



Knowledge economy, internal migration, and local labour markets

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ABSTRACT

The spatial concentration of knowledge-intensive activities can generate multiplicative effects at the local level. This paper examines how employment growth in knowledge-intensive and tradable sectors affects wage, days worked, and internal migration of non-tradable workers in Italy. We leverage matched employer-employee data (2005–2019) to track individuals across jobs and locations. Our empirical strategy combines a two-step estimation with a shift-share instrument to disentangle the roles of worker sorting and local spillovers. We find that knowledge sector expansion increases the number of days worked locally and attracts non-tradable workers. It also raises nominal wages, but only when sorting is not accounted for, suggesting selective inflows of more productive workers into knowledge hubs. However, rising local living costs offset nominal wage gains, leading to lower real wages.

1. Introduction

The rise of the so-called ‘knowledge economy’ has led to a concentration of human capital-intensive activities, fostering clusters of knowledge-intensive sectors within confined areas. This spatial agglomeration can generate significant multiplicative effects at the local level (Moretti, 2010b), as highly-innovative industries demand more intermediate services, offer higher wages, and create stronger productivity spillovers (Moretti, 2012; Lee, 2014; Lee and Clarke, 2019). Consequently, the concentration of human capital can shape local labour market conditions and influence the location decision of workers, ultimately driving spatial inequalities within a country (Rosés and Wolf, 2018; Moretti, 2012; OECD, 2019).

This paper investigates the impact of knowledge-intensive employment growth in certain geographical areas on other workers within the same local labour markets. Specifically, we assess the impact of labour demand shocks – measured as the expansion of employment in knowledge-intensive tradable sectors (‘TK workers’) – on wage, days worked, and migration probability of workers in non-tradable industries (‘NT workers’).

While considerable evidence exists on the local multiplier effects of labour demand shocks, no study has systematically examined the local impact of the rise of the knowledge economy as we do in this paper. Most research has focused on the local price adjustments and employment effects driven by changes in labour demand (Bartik, 1991;

Blanchard and Katz, 1992; Moretti, 2010a,b), analysing shocks in key sectors such as biotech and energy (Allcott and Keniston, 2017; Marchand, 2012; Moretti and Wilson, 2014), trade shocks (Dix-Carneiro and Kovak, 2019), or local public spending (Acconcia et al., 2014; Faggio and Overman, 2014; Suárez Serrato and Wingender, 2016). In contrast, we investigate the localised labour market effects of the structural transformation of the economy which has expanded the scope of knowledge-intensive activities. Different from studies focusing on sector-specific shocks, we select industries of interest based on the criterion of knowledge intensity.

Unlike most works focused on the US context, we examine Italy, a context that can offer insights into the role played by specific institutional features such as wage-setting mechanisms and labour mobility in labour market dynamics (Moretti and Thulin, 2013; Ottaviano and Peri, 2010; Faggio and Overman, 2014).

We leverage a unique administrative individual-level dataset containing matched employer-employee information on the complete work histories of all social-security-paying Italian workers from 2005 to 2019. Workplace data allows us to track workers across different locations and occupations. The richness of this dataset helps mitigate key empirical concerns. We implement fixed effects models to disentangle the role of place-specific effects and the sorting of workers into local labour markets based on unobservable characteristics. This approach accounts for the natural tendency of higher-paid workers to cluster in

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larger urban areas (Combes et al., 2008; De La Roca and Puga, 2017; Dauth et al., 2022; Card et al., 2023).

To address the potential correlation between idiosyncratic local shocks and the inflow of TK workers to local areas, we combine a two-step procedure *à la* Combes et al. (2008) with a shift-share instrumental variable strategy (Bartik, 1991). In the first step, we estimate wage, days worked, and in/out-migration probability of NT workers, controlling for observable time-varying worker and firm-level characteristics as well as time-invariant individual unobservables. In the second step, we regress the predicted local labour market area-year characteristics on our treatment variable – the share of TK workers – instrumenting it to account for idiosyncratic local labour market shocks. Second-step equations are estimated on an area-year panel and exploit variation over time in the local share of TK workers. This allows us to isolate the effect of an increase in TK worker share on wages, days worked, and in/out-migration probability for NT workers.

Our findings indicate that workers of TK industries are highly geographically concentrated, and the clustering of knowledge-intensive activities generates significant multiplicative effects at the local level. Specifically, we find that the expansion of the TK sector leads to an increase in the number of days worked in non-tradable industries. Additionally, out-migration probabilities decline, while in-migration probabilities rise, suggesting that local economies with growing TK employment become more attractive. However, we find no significant effect on wages, highlighting their limited responsiveness to local labour market conditions in the Italian context. Notably, nominal wages appear positively associated with TK worker shares only when worker sorting is not accounted for, implying that higher nominal wages attract inherently more productive workers. Instead, local housing prices respond more strongly than nominal wages, leading to a negative overall impact on real wages.

Thus, while knowledge clusters emerge as dynamic and attractive labour markets, they also become expensive cities where rising housing costs – driven by an influx of knowledge-intensive workers – reduce real wages. These findings suggest an improvement in local amenities and/or the presence of learning externalities in knowledge-intensive areas.

The paper is structured as follows. Sections 2 and 3 respectively discuss the theoretical insights from the literature and motivate the setting choice; Sections 4 and 5 present the data employed and some descriptive statistics; Sections 6 and 7 explain the empirical strategy adopted and report the related results, including the analysis of sorting *versus* local spillovers (Section 7.2) and the comparison between nominal and real wage effects (Section 7.3); Section 8 concludes.

2. Theoretical insights and empirical expectations

In standard spatial general equilibrium models (Roback, 1982), localised productivity shocks translate into higher nominal wages, reflecting enhanced labour productivity. This, in turn, attracts workers, driving up housing prices. The adjustment process continues until real wages equalise across local labour markets. If differential amenities and/or idiosyncratic preferences for locations are incorporated in the model, equilibrium is reached when the marginal worker is indifferent across locations, even if real wages remain unequal (Moretti, 2010a). Greenstone et al. (2010) extend this framework by explicitly modelling spillovers between producers. When a firm enters a labour market, additional firms follow to benefit from local spillovers, such as thicker labour markets, access to intermediate inputs providers, and localised knowledge diffusion. These agglomeration forces are counterbalanced by rising input costs due to the increased demand for labour and land. The model predicts that, if spillovers are large enough, new firms will enter the labour market and the prices of locally traded goods will rise due to stronger local demand.

We conceptualise the spatially-uneven growth of the TK sector as the entry of new TK firms into *some* local labour markets, driving an agglomeration process that forms TK-sector clusters within a country.

According to this theoretical framework, TK-sector growth should increase nominal wages in NT sectors, as well as the prices of locally traded goods. Yet, this applies only to institutional contexts where wages are flexible and negotiated in an independent and decentralised manner, thus adjusting to local labour market shocks. In contrast, in contexts where institutional constraints limit wage flexibility, the literature predicts that upward wage pressures translate into *employment* growth instead. Ottaviano and Peri (2010), for example, show that in Germany's rigid-wage setting, employment serves as the primary margin of adjustment to shocks. This is particularly relevant in Italy, where most employees are subject to national collective labour agreements (Belloc et al., 2023), making wages less responsive to local labour conditions. In this context, while collective bargaining imposes a downward constraint on wages, it does not prevent employers from offering wages above the nationally negotiated level (*in melius* clause). This means wage increases are possible in local labour markets experiencing higher growth in TK workers, but downward constraints limit wage differentials across local areas.

Furthermore, Roback-type models predict that local prices rise in response to increased local demand. If local prices react more strongly than *nominal* wages, *real* wages may even decline. This seemingly counterintuitive outcome has already been documented in the Italian context, where Belloc et al. (2023) find a negative real urban wage premium, and in the US, where Card et al. (2023) show that rising housing costs offset more than 100% of the nominal earnings gains from moving to larger labour markets. These findings align with the Roback theoretical framework if we account for the presence of better consumption amenities (Albouy, 2008; Albouy et al., 2021). Additionally, workers may give up immediate earning gains in exchange for dynamic advantages of working in denser or growing areas, consistent with the learning externalities described by De La Roca and Puga (2017).

Given these considerations, we expect employment to be a key adjustment margin in our setting. However, the net employment effect remains uncertain. On the one hand, positive labour demand shocks can create a multiplier effect by increasing demand for locally traded goods and services (Moretti, 2010b). On the other hand, if labour supply is inelastic, sector-specific shocks may displace workers from other local industries, reducing employment in the broader local economy. Faggio and Overman (2014) provide an example of this dynamic, estimating that public sector expansion in the UK crowded out employment in tradable industries due to labour market rigidities (e.g. generous benefit system) and strict housing regulations that constrained labour supply responses to local demand shocks.

While Italy's low labour mobility suggests potential crowding-out effects, the presence of involuntary unemployment means that employment adjustment need not rely solely on migration. Instead, job growth may come from previously unemployed residents (Moretti, 2010a). Given Italy's significant unemployment levels over the study period, it is plausible that the employment response of incumbent residents outweighs the limited inflow of new migrants, leading to a net positive employment effect. In sum, without precise knowledge of the labour supply elasticity, we cannot *a priori* predict the sign of the employment response to the increased presence of TK workers.

As detailed in Section 4, our data allow us to measure employment adjustments at the intensive margin (i.e. days worked). In addition, we estimate the response to TK sector growth in terms of *in-* and *out-migration*, capturing key components of the extensive margin effects. The above theoretical considerations also apply to these two additional outcomes. While the mobility response of workers in other sectors of the local economy is not explicitly discussed in Roback-type models, they predict an increased demand for locally traded goods and services. This should *reduce* the incentives for NT workers to out-migrate and *increase* the incentives for in-migration, as more and better job oppor-

tunity become available.¹ Therefore, we expect positive demand shocks in the TK sector to increase in-migration and reduce out-migration probabilities for NT workers.

3. Knowledge economy in Italy

Italy represents an especially interesting case for the issue at hand. The country has experienced substantial internal migrations (on top of international outflows) with young, highly skilled adults predominantly moving towards major urban areas (ISTAT, 2019). A striking indicator of this trend is the increased commuting flows around Northern metropolitan areas and the decline in the number of local labour markets (LLMs) recorded between the last two censuses (ISTAT, 2010). Since the 2000s, all Italian regions have witnessed a growing international outflow of skilled workers ('brain drain'). However, when considering both internal and international migration together, some Italian regions come to display positive net inflows of young qualified population, benefitting at the expense of less dynamic areas. In other words, when young talent does not leave the country, it tends to concentrate in the most dynamic and productive areas of the country, depriving their places of origin of valuable human capital necessary for local development.

This loss of talent is a critical driver of emerging spatial disparities, which are not limited to the traditional North-South divide, but rather are visible at a more refined geographical scale, arising across the entire country. Italy today is characterised by pronounced polarisation in terms of population, opportunities, services, and investments. These growing disparities have led policy-makers to speak of an Italian 'territorial issue' (Borghi, 2017), prompting targeted interventions such as the National Strategy for Inner Areas (MUVAL, 2014).

The rise of regional inequalities is not unique to Italy but reflects a global trend. Structural economic transformations, particularly the expansion of the knowledge economy, have reinforced spatial disparities by favouring the geographic clustering of high-skill industries and talent.² In Italy, the Italian institute of statistics (ISTAT) reports that certain regions and provinces are catching up with European standards in key knowledge-based indicators, such as R&D investments, brands registration, industrial design, employment in research and cultural activities (ISTAT, 2018). However, these improvements remain highly localised, with large portions of the country lagging behind.

In sum, Italy exhibits a distinct geography of knowledge, where migration patterns and access to high-skilled opportunities are deeply interconnected. We hypothesise that this dynamic plays a crucial role in shaping the country's emerging territorial disparities.

4. Data

The data used for the analysis are drawn from matched employer-employee datasets collected by the Italian National Institute of Social Security (INPS). We gained access to these data through the VisitINPS Scholars programme, which allows selected scholars to employ social-security data for research purposes.³ These data cover the universe of

social-security-paying Italian workers employed in the private sector. However, self-employed workers and public servants are not included in the datasets we use. Consequently, when a worker exits the dataset, we cannot determine with certainty whether they have become unemployed, transitioned to the public sector, or moved to self-employment. Therefore, our analysis focuses on the *intensive* margin of employment, which we measure by the number of days worked per year. Additionally, to gain insights into the *extensive* margin of employment, we examine workers' in- and out-migration probabilities relative to a local labour market.

INPS data report the whole working history of private-sector employees, tracking individuals across different occupations, employers, and working locations since the 1970s. However, geographical information on the employment municipality of each worker is available only from 2005. Consequently, our study focuses on the period 2005–2019.

Our sample includes workers aged 15 to 64 who are not retired and for whom we have sectoral and geographical employment data. We exclude individuals working less than 30 days per year, as well as those in the top and bottom 1% of the wage distribution. To account for part-time employment, we compute full-time equivalent wages before applying this restriction. This is done to focus on 'average workers', discarding extreme and marginal working situations. For consistency, we assign each worker a single dominant job contract per year, identified as the employment providing the highest annual income and displaying the highest number of days worked. After implementing these selection criteria, our final dataset consists of over 100 million observations.

In addition to INPS data, we incorporate information on local house prices from the Italian Revenue Agency.⁴ These data provide minimum, maximum, and average prices at sub-municipal level, that we then aggregate at the local labour market (LLM) level. We employ this information as a proxy for local living costs to calculate real wages.

Given our study period, we define LLMs according to the 2011 definition of ISTAT's *Sistemi Locali del Lavoro*. This classification, based on commuting flows recorded in each census year, partitions the country into 611 LLMs. As a result, these units provide the most accurate definition of local labour markets.⁵

4.1. Tradable-knowledge (TK) workers

We identify TK workers on the basis of their employment sector.⁶ This choice aligns with the literature on local multipliers, which examines the labour market effects of sector-specific shocks (Moretti, 2010b; Marchand, 2012; Allcott and Keniston, 2017), and is particularly suited to estimating the labour market consequences of the TK sector growth.

⁴ For more details, see <https://www.agenziaentrate.gov.it/portale/schede/fabbricatiterreni/omi/banche-dati/quotazioni-immobiliari>.

⁵ For further details on the construction of *Sistemi Locali del Lavoro*, see <https://www.istat.it/en/labour-market-areas>. We employ the 2011 definition, since that seems the most representative description of local labour markets in our period of analysis (2005–2019).

⁶ An alternative choice would have been to select workers by looking at their occupation and/or education. Unfortunately, those variables report relevant percentages of missing information in INPS data. More importantly, the sample for which we have such information appears to be a non-random selection with respect to key worker characteristics. Also for that reason, we opt for an identification based on sectors. To provide some information on the skill composition inside and outside the TK sector, Table A.1 in the Appendix shows the distribution of (non)TK-sector workers by education group and job position. Within the TK sector, the percentage of college-educated workers is twice as much as outside it, while high-school dropouts are half of non-TK sector workers. Similarly, almost 70% of TK sector workers are white collars or managers compared to the 36% outside the TK sector. Moreover, Figure A.1 plots the wage distributions of TK-sector and NT workers. The former distribution is shifted to the right, with the right tail displaying considerably more weight. This suggests that, among TK-sector workers, a larger mass of individuals earns more than the average.

¹ Notice that this prediction holds in either case of a multiplier or crowding out effect on employment. In case of a dominant crowding out effect, the displacement of non-tradable workers who go to work in tradable industries decreases workers' competition for jobs in non-tradable sectors and therefore (increase) reduces the incentives for workers in these industries to (in)out-migrate.

² In the European context, Rosés and Wolf (2018) offer a historical perspective on the evolution of territorial inequalities, showing a new rise from the '80s and mainly relating it to technological change. Similarly, for the US, Moretti (2012) speaks of 'great divergence' among areas of the country, driven precisely by the concentration of high-tech firms and qualified workers.

³ For more information about the programme, visit <https://www.inps.it/dati-ricerca-e-bilanci/attivita-di-ricerca/programma-visitinps-scholars>.

To define workers in knowledge-intensive sectors, we follow the EUROSTAT classification, which designates an industry as ‘knowledge-intensive’ if at least 33% of its workforce holds a college degree.⁷ That listing of sectors is based on the average number of employed people between 15 and 64 years old at aggregated EU-27 level in 2008 and 2009, according to the NACE Rev.2 at 2-digit, using the EU Labour Force Survey data. Note that this criterion is broader in scope compared to more traditional ones (e.g., Moretti and Thulin, 2013), which focus solely on manufacturing sectors with high technological intensity in production. Our definition, by contrast, also includes knowledge-intensive services and sectors with high human capital concentration, even when technological adoption is low.⁸

To construct our TK workers variables in line with the local multipliers literature, we focus on knowledge workers within *tradable* sectors. Following Moretti (2012), we aim to assess the impact of ‘cause jobs’—those generated by external demand—on local labour market dynamics.⁹ To classify tradable sectors, we follow Faggio and Overman (2014) and adopt the Jensen and Kletzer (2006) classification of tradable service sectors, together with its extension to manufacturing activities provided by Hlatshwayo and Spence (2014). Jensen and Kletzer (2006) classify service activities according to their degree of tradability based on a locational Gini index. The assumption underlying such a criterion lies in the fact that sectors which serve a more widespread demand—therefore, tradable ones—happen to be more geographically concentrated.¹⁰ Thus, they use spatial clustering as an indicator of that service being potentially traded nationally and internationally. Hlatshwayo and Spence (2014) build on that criterion to classify manufacturing sector by degree of tradability. Both contributions refer to US data (thus, to NAICS sector codes) and make the assumption that sector tradability stays constant over a few decades.¹¹ To adopt such classification with Italian data, we follow Faggio and Overman (2014) and map the 2-digit NAICS codes and industry description into our 4-digit Ateco codes, assuming sectoral tradability patterns are similar across countries.¹²

By combining knowledge-intensity and tradability criteria, we identify 93 4-digit Ateco industries as part of the TK sector.¹³ We refer to workers in these sectors as TK workers (i.e. tradable and knowledge-intensive). These workers will constitute our treatment variable—specifically, the percentage of TK workers in a given LLM.¹⁴

⁷ For further details, see [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge_Intensive_Activity_\(KIA\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge_Intensive_Activity_(KIA)) and related annex ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an8.pdf.

⁸ Moretti and Thulin (2013)’s definition of high-technology manufacturing firms includes only pharmaceuticals; office machinery and computers; radio, television, and communication equipment; medical, precision, and optical instruments, watches and clocks; and aircraft and spacecraft; while leaving out knowledge-intensive sectors as, for example, activities of architectural firms, news agencies, research and experimental development. Combining their classification of high-tech industries with our notion of tradable sectors (see below), we would get a TK sector consisting of 59 4-digits Ateco industries, instead of the 93 we currently have in our definition, which seems therefore wider in scope and more comprehensive.

⁹ Tradable industries derive a significant portion of their revenues from external (non-local) demand. These ‘cause jobs’ can, in turn, stimulate job creation in non-tradable local industries (‘consequence jobs’).

¹⁰ Besides supported by empirical evidence, that assumption is theoretically demonstrated by the works of Helpman and Krugman (1985) and Krugman (1991).

¹¹ Such an assumption could be somehow restrictive for sectors benefiting from ICT revolution; however, most of them are already classified as tradable (Hlatshwayo and Spence, 2014).

¹² Specifically, we assume that sectors are as spatially concentrated in the US as in Italy, an assumption made also by Faggio and Overman (2014) for the UK.

¹³ A summary is provided in Figure A.2, with the full list of industries included in Table 5 of the Appendix.

¹⁴ If TK workers switch from a non- to a knowledge-intensive sector, they will contribute to treatment variables only for the years in which they are employed in knowledge-intensive sectors.

We define ‘TK migrants’ as workers who relocate between LLMs and are employed in the TK sector at their destination. We only consider *internal* migration, i.e. within-Italy, since cross-border relocations are not captured in the INPS data.¹⁵

4.2. Non-tradable (NT) workers

We define workers employed in *non-tradable* sectors as NT workers. This group constitutes the population which we expect to be affected by changes in TK employment. By definition, NT sectors primarily serve *local* demand, making them particularly sensitive to local labour market shocks. While some tradable sectors may also experience sector-specific shocks, part of the impact is likely diffused across multiple LLMs, resulting in a milder effect (Moretti, 2010b).

NT workers do not need to remain in the same LLM throughout 2005–2019; but may migrate to other LLMs. We assume they are affected by TK workers growth when they are located in an LLM experiencing an increase in the share of TK workers.

5. Descriptive analysis

During the analysed period (2005–2019), TK workers represent around 10% of the Italian workforce, with a slight upward trend over time.¹⁶ Regarding internal migrations, 8% of the whole working population relocates across LLMs each year, with a significant proportion under the age of 40. However, only one-quarter of these migrants are employed in knowledge-intensive sectors.¹⁷ Interestingly, a great portion of migrants in knowledge-intensive industries is employed in tradable sectors, supporting the notion that geographical concentration mainly concerns tradable industries. In addition, the majority of these migrants are young, reinforcing the stylised facts presented in Section 3.

Examining the spatial distribution of TK workers (Fig. 1), we observe an overall increase in TK employment over time, with many LLMs reaching 15% or more of TK workers by 2019. However, their distribution remains spatially concentrated, particularly in the centre-North. Moreover, considerable variability exists within regions, with neighbouring LLMs often exhibiting markedly different TK employment shares.

To further explore the spatial dispersion of TK workers over time, Fig. 2 presents kernel density distributions of TK employment shares across LLMs for selected years (2005, 2010, 2015, and 2019). The distribution slightly shifts to the right, due to the overall increase in TK sector employment. Additionally, the curve flattens around the mean while gaining weight in the right tail, indicating that some LLMs pull ahead of the country average. This pattern aligns with our hypothesis that only a subset of LLMs is significantly benefitting from the rise of the knowledge economy.

¹⁵ To assign workers to an LLM, we use their ‘dominant’ employment location, defined as the LLM where they work the highest number of days in a given year. This allows to compute net migration into an LLM by subtracting outflows from inflows over the study period.

¹⁶ As explained in the previous section, TK workers are active in tradable and knowledge-intensive sectors. Tradable sector employment represents around 40% of total employment, on a decreasing trend due to the decline of manufacturing, while those in knowledge-intensive sectors are around 20% and show a slight upward trend in the last years of sample. See Table A.2 for a visual representation of the groups of workers we focus on and the related employment percentages over the span 2005–2019. In that time period, we observe low transition rates among the three groups: specifically, 0.75% of TK workers become NT workers and viceversa; 0.4% of TK workers move to tradable non-knowledge-intensive (TNK) jobs and viceversa; 1.3% of NT workers go to work in tradable non-knowledge-intensive (TNK) industries and viceversa.

¹⁷ While this may seem a relatively low percentage, a potential explanation is that we are not looking at individual education, but rather at employment sectors. Thus, a poorly educated workforce in knowledge-intensive sectors can partially motivate this finding, as well as the possibility for highly educated migrants to find qualified occupations in non-knowledge-intensive sectors.

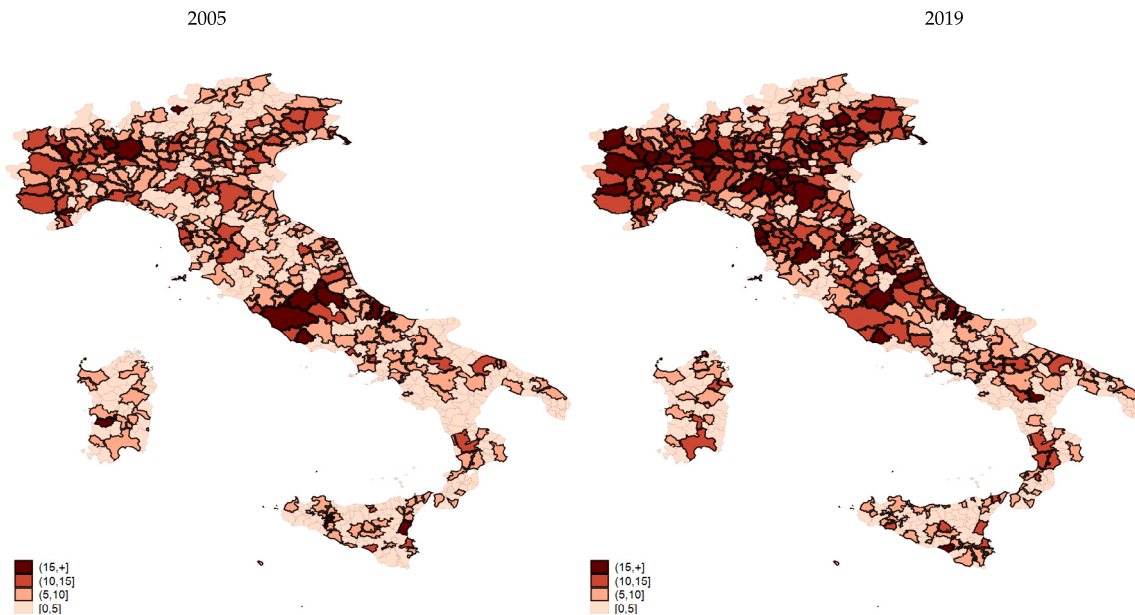


Fig. 1. % jobs in the TK sector.

Note: The maps show the percentages of workers employed in the TK sector by LLM, at the beginning (2005 — Panel a) and at the end (2019 — Panel b) of the period considered.

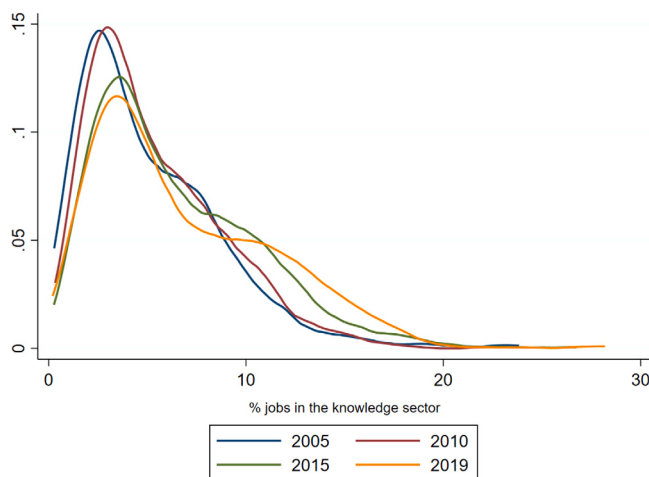


Fig. 2. Dispersion of TK across LLMs.

Note: The graph reports the kernel density distributions of the percentages of workers in the TK sector across LLMs in 2005, 2010, 2015, 2019.

We also conduct a basic correlation analysis to examine the relationship between TK employment and labour outcomes of NT workers. Fig. 3 plots average daily wage and days worked at LLM level against TK employment shares. The average labour outcomes are computed from individual adjusted wages and days worked, predicted through a regression including gender, age, labour market entry year, and a set of occupational dummies. In both cases, correlations are clearly positive, providing preliminary evidence of a positive relationship between the share of TK sector workers and local labour market conditions (Fig. 3).

Turning to net migration patterns (Fig. 4), most LLMs experienced net outflows of workers over the study period. However, when focusing specifically on TK workers, a larger number of LLMs recorded positive net migrations. Nevertheless, the majority of LLMs received fewer than 1000 TK migrants over 15 years. Some highly dynamic LLMs, such as Rome, Bologna, Florence, and Padua, stand out for their significant inflow of TK workers. In the islands, LLMs with regional administrative

centres also experienced relatively high inflows, suggesting that much of the observed mobility occurs within regions.

For an overview of mobility patterns, we classify LLMs by initial population density and compute average origin–destination flows over 2005–2019. Fig. 5 presents these flows, distinguishing between overall migration (Panel a) and migration within the TK sector (Panel b).¹⁸ In both panels, migration flows are largely dominated by moves between large cities, likely due to a size effect, since these are the most densely populated areas. The main destination of migrants coming from large or small cities is large cities. Migration from large cities to small cities or rural areas is relatively rare, a pattern that becomes even more pronounced among TK workers (Panel b). This suggests that large cities serve as the primary destination for skilled labour, while most rural areas experience outmigration.

6. Empirical strategy

Our aim is to identify the labour market impact of relative employment growth in the TK sector. In estimating such relationship, we face two main identification issues.

First, NT workers may self-select into certain LLMs based on unobservable characteristics (e.g. ability) that correlate with the presence of TK workers. In other words, it can be that NT workers inherently display better labour outcomes in LLMs with a higher concentration of TK workers.

Second, unobserved idiosyncratic shocks affecting labour outcomes may be correlated with the growth in local shares of TK workers, potentially biasing our estimates. Specifically, if unobserved demand shocks drive both TK employment growth and improved labour outcomes, our estimates would be upward biased; conversely, if unobserved supply shocks influence the labour market, our estimates could be downward biased.

To address these concerns, we employ a two-step estimation approach (Combes et al., 2008) combined with a shift-share instrument.

¹⁸ Specifically, areas are classified as ‘large city’ if they belong to the 4th quartile of the population density distribution in 2006, ‘small city’ if to the 3th quartile, ‘rural’ if to the 1st or 2nd quartile.

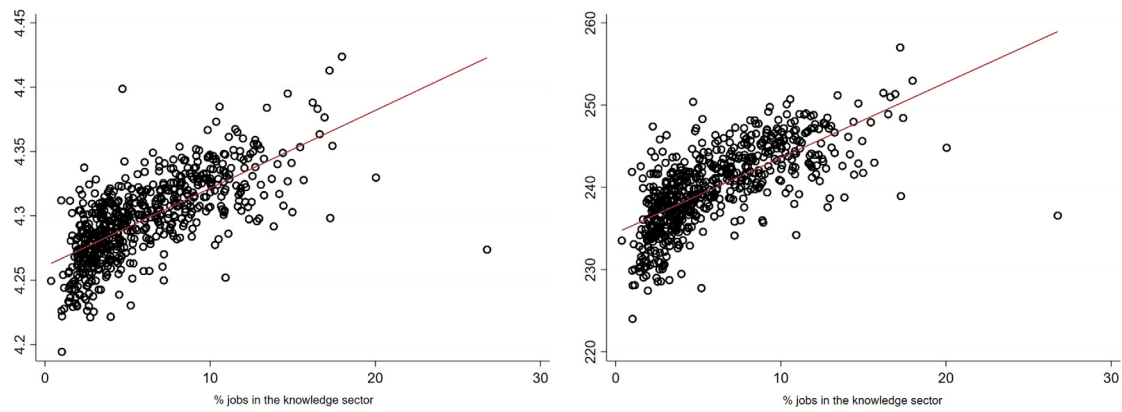


Fig. 3. Correlation between adjusted local wage/days worked and % jobs in the TK sector.

Note: The graphs report the correlation between local adjusted daily wage (Panel a) and days worked (Panel b) at LLM level, and the percentages of TK workers. The adjusted labour outcomes are obtained through a regression including sex, age, year of entrance in the labour market and a set of occupational dummies.

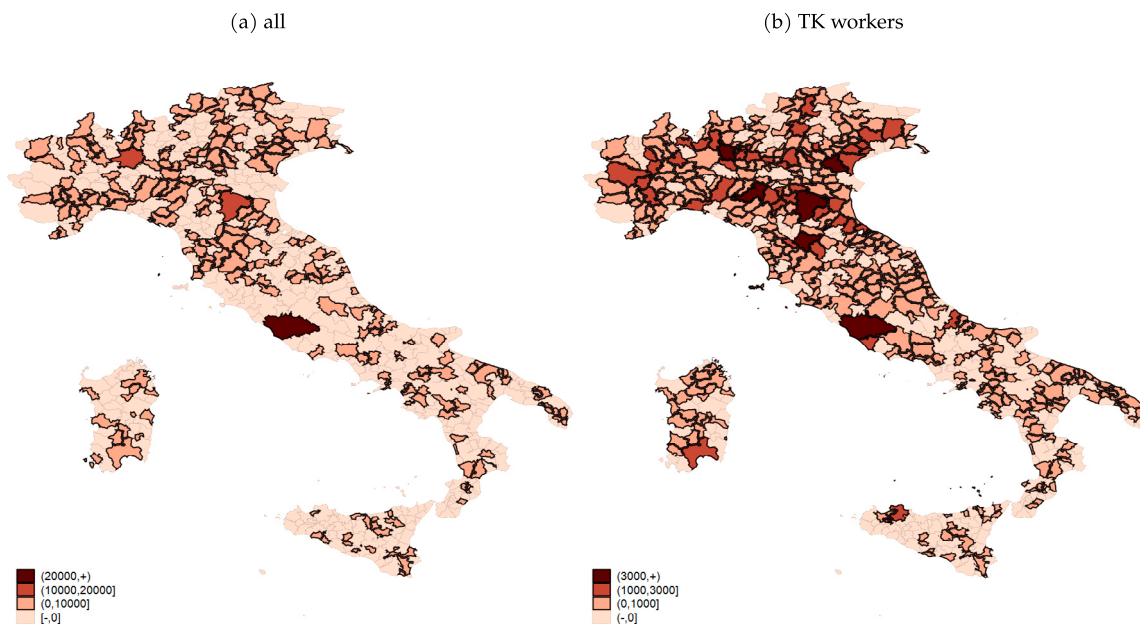


Fig. 4. 2005–2019 net migrations.

Note: The maps plot the number of migrants received by each LLM over the span 2005–2019. Panel a refers to all workers, while Panel b focuses on workers of the TK sector.

The two-step estimation controls for individual sorting, while the shift-share instrument mitigates concerns about unobserved idiosyncratic shocks at LLM level. More broadly, this instrumental variable strategy helps account for time-varying unobservables that might influence labour outcomes while also being correlated with the presence of TK workers.

6.1. Two-step model

We begin with an individual-level estimation where we regress the following labour market outcomes on a set of worker characteristics: (1) individual log daily wage, (2) log days worked, (3) out-migration status (dummy for whether the worker leaves the LLM in the following year), (4) in-migration status (dummy for whether the worker moves into the LLM in a given year). The explanatory variables include indicators for whether the worker has a part-time, fixed-term, or seasonal job, and occupational dummies (white/blue collar, manager, apprentice). We also include employment sector dummies (2-digit Ateco), worker, and

LLM-year fixed effects.¹⁹ Formally:

$$y_{it} = \alpha + \beta X_{it} + \gamma_i + \delta_{c(it)t} + \epsilon_{it}, \quad (1)$$

where y_{it} is the individual outcome of NT worker i in year t ; X_{it} represents time-varying worker characteristics; γ_i are worker fixed effects and $\delta_{c(it)t}$ are LLM-time fixed effects, with c referring to the LLM where individual i works in year t . We estimate this equation exclusively for NT workers. If workers switch from non-tradable to tradable employment, we discard them for the spells in which they were employed in tradable sectors.

The fitted values of $\delta_{c(it)t}$ capture the labour outcome premium for NT workers to work in LLM c in year t (Combes et al., 2008, 2011).

¹⁹ Note that by including individual and time fixed effects, we are also indirectly controlling for age and the year of career start, both of which are likely relevant variables in explaining labour market outcomes. We do not include time-varying firm characteristics in our baseline estimation to avoid possible endogeneity concerns. However, we verified that the inclusion of (log) firm size does not alter our results.

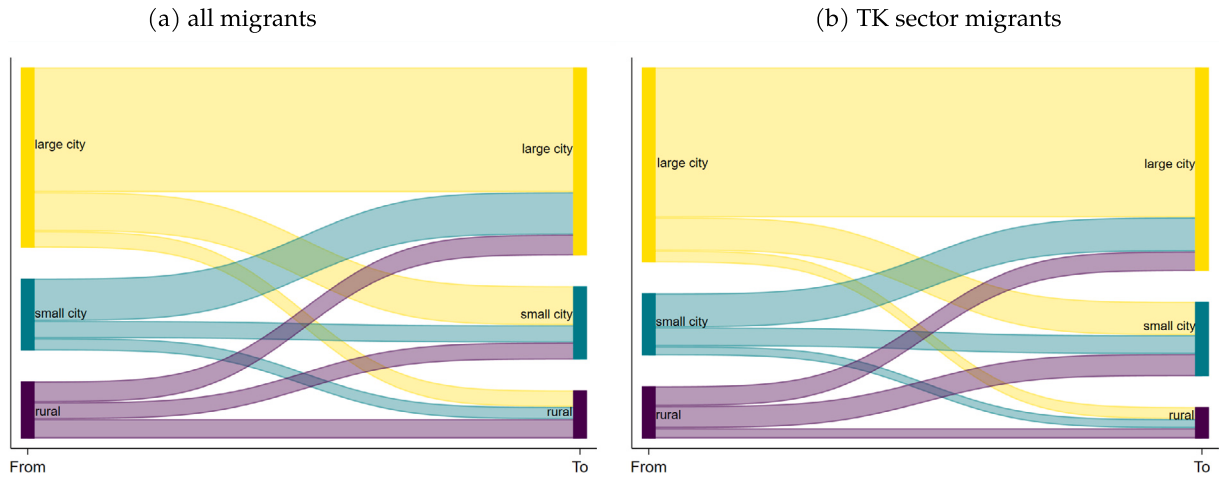


Fig. 5. Mobility patterns (average flows over 2005–2019).

Note: The graphs report average migration flows by pair of origin–destination LLMs, over the span 2005–2019. We distinguish LLMs by initial population density and classify them as ‘large city’, ‘small city’, and ‘rural’. Panel a refers to all migrants, while Panel b focus on migrants within the TK sector.

These become the dependent variable of the 2nd-step estimation, which is conducted at the LLM level. In this equation, the main explanatory variable is the percentage of TK workers in an LLM (TKW).

$$\hat{\delta}_{ct} = \zeta + \eta TKW_{ct} + \theta_t + \lambda_c + \phi_{ct} \quad t = 2005, 2019. \quad (2)$$

To account for sampling error in the first-step estimates, we apply analytical weights based on the number of observations contributing to each LLM-year estimate (Combes et al., 2008). We also control for year and LLM fixed effects. Both in the 1st and in the 2nd-step estimation we cluster standard errors at the LLM level.

This two-step estimation allows us to control for a wide range of individual characteristics which can influence labour outcomes, and clean out unobserved individual heterogeneity through worker fixed effects, reducing bias from ability sorting. Compared to a one-step estimation it enables the inclusion of LLM-time fixed effects in the first step, separately identifying individual and time-varying area-level characteristics. Area-year effects are our outcomes of interest when we estimate treatment effects at LLM level.^{20,21}

²⁰ The two-step approach is discussed in details by Combes et al. (2008) and (2011). Other applications are also Mion and Naticchioni (2009) and Belloc et al. (2023). Working with large samples, this procedure improves computational tractability, compared to a one-step individual estimation with LLM fe. Moreover, it allows to include time-varying area effects to avoid estimating the LLM fixed effects only from movers, which represent a highly selected sample of the population. By including time-varying LLM fixed effects, the approach also exploits variation in the labour outcomes of stayers over time. In other words, even if intrinsically better workers tend to sort into intrinsically better places, the evolving labour trajectories of stayers contribute – alongside movers – to the estimation of time-varying area characteristics. Finally, by working at LLM level in the 2nd-step we avoid the ‘shock bias’ (Combes et al., 2011) deriving from non-zero covariance between the treatment and individual error term. This procedure also addresses the concerns raised by Card et al. (2024) regarding ‘hierarchy effects’ in regression models that include area (only) fixed effects.

²¹ As a robustness check, we also estimate the above specification in one step. Formally: $y_{it} = \alpha + \beta_0 TKW_{ct} + \beta_1 X_{it} + \gamma_t + \delta_{c(it)} + \eta_t + \epsilon_{it}$. One-step estimates – available upon request – substantially confirm our main results. Wage, days worked and in-migration coefficients are equally signed and significant compared to two-step estimates. As for out-migration, point estimates are almost identical to two-step coefficients, but standard errors are larger, providing insignificant estimates. This is likely due to the considerable reduction in sample size resulting from the inclusion of LLM fixed effects (in the one-step estimation, we just rely on movers). In the two-step estimation we compute standard errors of means, i.e. area-year estimates, while here we deal with original individual outcomes, displaying larger variance.

Labour market changes require time to materialise. To estimate long-run effects, we employ observations from the starting and ending years, 2005 and 2019, and include LLM and year fixed effects. With only two time periods, including LLM fixed effects in the second-step is equivalent to taking first differences, ensuring that our model captures the long-run impact of TK employment growth on NT workers. Our model can be interpreted as a long-differences estimation, where variations refer to the whole period considered (2005–2019).²² The coefficient η thus represents the long-run changes in wage, days worked, and in/out-migration probabilities for NT workers, induced by the increased presence of TK workers over the 2005–2019 period. For completeness we also estimate a cross-sectional specification in first-differences.²³

Our treatment is defined as follows:

$$TKW_{ct} = \frac{TK_{ct}}{N_{ct}} \quad (3)$$

where TK_{ct} and N_{ct} are the total number of TK and overall workers in LLM c , year t , respectively. Hence, η captures the percentage variation in the outcome – daily wage, days worked, or in/out-migration probability premium for NT workers – due to a 1 percentage point increase in the share of TK workers in the LLM.²⁴

²² The inclusion of LLM fixed effects controls for any time-invariant differences across labour markets, including the baseline size of the TK sector.

²³ The cross-section equation is: $\Delta_{05-19} \hat{\delta}_c = \zeta + \eta \Delta_{05-19} TKW_c + \phi_c$ where $\Delta_{05-19} \hat{\delta}_c$ is the first-difference of the area-year estimates from Eq. (1) over the considered period 2005–19; $\Delta_{05-19} TKW_c$ is the first-difference (2005–19) of our treatment variable in (3). We instrument the endogenous treatment variable with the first-difference (2005–19) of the shift-share instrument (Eq. (4)). In this first-difference cross-section estimation, weights corresponding to the number of observations employed in first-step estimation to obtain area-year estimates $\hat{\delta}_{ct}$ are averaged across the two years considered.

²⁴ In Appendix E we also explore the effect of the net (cumulative) inflows of TK migrants from 2005 up to year t , discounted by the 2005 number of TK workers in that LLM. Discounting for the initial number of TK workers in the LLM accounts for the different sizes of the sector among LLMs at the beginning of the period. $TKW2_{ct} = \frac{\sum_{t=2005}^t m_{TK,05}^{TK}}{TK_{c,2005}}$, where $m_{TK,05}^{TK}$ is the net inflow of TK migrants to LLM c in year t and $TK_{c,2005}$ is the total number of TK workers in LLM c in 2005. Note that for LLMs with greater outflows than inflows, $TKW2_{ct}$ will have negative sign. In this case, the coefficient of interest η can be interpreted as the percentage outcome variation deriving from a 1 percentage point increase in the net migration rate of TK workers with respect to their initial presence.

6.2. Shift-share instrumental variable strategy

Eq. (2) may suffer from omitted variable bias if unobserved local labour market shocks correlate with TK employment growth. To address this, we employ a shift-share (Bartik, 1991) instrumental variable strategy, following the implementation in first-differences adopted by Moretti (2004). The purpose of this IV strategy is to isolate the exogenous shift in the demand for labour in the TK sector. The instrument multiplies historical local shares of each 4-digit TK sector with the overall percentage of employment of that sector at national level over the sample period:

$$Instrument_{ct} = \sum_s w_{c,95}^s \cdot \%S_t \quad (4)$$

where

$$w_{c,95}^s = \frac{S_{c,95}}{N_{c,95}} \cdot 100 \quad (5)$$

are the shares of LLM c employment in industry s in the year 1995, and

$$\%S_t = \frac{S_t}{N_t} \quad t = 2005, 2019. \quad (6)$$

is the share of employment in sector s at national level, measured at the beginning and end of the observed period. We employ this instrumental variable in the fixed effects specification (Eq. (2)), which is equivalent to first-differencing the regression variables. Therefore, we can interpret the instrument as a LLM-specific weighted average of national changes in the employment shares of TK industries.²⁵

The validity of shift-share instruments hinges on either the exogeneity of initial industry shares or the exogeneity of national employment shifts. According to the ‘shares’ approach, Bartik-type instruments mainly derive identification from differing initial industry composition across LLMs, which result in differential exposures to common shocks (Goldsmith-Pinkham et al., 2020). The instrument isolates the shift in local labour demand only coming from national changes, provided that neither past industrial composition nor related unobservables predict the outcome of interest, conditional on controls (Baum-Snow and Ferreira, 2015). A different, ‘shift’, approach demonstrates that shares exogeneity is not a necessary condition for the identification of causal effects (Borusyak et al., 2022). It is sufficient that shares are not correlated with the differential changes associated with the national shock itself. This approach applies to settings characterised by quasi-experimental exogenous shocks (e.g. Autor et al., 2013; Peri et al., 2015), but it can be appropriate also when the researcher can conceive an underlying set of shocks that, if observed, would be a useful instrument (Bartik, 1991; Blanchard and Katz, 1992). While we do not exploit quasi-experimental shocks, we can still imagine exogenous variation in industry-specific productivity within the TK sector, deriving from global technological change. Moreover, we employ sector shares at the 4-digit level (covering 93 industries within the TK sector), thus relying on a large number of shifts - an important condition for the exogeneity-of-shifts assumption in the approach by Borusyak et al. (2022). It is worth noting that, in our setting, the instrument derives most of its identifying variation from the baseline size of the TK sector, rather than from differences in its composition.

We perform a series of validity checks to confirm the robustness of our instrument. First, to mitigate any confounding role of contemporaneous shocks in NT industries, we construct a Bartik-type variable for NT industries by computing a weighted average of national employment growth in NT sectors, using 1995 industry shares in each LLM as weights. We first check whether this NT-Bartik measure correlates

with our instrument, finding a small negative correlation (−0.09). Next, we include this NT-Bartik measure as a control in the reduced form estimation, where area-year estimates from first-step estimation are directly regressed on our Bartik instrument. Including this control does not alter the estimated coefficient of interest (see Table C.1 in the Appendix), mitigating concerns that our estimates may reflect a direct effect of employment growth in NT sectors, potentially correlated with employment growth in the TK sector.

Then, we test the robustness of our findings using standard errors computed following (Adao et al., 2019), which accounts for cross-regional correlation in regression residuals of models adopting shift-share IVs. The results, reported in Table C.2 of the Appendix, show a pattern largely comparable to our main findings, suggesting that cross-regional correlation is not a major concern in our setting.²⁶

Finally, in Appendix D we develop a dynamic version of our IV model to account for potential gradual adjustments to past shocks, which may generate serial correlation in the shift-share variable (Jaeger et al., 2018). Details on the empirical strategy and results – confirming our main findings – are provided in the Appendix.

6.3. Spatial clustering

Our analysis focuses on the Italian *Sistemi Locali del Lavoro*, which accurately delineate LLMs based on actual commuting flows. Though most commuting occurs within LLM boundaries, a small fraction (6% in 2011) involves cross-LLM commuting.²⁷ This could lead to overestimated internal migration if individuals taking new jobs in neighbouring LLMs are counted as migrants despite not changing residence. Additionally, cross-LLM commuters typically contribute more to the labour outcomes of their residence LLM than their workplace LLM. Spillover effects from TK sector growth could also create multiplier or displacement effects in neighbouring LLMs, potentially generating spatial correlation in standard errors.

To address spatial correlation concerns, we cluster standard errors following Conley (1999), which allows clustering based on geographic buffers rather than administrative boundaries. Using LLM centroids, we re-estimate our long-difference IV specification clustering standard errors at different buffers of radius 10, 20, and 30 kilometres. These distances are chosen based on the median LLM land area (~400 km²), where 10 km approximates LLM-level clustering, and 30 km encompasses neighbouring LLMs. The results confirm the robustness of our findings to spatial correlation adjustments.

7. Results

7.1. Main results

We present the second-stage results of the instrumented versions of Eq. (2) in Table 1. These estimates refer to long-difference regressions over the full 2005–2019 period and use as dependent variables the area-year fixed effects predicted from Eq. (1), estimated on the sample of NT workers.²⁸ Table C.4 in the Appendix shows the results from reduced form estimations regressing area-year estimates directly on the instrument, while Table C.5 reports first stage estimates with

²⁵ To construct the historical shares we refer to the municipality where the employer was located, since before 2005 we do not have data on individuals’ workplace location.

²⁶ To implement Adao et al. (2019) standard errors, we rely on the cross-sectional specification of our model. Therefore, standard errors in Table C.2 have to be compared to those in Table C.3.

²⁷ Cross-LLM commuting flows in 2011 are computed through the ISTAT application BTFIussi (<https://gisportal.istat.it/bt.flussi/>).

²⁸ Estimating Eq. (2) is run on a short-panel with two time periods (2005, 2019). In Table C.3 we also report estimates from cross-section equations where variables are expressed in first-differences. See Section 6.1 for estimation details.

Table 1
IV estimation, second stage results.

	Wage	Days worked	Out-migration	In-migration
% TK workers	−0.841 (0.6756)	0.613** (0.2585)	−0.226*** (0.0770)	1.009*** (0.2183)
Kleibergen-Paap <i>F</i> -test	12.47	12.47	12.47	12.47
year fe	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓
Mean (2005)	−0.194	−0.069	0.032	−0.072
St. dev. (2005)	0.027	0.010	0.042	0.047
N	1,222	1,222	1,222	1,222

Note: Standard errors clustered at LLM level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Table reports the estimated coefficients from the second stage regression corresponding to Eq. (2), where the treatment variable TKW is instrumented by the shift share measure of Eq. (4). The outcome variables are the area-year effects predicted from Eq. (1), estimated on the sample of NT workers. Variables refer to 2005 and 2019, to estimate the model in long-differences. We also include area and year fixed effects, and as weights the number of NT workers in the LLM, to account for different precision in 1st-step estimates.

F-tests demonstrating the instrument's relevance.²⁹ OLS results are reported and discussed in Appendix B. Tables C.6 to C.8 in the Appendix replicate our main estimation adopting Conley (1999) clustered standard errors, accounting for any spatial correlation among neighbouring LLMs. Our main estimates are robust to different levels of spatial clustering, with buffer radii ranging from 10 to 30 kilometres around the LLM's centroid.

Table 1 indicates that an increase in the share of TK workers determines a positive effect on days worked locally, and a decrease in out-migration probability, while wages remain unaffected. A 10 percentage points increase in the share of TK workers results in a 6% rise in days worked, a 2 percentage points decline in out-migration probability, and a 10 percentage points increase in in-migration probability. To aid interpretation, we also report standardised coefficients, indicating the change in standard deviations of the outcomes associated with a one-standard-deviation increase in the share of TK workers. Standardised coefficients are 0.28 for days worked, −0.27 for out-migration, and 0.82 for in-migration.

These results, along with the estimates on in/out-migration responses, support the hypothesis of multiplicative effects of TK employment at the local level; while the insignificant effect on wages is consistent with previous studies on institutional contexts characterised by labour market rigidities (Faggio and Overman, 2014; Belloc et al., 2023).

Comparing OLS to IV estimates, we can notice an increase in the days-worked and in-migration coefficients, along with a decrease in the out-migration coefficient, all becoming statistically significant. This suggests a labour supply bias in the OLS estimates, potentially due to better amenities in areas with a higher presence of TK workers. Places experiencing TK employment growth may also improve in life quality through cultural initiatives and enhanced services, a pattern consistent with the theory of endogenous amenities (Diamond, 2016). Conversely, the IV estimates of the impact of TK workers on wage premium for NT workers return insignificant coefficients, differently from the positive coefficients of OLS estimates. This difference likely stems from the construction of the outcome variable, as daily wage is defined as the ratio between yearly labour income and days worked. Thus, the OLS wage premium appears to result from a downward bias in days worked.

Relative to estimates of local multipliers, it is important to note that our analysis is conducted in relative terms.³⁰ The demand shock

we focus on is expressed as an increase in the local share of TK workers. Moreover, our estimated effect refers to the intensive margin (namely, days worked). As for the extensive margin of employment – to which most local-multiplier estimates refer –, indirect evidence is provided by the estimated coefficients for in/out-migration probabilities, which capture key components of the employment response to labour market shocks.³¹ Taken together, these findings indicate positive but modest employment effects on both the intensive and extensive margins. Consistent with previous evidence, Italy exhibits relatively small multiplicative effects on employment (Auricchio, 2015; De Blasio and Menon, 2011), likely due to institutional factors such as labour mobility and wage-setting mechanisms.

As for wage effects, previous studies that do not account for sorting may have overestimated the responsiveness of wages to local shocks.³² Studying the Italian context, Belloc et al. (2023) employ a fixed effects model and find a null urban wage premium in nominal terms, a result that closely aligns with our findings. The lack of significant wage effects may be partly attributable to controlling for unobservable individual heterogeneity and partly to the specific features of the Italian institutional context. We delve deeper into this discussion in the following sections.

7.2. The role of sorting

In our analysis, we have thus far treated sorting primarily as an identification issue. Failing to account for unobserved individual heterogeneity can bias the results if more productive workers self-select into areas with a higher presence of TK workers (Combes et al., 2008). However, it is interesting to distinguish the relative contribution of sorting and local spillovers to the overall effect on labour outcomes. A possibility is that NT workers increasingly sort in areas experiencing higher TK sector growth. Such a pattern would be part of the broader labour dynamics we aim to describe.

To assess this, we re-estimate the first-step regressions (Eq. (1)) without individual fixed effects, and run the instrumented 2nd-step estimation employing the area-year effects computed from the first-step as dependent variable. Table 2 reports the second stage results of the IV estimation when sorting is not accounted for. The coefficients on days worked and in-migration remain comparable to those obtained with the inclusion of individual fixed effects, slightly increased in significance and size. However, here we find a positive effect on wage which was absent in our main results (see Table 1). Moreover, the outmigration estimate appears insignificant when we do not account for individual sorting.

These findings suggest that more productive and more mobile NT workers self-select into areas with an increased presence of TK workers.

for various OECD countries (<https://whatworksgrowth.org/resource-library/toolkit-local-multipliers>). The toolkit confirms that larger multiplier effects are observed for tradable industries with higher technological content (1.88 multiplier in high-tech versus 0.9 in generic tradable industries). Moreover, the report quotes Auricchio (2015) focusing on Italy, who finds a 0.7 increase in non-tradable jobs for a unit increase in high-tech tradable industries. Such figure is considerably lower than the 1.88 average across OECD countries. Furthermore, Auricchio (2015) does not find any significant effect for employment growth in generic tradable-industries, which confirms previous findings by De Blasio and Menon (2011).

³¹ The residual components are inflows from or into non-employment within the same LLM, which, unfortunately, we are not able to measure precisely in our data.

³² Dix-Carneiro and Kovak (2019) highlight a negative wage impact of trade liberalisation on NT workers. Marchand (2012) find a positive wage impact of energy booms for non-energy workers in Canada. Similarly, Moretti (2004) and Peri et al. (2015) focus on the US context and find a positive wage effect of an increased supply of, respectively, college educated and STEM workers at local level.

²⁹ It is worth noting that the instrument draws most of its identifying variation from the baseline size of the TK sector, rather than from compositional differences. In fact, when we control for the TK sector size in 1995 in the first-stage regression, the shift-share instrument loses significance.

³⁰ The What Works Centre for Local Economic Growth has published a toolkit on multiplier effects where they summarise empirical results obtained

Table 2

IV estimation, not accounting for sorting.

	Wage	Days worked	Out-migration	In-migration
% TK workers	0.804*** (0.1588)	0.747*** (0.1816)	−0.104 (0.0903)	1.233*** (0.2164)
year fe	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222

Note: Standard errors clustered at LLM level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Table reports the estimated coefficients from the second stage regression corresponding to Eq. (2), where the treatment variable is instrumented by the shift share measure of Eq. (4). The outcome variables are the area-year effects predicted from Eq. (1), estimated on the sample of NT workers *without* individual fixed effects. Variables refer to 2005 and 2019, to estimate the model in long-differences. Regressors are our treatment variables (instrumented), area and year fixed effects. We also include as weights the number of NT workers in the LLM, to account for different precision in 1st-step estimates.

Said differently, workers with higher earnings potential and higher propensity to migrate increasingly concentrate in knowledge-intensive areas. This is consistent with an overall positive dynamics induced by the TK sector growth. It generates new labour opportunities, fostering a more prosperous and dynamic labour market that attracts workers with higher expected wages and propensity to move.

Moreover, these results suggest that nominal wages exhibit some upward flexibility in response to local labour demand shocks. However, this wage flexibility primarily serves to attract inherently more productive workers to the local labour market and does not translate into a proper wage effect. Because positive labour demand shocks create labour opportunities which are then filled by more skilled workers, we do not observe an overall increase in nominal wages when controlling for sorting (Table 1). Similarly, the non-significant out-migration result in Table 2 masks the underlying trend of more mobile workers sorting into knowledge-intensive cities. These findings further underscore the importance of accounting for unobserved individual heterogeneity when estimating local spillover effects.

This heightened self-selection process is intriguing *per se*, as it reveals compositional shifts among NT workers alongside the expansion of the TK sector. In knowledge-intensive areas there is an increased representation of high-earning, mobile individuals, whereas the areas experiencing weaker TK sector growth exhibit opposite patterns. These dynamics contribute to the growing spatial disparities between knowledge clusters and the rest of the country. Knowledge-intensive cities may become more productive and responsive to local shocks due to the higher productivity and mobility of their residents. In contrast, residual areas face the opposite effect. These trends do not benefit all residents equally. For instance, in knowledge clusters, the inflow of TK workers and high-earning locals may lead to increased living costs. These gentrification pressures could lead to the displacement of lower-earning incumbent residents. In the next section, we further analyse the impact of TK sector growth on local costs and real living conditions.

7.3. Nominal vs real wages

In the main analysis we focus on nominal wages. In this section, we extend our investigation to real wages to assess the impact of TK sector employment growth on local living conditions. If increased employment in the TK sector drives up the local cost of living, it could potentially result in a decline in real wages. This is particularly likely in our setting since *nominal* wages seem not to respond to the TK employment shock once we account for individual sorting.

To proxy for the local cost of living, we use average house prices in the LLM.³³ First, we employ house prices as a dependent variable to assess the impact on the cost of living of employment growth in the TK

sector. Second, we use them as a discounting factor for the area-year effects estimated in the first-step wage regression, which also includes individual fixed effects (Eq. (1)). Since both the area-year effects and house prices are expressed in logarithms, we compute the difference between those variables, interpreting it as the real wage premium for working in local sectors within the given area.³⁴ We run all these estimations at the LLM level and instrument our treatments with the usual shift-share instrument.

Table 3 presents the related IV estimates. The first three columns report results for minimum, maximum, and average (log) house prices in the LLM. We find a positive effect of TK sector employment growth for all three measures, confirming that knowledge clusters become more expensive. This is consistent with our hypothesis of increased demand for residence in these areas, due to more and better labour opportunities locally available. Moreover, the effect on house prices might be amplified by the endogenous response of local amenities to the inflow of TK workers (Diamond, 2016).

The fourth column of Table 3 reports the impact on real wages, computed as the difference between area-year estimates for nominal wages and the average house prices. We find a negative impact of TK sector employment growth on real wages. The cost of living increases, while nominal wages do not adjust accordingly. This pattern is consistent with previous evidence on the responsiveness of nominal and real wages in the Italian context. Belloc et al. (2023) estimate the urban wage premium for Italy, finding no effect in nominal terms and a negative premium in real terms.³⁵ Negative effects on real wages are not limited to the Italian context. In the US, Card et al. (2023) estimate an AKM model (Abowd et al., 1999) controlling for both individuals and firms sorting and conclude that the rise in housing costs outweighs the earning advantage of relocating to larger cities.

A comprehensive understanding of why workers prefer to stay in places where their real living conditions deteriorate in presence of local demand shocks is beyond the scope of this paper. We speculate that TK sector growth goes along with an improvement in local amenities, such as public services and cultural initiatives. This interpretation is consistent with Roback-type models and, in particular, with the argument of endogenous amenities by Diamond (2016). According to those models, amenities adjust in response to changes in the composition of residents in an area, potentially explaining persistent real wage differentials across locations.

In our setting, it seems plausible that areas attracting more TK workers experience a contemporaneous improvement in local amenities, an interpretation in line with the supply bias we detected with OLS

and average prices in the area. Within a given LLM, there can be significant variation in house prices, mostly due to amenity differentials. However, an individual working in the area can choose where to reside inside the LLM depending on her willingness to pay for amenities. Therefore, more or less variance in house prices within the LLM makes little difference for real wage analysis, and we can rely on average prices. As a robustness, we also compute the median of (average) prices across neighbourhoods in a LLM, obtaining very similar results. Estimates are available upon request.

³⁴ For the properties of logarithms: $\ln(\text{nominal wage}_{it}) - \ln(\text{house price}_{it}) = \ln\left(\frac{\text{nominal wage}_{it}}{\text{house price}_{it}}\right)$.

³⁵ Belloc et al. (2023) employ a Consumer Price Index (CPI) which accounts for housing and non-housing living costs. However, house prices are among the main drivers of spatial variation in the local cost of living. Therefore, we focus solely on housing price indexes to compute real wages. House prices account for approximately 30%–40% of the housing share of expenditure, ranging from 33% in the South to 39% in the Center. Information on the housing share of expenditure is provided by the Italian Institute of Statistics only at the macro-regional level. Despite the limited geographical detail, we verified that accounting for the housing share of expenditure does not affect our results on living standards. Table C.9 in the Appendix reports the related results, where we multiplied house prices by the housing share of expenditure in the region and re-ran the analysis.

³³ Original data on house prices are provided at sub-municipal level. We aggregate them at LLM level, taking the average of minimum, maximum,

Table 3
IV estimation: impact on living conditions.

	Local housing prices			Real wages
	Minimum	Maximum	Average	
% TK workers	2.567** (1.0211)	1.529* (0.8340)	2.001** (0.8545)	−2.829*** (1.0599)
year fe	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓
N	1,132	1,132	1,132	1,132

Note: Standard errors clustered at LLM level * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The Table reports the estimated coefficients from the second stage regression corresponding to Eq. (2), where the treatment variable KW1 is instrumented by the shift share measure of Eq. (4). The outcome variables in the first three columns are minimum, maximum, and average house prices at the local level; while in fourth column we report estimates on real wages. These are the area-year effects predicted from Eq. (1) referring to wage of NT workers, discounted by local housing prices. Variables refer to 2005 and 2019, to estimate the model in long-differences. We also include area and year fixed effects, and as weights the number of NT workers in the LLM, to account for different precision in 1st-step estimates.

estimates. In that case, workers might be willing to bear higher living costs to remain in cities with better job opportunities and amenities. Furthermore, in the previous section we have shown that TK sector growth fosters the self-selection of intrinsically more productive workers into the area. This enhanced sorting may contribute to explain the real wage puzzle by highlighting possible dynamic advantages of living in knowledge-intensive LLMs. In those areas, workers may enjoy learning externalities of the kind described by De La Roca and Puga (2017), which offset lower real wages by fostering skill accumulation and career advancement. Workers may willingly sacrifice immediate earnings in exchange for long-term gains associated with better labour market prospects in knowledge clusters.

8. Concluding remarks

This paper examines the impact of employment growth in knowledge-intensive and tradable (TK) activities on the labour outcomes of other local workers, focusing on wages, days worked, and in/out-migration probability of workers in non-tradable (NT) sectors. We disentangle the effects of individual sorting from local spillovers. Our analysis covers Italy from 2005 to 2019 and yields several key findings.

First, we find no significant effect on nominal wage resulting from employment growth in TK activities. This aligns with the expectation that, in a context of industry-level national wage bargaining, local labour market conditions have limited influence on wages. However, we do observe a rise in living costs following TK sector expansion, leading to a negative effect on real wages.

Second, we find evidence that the expansion of the TK sector has a positive impact on the intensive margin of employment at the local level. Rising employment in the TK sector stimulates labour demand, potentially through increased consumer spending, intermediate service demand from local firms, productivity spillovers, or a combination of these mechanisms. Moreover, cross-industry agglomeration effects may arise within the TK sector (Helm, 2020). We do not estimate the magnitude of such intra-TK-sector spillovers, as our goal is to investigate the spillover effects from the TK sector as a whole to NT industries. Our findings refer to the aggregate effect and we cannot estimate the specific contributions of each potential channel, which we leave to future investigations.

Third, the increase in in-migration and decrease in out-migration is in line with theoretical predictions that an increase in local labour demand in NT sectors induced by TK workers growth reduces incentives to migrate. The demand shock induced by the rise of the knowledge economy increases the attractiveness of local labour markets and fosters agglomeration. However, the observed decline in real wages suggests a potential counterbalancing effect. If wages were more flexible and

adjusted to rising living costs, migration responses might be even more pronounced.

While a comprehensive explanation of the observed decline in both real wages and outmigration is beyond the scope of this paper, our findings can be rationalised within the framework of Roback-type models. The expansion of the TK sector may improve local amenities, making cities more attractive despite rising living costs (Diamond, 2016). Additionally, TK-sector growth may generate learning externalities (De La Roca and Puga, 2017), which could offset short-term losses in real wages by enhancing long-term career prospects.

Our results account for worker sorting based on unobservable characteristics. While sorting represents a confounding factor in estimating local labour market effects, it is also an integral part of the broader economic dynamics we aim to describe. Comparing estimates that account for unobserved individual heterogeneity with those that do not, we identify a self-selection of more productive and more mobile workers into areas with increased presence of TK workers. This pattern aligns with an overall dynamic induced by TK sector growth, generating new labour opportunities, making the labour market more prosperous, and thus more appealing to high-earning and more mobile workers. Furthermore, our findings suggest that while nominal wages exhibit some degree of upward flexibility, this primarily serves to attract highly productive workers rather than generating a broad wage effect.

These results contribute to a broader understanding of the uneven geographic expansion of the knowledge economy, a pattern resembling the ‘great divergence’ process described by Moretti (2012). Some local labour markets benefit disproportionately from the technological change, attracting skilled workers that induce positive multiplicative effects in other local sectors, while others fall behind, losing human capital and experiencing negative local economic spirals. Our findings suggest that the uneven growth of the knowledge economy with its related internal migrations contributes to spatial inequalities.

Whether these dynamics yield net aggregate gains at the national level or merely redistribute economic activity across local labour markets remains an open question. In either case, rising spatial inequalities represent a policy challenge. Some workers may face mobility constraints preventing them from relocating to more dynamic areas, while others may have strong idiosyncratic preferences for living in less knowledge-intensive areas and be forced to relocate by the lack of job opportunities. This internal ‘brain drain’ contributes to the decline of left-behind areas, leaving their economic potential untapped. Moreover, even the more dynamic areas may struggle to absorb large inflow of workers. Internal migrations – if not properly addressed by policy-makers – can lead to congestion and worsened living standards in the destination areas.

Our findings highlight that knowledge-intensive cities experience a rise in house prices, deteriorating real living conditions, which may potentially cause the displacement of low-earning residents. If regional disparities are a policy concern, targeted interventions may be necessary to mitigate the disadvantages faced by left-behind areas and their residents, who cannot or will not move. Potential measures include promoting specialisations in sectors different from knowledge-intensive ones or facilitating the diffusion of the benefits of the knowledge economy to less competitive areas.

CReDiT authorship contribution statement

Agar Brugiavini: Writing – original draft, Methodology, Investigation, Conceptualization. **Marco Di Cataldo:** Writing – original draft, Methodology, Investigation, Conceptualization, Formal analysis, Data curation. **Giulia Romani:** Writing – original draft, Methodology, Investigation, Conceptualization, Formal analysis, Data curation.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.labeco.2025.102820>.

Data availability

The authors do not have permission to share data.

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