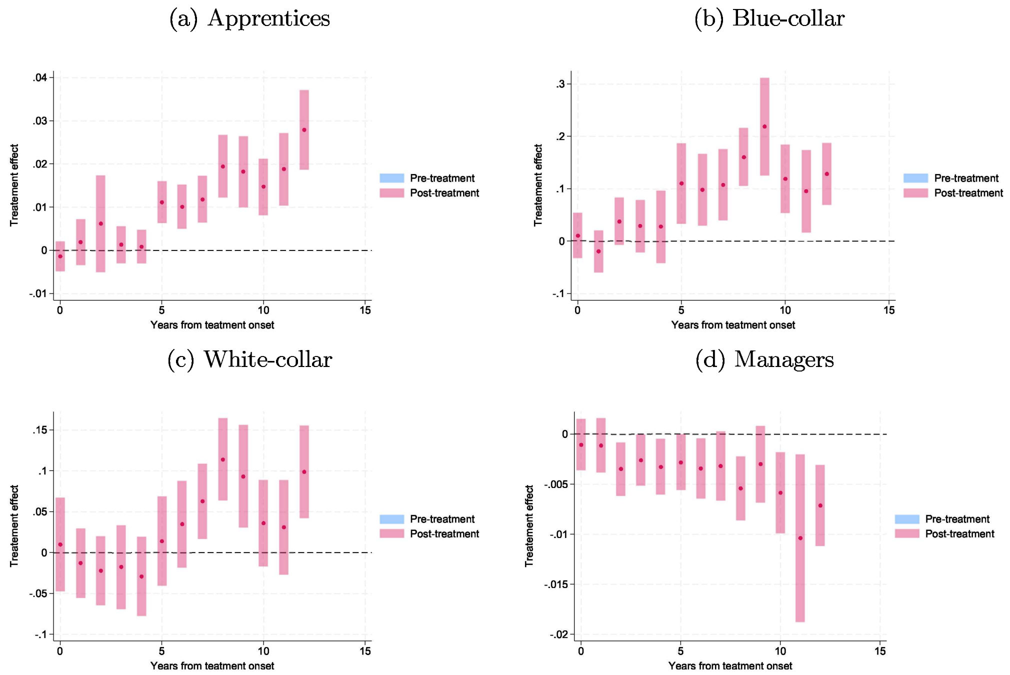


(f) Temporary



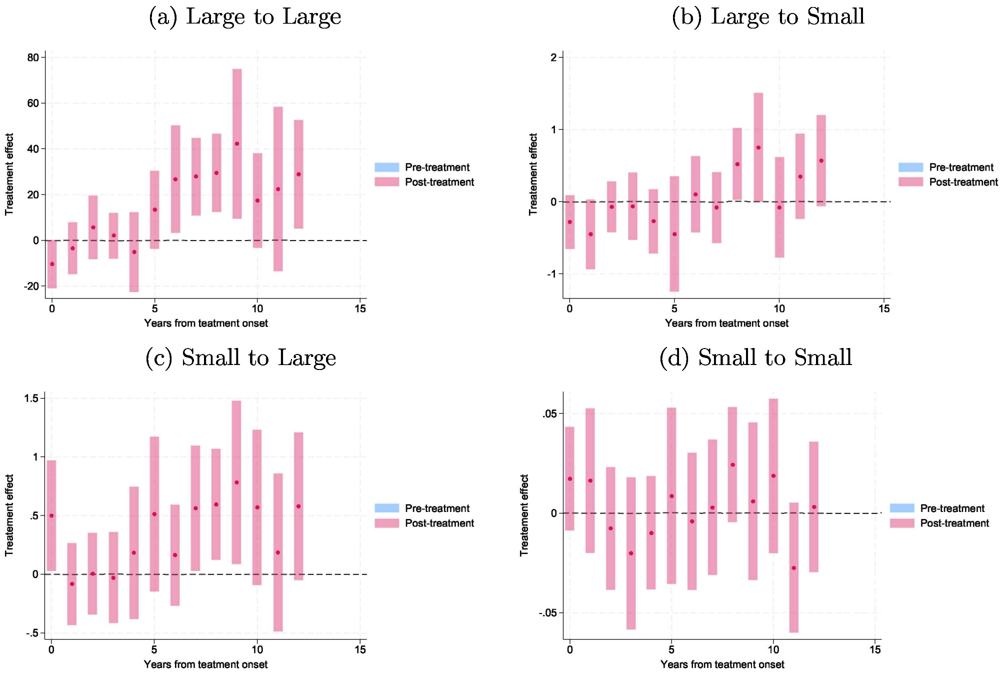
Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of the lag terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.

Figure A5. Post-treatment effects by occupational type



Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of the lag terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.

Figure A6. Post-treatment effects of flows by municipality size



Notes: The graphs plot the point estimates and the 95% confidence intervals from Equation (1) of the lag terms of the event-study DiD estimated with ETWFE. Worker mobility is measured as the number of workers who change employer location from municipality o (origin) to municipality d (destination) between two consecutive years. Time zero is the time of the new HSR route opening. Standard errors are clustered at the dyad level.