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Maurizio Franzini

Knowledge economy, internal migration, and the effect on local labour markets

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Economia della conoscenza, migrazioni interne, e gli effetti sui mercati locali del lavoro

Abstract

Le attività ad alto contenuto di capitale umano possono generare effetti moltiplicativi rilevanti a livello locale. In particolare, un influsso di lavoratori dei settori ad alta intensità di conoscenza può contribuire a rendere il mercato del lavoro locale più attrattivo anche per altre tipologie di lavoratori. Questo articolo indaga come la crescita dell'occupazione e l'influsso di lavoratori dei settori ad alta intensità di conoscenza influenza salario, occupazione e probabilità di emigrare dei lavoratori locali occupati in altri settori. Ci focalizziamo sull'Italia nel periodo 2005-2019, sfruttando dati amministrativi con informazioni a livello di lavoratore-impresa, che consentono di seguire gli individui attraverso diversi impieghi e luoghi di lavoro. Per affrontare i problemi di identificazione legati all'autoselezione dei lavoratori e a *shocks* idiosincratici, implementiamo una strategia a due stadi combinata con variabili stumentali di tipo *shift-share*. Identifichiamo separatamente il contributo agli *outcomes* lavorativi locali dell'autoselezione dei lavoratori e degli *spillovers* tra settori. I nostri risultati sufferiscono che la crescita dell'occupazione e l'influsso di lavoratori dei settori ad alta intensità di conoscenza hanno effetti moltiplicativi sull'occupazione, aumentando il numero di giorni lavorati dai lavoratori locali, e riducono inoltre la probabilità di lasciare il mercato del lavoro locale. I salari nominali dei lavoratori locali non sembrano influenzati, mentre i prezzi delle case aumentano producendo un impatto negativo sui salari reali.

Key words: *shocks* di domanda di lavoro, migrazioni interne, moltiplicatori locali, economia della conoscenza, Italia.
JEL: J23, J61, R12, R23

Knowledge economy, internal migration, and the effect on local labour markets

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Abstract

Knowledge-intensive activities may generate significant multiplicative effects at the local level. In particular, inflows of workers in knowledge-related sectors may contribute to make local labour markets more attractive for other kind of workers as well. This paper assesses how the employment growth and inflow of workers in knowledge-intensive sectors affect wage, employment, and probability of outmigration of local workers in other sectors. We focus on Italy during the 2005-2019 period, taking advantage of matched employer-employee social-security data, which allows to track workers' histories across jobs and locations. To address the identification concerns of sorting and idiosyncratic shocks, we implement a two-step procedure combined with a shift-share IV strategy. We separately identify the contribution of sorting and spillovers to labour market outcomes. Our results suggest that the employment growth and inflow of workers in knowledge-intensive sectors have multiplicative effects on employment, increasing the number of days worked by local workers, and they also seem to reduce the probability of outmigration. Nominal wages of local workers seem unaffected, while house prices increase producing a negative effect on local real wages.

Keywords: labour demand shocks, internal migration, local multipliers, knowledge economy, Italy.
JEL: J23, J61, R12, R23

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1 Introduction

The emergence of the so-called 'knowledge economy' has led to a territorial concentration of human capital-intensive activities. This tendency of knowledge-intensive sectors to cluster in space can generate significant multiplicative effects at the local level (Moretti, 2010b), as highly-innovative industries require more intermediate services, pay higher wages, and generate larger productivity spillovers (De La Roca and Puga, 2017; Duranton and Puga, 2001; Moretti, 2012; Peri, 2002). In turn, these concentration patterns may significantly affect local labour market conditions and drive the location decision of workers. Because of these processes of human capital concentration, the rise of the knowledge economy has been regarded as a determinant of spatial inequalities within countries (Rosés and Wolf, 2018, Moretti, 2012, OECD, 2019).

This paper investigates how the progressive increase (or decline) in knowledge-intensive activities in some areas can impact the local conditions of workers in those territories. We evaluate the effect of labour demand shocks in the form of a growth of workers operating in knowledge-related sectors (henceforth labelled as 'knowledge workers') on the rest of the local economy. We also disentangle the effect's component due to the internal migrations of knowledge workers, as these labour flows represent endogenous supply shocks which may produce their own effects on local labour markets (Anelli et al., 2023; Card, 2009; Ottaviano and Peri, 2010). We observe the local response to these changes in terms of wage and employment, and outmigration probability of local workers.

We focus on Italy during the period 2005-2019, and resort to an extremely rich administrative individual-level dataset containing matched employer-employee information on the working histories of all social-security-paying Italian workers. In addition, since 2005, we have information about the workplace, which allows us to track workers across localities and occupations.

Our work speaks to different literature streams. First, it relates to the studies looking at the impact of labour demand shocks, and in particular their local multiplier effects (Bartik, 1991; Blanchard and Katz, 1992; Moretti, 2010a, 2010b). This literature has focused on shocks in specific sectors, such as biotech and energy (Allcott and Keniston, 2017, Marchand, 2012, Moretti and Wilson, 2014), or it has devoted attention to the local impact of public spending (Acconcia et al., 2014, Faggio and Overman, 2014, Suárez Serrato and Wingender, 2016) and trade shocks (Dix-Carneiro and Kovak, 2019). Second, by investigating the effect of employment growth in knowledge-intensive sectors, we also build on the literature on the social returns to education, which demonstrated the existence of productivity spillovers accruing from educated workers to the advantage of other local workers and firms (Moretti, 2004a and 2004b, Peri et al., 2015). Lastly, this work also connects to the literature on the labour market impacts of migrations, which has traditionally focused on cross-countries labour flows (Card, 2001 and 2009, Ottaviano and Peri, 2010, Anelli et al., 2023) while devoting relatively less attention to the effects of *internal* migrations, the focus of our paper.[1]

[1] Relevant exceptions in this respect are the contributions by Bound and Holzer (2000) and Cadena and Kovak (2016), framing migrations as supply-side responses to labour demand shocks as we do in the present work.

No study has systematically assessed the local impact of the rise of the knowledge economy in the way we do in this paper. Most studies in the local multipliers literature focus on manufacture (Moretti, 2010b, Moretti and Thulin, 2013) or macro-sector shocks (Allcott and Keniston, 2017, Marchand, 2012, Acconcia et al., 2014). Here we take a different perspective, selecting the industries of interest based on knowledge-intensity[2]. Moreover, most works have thus far focused on the US context. Analysing a different setting - Italy, in this case - can help to better understand the role played by institutional factors in labour market dynamics. Indeed, the local impact of changes in labour demand crucially depends on specific institutional features, such as wage-setting mechanisms, unemployment rates, and labour mobility (Faggio & Overman, 2014; Moretti & Thulin, 2013; Ottaviano & Peri, 2010). One close contribution to ours is the work by Serafinelli (2019), who focuses on the Italian region of Veneto and addresses the local spillovers due to workers job mobility within local labour markets (LLMs). Instead, we consider the whole country and look at cross-sector spillovers. Moreover, we also disentangle the contribution to local spillovers of cross-LLM migrations of knowledge workers. This can highlight a competitive dynamics among LLMs, where those with a high concentration of knowledge-intensive activities drain qualified human resources from others, imposing them a '*negative* local multiplier'. Last but not least, the richness of our data allows us to develop an estimation strategy mitigating some empirical concerns generally encountered by previous studies. In particular, we can employ fixed effects specifications, which enable us to separately identify sorting and spillover effects.

In this work we face two major identification issues. First, workers may sort across local labour markets according to some unobservable characteristics (e.g. ability). As a consequence, it is possible that local workers display better labour outcomes

[2]An article adopting a similar methodology to define knowledge sectors - yet not controlling for individual unobserved heterogeneity as we do - is Lee and Clarke (2019), looking at the impact of high-tech employment growth in the UK.

in areas with greater increases in knowledge jobs because they are inherently better workers. Second, idiosyncratic shocks at the local level can correlate with our treatment, thus generating a downward or upward bias, depending on whether they are labour supply or demand shocks. To address those concerns, we combine a two-step procedure *á la* Combes et al. (2008) with a shift-share instrumental variable strategy (Bartik, 1991). In the 1st step we estimate wage, employment, and outmigration probability of local workers, accounting for observable time-varying worker and firm-level characteristics as well as time-invariant individual unobservables, while in the 2nd-step we regress the predicted local labour market area-year characteristics on our treatment variables - the stock and inflow of knowledge workers - instrumenting them to account for idiosyncratic local labour market shocks. In doing so, we capture the wage, employment, and outmigration probability premium derived from an increase in the stock or the inflow of knowledge workers.

Our results suggest that knowledge-workers are highly geographically concentrated and display relevant multiplicative effects at the local level. Specifically, looking at the employment in local sectors, we find evidence of a multiplier effect, arising both from the employment growth and inflow of workers in knowledge-intensive sectors. Moreover, we observe a significant reduction in outmigration probability, signalling an increased attractiveness of the local economy, again determined both by the share variation in knowledge workers and by their net migration rate. Conversely, we do not find any significant effect on wages, which highlights their limited responsiveness to local labour market conditions in the Italian context. Nominal wages appear to be positively affected only when we do not account for workers sorting. This suggests that the rise of the knowledge economy fosters the self-selection of more productive workers into 'knowledge-intensive' areas, thus only *indirectly* affecting nominal wages. In fact, local prices seem more reactive than nominal wages, resulting in a negative impact on real ones. Sorting plays a role also for the outmigration probability of local workers. The rise of the knowledge economy seems to increase the self-selection of more mobile workers into knowledge-intensive areas, resulting in an insignificant effect of stock and inflow of workers in knowledge-intensive sectors on the outmigration probability of local workers when one does not account for sorting.

The effects on the local economy produced by an inflow of knowledge workers appear smaller in size than those of an increase in their stock, consistent with our prior that migration response is just a component of the overall adjustment process.

The paper is structured as follows. Sections 2 and 3 respectively review the relevant literature and motivate the setting choice; sections 4 and 5 present the data employed and some descriptive statistics; section 6 and 7 explains the empirical strategy adopted and reports the related results; section 8 investigates the role of sorting (versus spillovers); section 9 compares the effects on nominal and real wages; section 10 concludes.

2 Related literature and predictions

2.1 Literature review

This work mainly relates to three streams of the literature. First of all, it speaks to the contributions concerning local multipliers and, more generally, the local impacts of sector-specific labour demand shocks. The notion of local multipliers has been popularised by Moretti (2010a, 2010b), even if the analysis of the local impacts of productivity shocks has a longer history, stemming from the contributions of Bartik (1991) and Blanchard and Katz (1992) which have recently been resumed for methodological purposes. Thereafter, a rich literature has developed on the local price adjustments and employment effects of local labour demand shocks, focusing mainly on specific sectors.

Among others, Marchand (2012) and Allcott and Keniston (2017) investigate the local impact of booms and busts in the energy sector, testing the hypothesis of positive spillovers to other local industries against that of manufacturing crowding out (the 'Dutch disease'); while Walker (2013) analyses the transitional dynamics produced by regulatory shocks, both on the workers of the interested sector and on other workers within the same LLM. Moretti and Wilson (2014) address the effects of state subsidies to the biotech sector, looking both at labour outcomes within biotech and at employment responses in other local sectors. Lee and Clarke (2019) and Lee (2014) respectively investigate the labour market impact of employment growth in high-tech or creative industries in UK, focusing on wage and employment responses of workers in other local sectors. Looking at trade shocks, Dix-Carneiro and Kovak (2019) investigate the impact of trade liberalisation in Brazil on earnings, employment, and migration responses of both tradable and non-tradable workers.

The studies on local multiplier effects have also devoted attention to the local impact of public spending. Acconcia et al. (2014) estimate the static and dynamic multiplier of sharp fiscal contractions, exploiting national rules to contrast Mafia in Italy, while Suárez Serrato and Wingender (2016) propose an analogous exercise and causally identify the impact of local multipliers through variations in accounting methods at censuses. Faggio and Overman (2014), instead, investigate the impact of public sector employment growth on private sector employment and other labour market indicators.

This literature investigates different margins of adjustments to labour demand shocks. However, the common feature of all the above references is that they address the *indirect* effect of labour demand shocks in a given sector, namely the consequences for the rest of the local economy. Institutional factors play a key role in determining the sign and size of the multiplier. Specifically, any cultural or regulatory/institutional aspect influencing the elasticity of labour supply affects the magnitude the impact and can make the difference between a multiplier or crowding out effect (Faggio and Overman, 2014; Moretti and Thulin, 2013). As shown by Moretti and Thulin (2013), estimating the local multiplier of tradables in Sweden and comparing it with the US benchmark, the size of local multipliers is context-dependent.[3] This *per se* motivates any study focusing on novel institutional settings.

The second strand of the literature this work relates to is the set of works on social returns to education. By investigating the effect of employment growth in knowledge-intensive sectors, we build on previous contributions examining productivity spillovers accruing from educated workers to the advantage of other local workers and firms. Moretti (2004a) looks at workers' wages and disentangles the effect of productivity spillovers versus imperfect substitution of working in cities with different percentages of graduates, while Moretti (2004b) focuses on the productivity of manufacturing plants and investigates the human capital externalities of higher graduate presence in the local economy outside the firm. Similarly, the literature on learning externalities in cities explains agglomeration processes in terms of better learning opportunities in large urban areas, due to knowledge spillovers. These opportunities are especially attractive for young workers investing in their human capital (De La Roca and Puga, 2017; Peri, 2002) and for newly-created innovative firms (Duranton and Puga, 2001), which are indeed over-represented in cities.

Lastly, as our aim is to study the impact of knowledge workers brought by internal migrations, this work also links with the literature on the labour market impacts of migrations. This has traditionally focused on cross-country labour flows, mainly

[3] Furthermore, the What Works Centre for Local Economic Growth in its toolkit on multiplier effects compares the magnitude of estimated multipliers in various OECD countries (available at: https://whatworksgrowth.org/resource-library/toolkit-local-multipliers/). Accounting for differences due to estimation methods, it seems evident that institutional factors play an important role in determining such variability in estimates. As discussed in that report, Auricchio (2015) focusing on Italy finds evidence of a multiplier for high-tech industries which is smaller compared to other OECD countries, while no significant effect for generic tradable-industries, confirming previous findings by De Blasio and Menon (2011). In sum, in Italy multiplicative effects on employment seem smaller than in other countries.

conceived as labour *supply* shocks. Moreover, most papers dealing with developed countries have focused on *in*-migrations (e.g. Card, 2001, 2009).[4] Considering *out*-migrations, instead, a study by Anelli et al. (2023) focuses on Italy and finds that outflows decrease place of origin's labour demand more than labour supply, due to the positive selection of outmigrants among highly innovative potential people. This result questions the traditional approach of modelling outmigration as a reduction of labour supply and highlights the existence of a demand channel driven by *brain drain* outflows. Despite international outmigration being an important part of the brain drain picture in countries like Italy, brain drain can also occur *within* national boundaries, generating a divergent geography of human capital resources. We focus on this aspect in our analysis. Among the few studies that analyse internal migrations, it is worth mentioning Bound and Holzer (2000), Cadena and Kovak (2016) and Dix-Carneiro and Kovak (2019), who frame migrations as mobility responses to labour *demand* shocks.[5] In a similar fashion, our work aims to investigate the labour market impact of migration responses to labour demand shocks in the knowledge sector.

2.2 Theoretical predictions

From those streams of the literature, we draw some theoretical predictions on how wage and employment of workers in non-tradable sectors respond to the employment growth or inflows of workers in knowledge-intensive tradable sectors. In addition, we are also interested in observing the response in terms of probability of outmigration of workers in non-tradables.

[4] For an overview of the literature on migrations, see Lewis and Peri (2015).

[5] Bound and Holzer (2000) look at a variety of workers demographic groups and uncover large wage effects of relative supply response to exogenous demand shocks. Cadena and Kovak (2016) find that the high mobility response of Mexican-born workers to demand shocks has a smoothing effect on labour market outcomes of US natives. Dix-Carneiro and Kovak (2019) investigate how negative demand shocks in the tradable sector transmit to non-tradable workers through reduced consumer demand for local services and workers competition for jobs in both sectors.

The effects of increased exposition to qualified workers on local *wages* can materialise through two channels: (1) the imperfect substitutability in the production process of different types of workers, or (2) productivity spillovers (Moretti, 2004a). Here, we identify knowledge workers based on sector employment. Therefore, possible complementarities should act across sectors rather than across skill levels. At the same time, we select industries based on a knowledge-intensity criterion, so it is reasonable to expect knowledge workers to produce externalities enhancing productivity and wages of other sectors of the local economy. Hence, this framework predicts positive wage effects on other local workers, either deriving from complementarities between knowledge sector and other local industries, or from education externalities due to high average skill level in the knowledge sector.

Yet, this applies only to flexible wages, negotiated in an independent and decentralised manner and reacting to local labour market shocks, while wages determined through collective bargaining at the industry level should not be affected by changes in local labour demand. This is the case for Italy, where most employees are subject to national collective labour agreements (Belloc et al., 2023), implying that wages should not be particularly reactive to local labour conditions in our setting.[6]. In addition, local prices can respond to changes in labour market conditions. If local prices are more reactive than *nominal* wages, we could also have a negative impact on *real* ones.

In case of rigid wages, the literature predicts that any upward wage push will be transferred to *employment*. Ottaviano and Peri (2010), analysing the labour market

[6]The employer-employee INPS dataset we use also includes information on independent contractors and standard self-employed, which we plan to use in future work to compare differential responses depending on the wage-setting scheme. Using INPS data, Belloc et al. (2023) estimate the urban wage premium for employees vs self-employed and independent contractors, finding different results for the two categories. Collective bargaining imposes a downward constraint to wages, while leaving the possibility to the employer to raise wages above the level nationally negotiated (*in melius* clause). Therefore, in principle, there is no institutionally-binding upward constraint to wages and this makes it possible to observe wage increases in local labour markets experiencing higher growth in knowledge workers.

impact of immigration in Germany, address the role of labour market institutions and, specifically, of wage rigidities. The authors show that, in the context of rigid wages, employment represents an important margin of adjustment to shocks.

However, the net employment effect may go in different directions. On the one hand, positive labour demand shocks can have a multiplier effect acting through increased demand for local services (Moretti, 2010b). On the other hand, if labour supply elasticity is very low, positive sector-specific shocks can displace workers from other local industries, therefore causing a decrease in employment in the rest of the local economy. As an example of the latter dynamic, Faggio and Overman (2014) estimate a crowding out effect of public sector growth on other tradable industries, attributing this to labour market rigidities (e.g. generous benefit system) and strict housing regulation that prevent labour supply to respond to positive local demand shocks.

While Italy is characterised by low labour mobility - which may suggest these crowding out effect may materialise in such context - in presence of involuntary unemployment not all the employment adjustment has to come from immigrants, but it can also derive from incumbent residents previously unemployed (Moretti, 2010a). Specifically, the less mobile the workers are, the more incumbent residents will benefit from positive local labour demand shocks (Bartik, 1991). Since unemployment is sizeable in Italy over the period observed, a possibility is that the employment response of incumbent residents outweighs the little inflow of immigrants, making the overall employment effect positive.

In sum, without knowing the size of labour supply elasticity, we cannot predict the sign of the employment response to an increase in the level of knowledge workers. With regards to the effect produced by an inflow of knowledge migrants, instead, we should not observe any displacement of non-tradable workers and therefore expect a positive employment impact for locals.

The above considerations also relate to our third outcome of interest, namely the probability of *outmigration* of local workers. According to the literature, negative demand shocks in the tradable sector transmit to non-tradable workers through reduced consumer demand for local services and increased workers' competition for jobs in both sectors (Dix-Carneiro and Kovak, 2019). Dealing with *positive* demand shocks, we expect both increased demand for local services and possibly reduced labour supply in case of relevant displacement effects of non-tradable workers. Therefore, we would predict the outmigration probability of local workers to decrease in response to positive demand shocks in the knowledge sector.

3 Knowledge economy and internal migration in Italy

Some key stylised facts make Italy a very interesting case for the issue at hand. Italy displays significant internal migrations (on top of international outflows), which mainly concern young qualified adults, directed towards big urban areas of the country (ISTAT, 2019). Indicative, in this regard, are the increased commuting flows around big urban centres of the North and the reduction in the number of LLMs between the last two censuses (ISTAT, 2010). From the 2000s, all Italian regions have experienced an increased international outflow of qualified workers ('brain drain'). However, if we consider both internal as well as international migration, some Italian regions come to display positive net inflows of young qualified population, to the detriment of the rest of the country. In other words, young qualified people, when not moving abroad, migrate towards the most dynamic and productive centres of the country, leaving territories of origin without valuable resources for local development.

That loss is a key aspect 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 whole national territory. Nowadays, Italy seems characterised by a significant polarisation of population, opportunities, services and investments. That evidence has made policy-makers speak of an Italian 'territorial issue' (Borghi, 2017) and motivated policy efforts to reduce territorial disparities, such as the National Strategy for Inner Areas (MUVAL, 2014).

The issue of growing territorial inequalities within countries is actually a global trend, which is often associated with structural changes in the economy and, specifically, to the consolidation of the knowledge economy, which shows a remarkable tendency to cluster in space.[7] In this regard, the Italian institute of statistics (ISTAT) provides evidence of a catching up with European standards by some Italian regions and provinces, regarding - for example - R&D investments, brands registration, industrial design, employment in research and cultural activities (ISTAT, 2018). However, that improved performance in knowledge-related dimensions appears to be spatially concentrated, with a large part of the country lagging behind. In summary, Italy seems to display a specific geography of knowledge, with migrations and qualified opportunities deeply interconnected. Our hypothesis is that this channel can represent an important determinant of the 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 se-

[7] 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.

lected scholars to employ social-security data for research purposes.[8] These data contain information on the universe of social-security-paying Italian workers, employed in the private sector.[9] For those workers, INPS data report the whole working history, tracking them across different occupations, employers and working locations up until the 1970s. However, geographical information on the employment municipality of each worker is available only from 2005. For this reason, our study focuses on the period 2005-2019.

We restrict our sample to workers aged between 15 and 64, not retired, for which we have information on employment sector and location. In addition, we drop from the sample individuals working less than 30 days per year and outliers in the two 1% tails of the wage distribution, after having computed the full-time equivalent wage for part-time workers. This is done to focus on 'average workers', discarding extreme and marginal working situations. For analogous considerations, we choose to select a yearly-dominant contract for each worker, identified as the employment providing the highest annual income and displaying the highest number of days worked. After that sample selection, we are left with over 100 million observations.

In addition to INPS data, we collect information on local house prices from the Italian Revenue Agency.[10] These data provide minimum, maximum, and average prices at sub-municipal level, that we then aggregate at LLM area. We employ this information as a proxy for local living costs, used to compute average real wages in the area.

[8] For more information about the programme, visit https://www.inps.it/dati-ricerche-e-bilanci/attivita-di-ricerca/programma-visitinps-scholars.

[9] Note that self-employed workers and public servants are not included in the datasets we work on.

[10] For more details, see https://www.agenziaentrate.gov.it/portale/schede/fabbricatiterreni/omi/banche-dati/quotazioni-immobiliari.

4.1 Knowledge workers

We identify 'knowledge workers' on the basis of their employment sector.[11] This choice is in line with the literature on local multipliers, which deals with the labour market consequences of *sector*-specific shocks (Allcott and Keniston, 2017; Marchand, 2012; Moretti, 2010b). Most importantly, it is consistent with the aim of estimating the labour market consequences of the knowledge *sector* growth.

To identify workers employed in knowledge-intensive sectors, we adopt the classification provided by EUROSTAT, which establishes a threshold of 33% of graduates workers on whole sector employment to qualify an activity as 'knowledge-intensive'.[12] 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.

To construct our knowledge workers variables in accordance with local multipliers literature, we focus on knowledge workers within *tradable* sectors. Following Moretti (2012), our aim is to investigate the impact of 'cause jobs' created in a given labour market on all other local workers.[13] In order to select tradable sectors, we follow Faggio and Overman (2014) and adopt the Jensen and Kletzer (2006) classi-

[11] 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 knowledge sector, Table A.1 in the Appendix shows the distribution of (non)knowledge-sector workers by education group and job position. Within the knowledge sector, the percentage of college-educated workers is twice as much as outside it, while high-schools dropouts are half of non-knowledge sector workers. Similarly, almost 70% of knowledge sector workers are white collars or managers compared to the 46% outside the knowledge sector. Moreover, Figure A.1 plots the wage distributions of knowledge-sector and non-tradables workers. The former distribution is shifted to the right, with the right tail displaying considerably more weight. This suggests that, among knowledge-sector workers, a larger mass of individuals earns more than the average.

[12] For further details, see 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.

[13] The notion of 'cause jobs' refers to the fact that tradable industries derive a relevant part of their revenues from outside-LLM demand. In this sense, those job opportunities are generated by external factors and represent, in turn, possible causes for other jobs in the non-tradable industries at the local level ('consequence jobs').

fication of tradable service sectors, together with its extension to industry activities provided by Hlatshwayo and Spence (2004). 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.[14] Thus, they use spatial clustering as an indicator of that service being potentially traded nationally and internationally. Hlatshwayo and Spence (2004) build on that criterion to classify industrial 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.[15] 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 that US sector technology applies to the Italian economy as well.[16]

Combining knowledge and tradability criteria, we identify 94 4-digit ATECO codes relating to tradable, knowledge-intensive sectors.[17] Hereafter, we simply refer to those sectors and related workers respectively as knowledge sectors and knowledge workers. These workers will form part of our treatment variables; namely, the percentage and inflow of knowledge workers in a given area.[18]

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

[15]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, 2004).

[16]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.

[17]See a summarising table in Figure A.2 and the full list of industries included in Table A1 of the Appendix.

[18]Note that if a tradable worker switches from a non- to a knowledge-intensive sector, he will contribute to treatment variables only for the years in which he is employed in knowledge-intensive sectors.

4.2 Locals and migrants

With the term 'locals' we refer to the workers employed in *non-tradable* sectors. These constitute the population which we expect to be affected by variations in knowledge employment or net inflows. By definition, non-tradable sectors mostly produce for a *local* demand, which makes them especially sensitive to local labour market (LLM) shocks. Some tradable activities can also be affected by sector-specific shocks, but part of the effect is likely to be transferred to other LLMs, so that the impact is expected to be milder (Moretti, 2010b). Local workers do not need to be permanently observed in the same LLM over 2005-2019, but they can migrate to other LLMs. We assume they can be affected by knowledge workers when they are based in an LLM experiencing an increase in stock or an inflow of knowledge workers.

We identify as knowledge migrants those workers who move into (or out of) a LLM from one year to another and are employed in the knowledge sector in the destination area. It is worth clarifying that we only refer to internal migrants, i.e. within-Italy migrants, since we do not observe re-locations across country borders. To locate workers, we assign them to the LLM where they work the highest number of days in a year (hereafter, 'dominant LLM'). In this way, we can compute net migration into an LLM by simply subtracting in and out-flows of workers over the period of interest.[19]

Given the period under observation, as LLM units we employ the 2011 definition of ISTAT's *Sistemi Locali del Lavoro*. That partition is elaborated from effective commuting flows at each Census year and represents areas where most people live and work. Therefore, they constitute the most accurate definition of local labour mar-

[19] As explained, INPS data contain information on employment municipality, which can be easily associated to a given LLM. However, during the period considered, some Italian municipalities experienced mergers, which sometimes concern more LLMs. In this respect, we attribute the LLM of the new municipality to those merged before 2011, while for those merged after 2011 we assign to the new municipality the LLM of merged ones only if they were all part of the same LLM.

kets, characterised by homogeneous labour market conditions inside them.[20]

5 Descriptive analysis

In the 2005-2019 time span, the analysed period, knowledge workers represent around 10% of the Italian workforce, slightly increasing over the observation period.[21] Looking at internal migrations , 8% of the whole working population migrates each year across local labour markets. A considerable fraction of them is below 40 years old ('young'). Instead, just one fourth is employed in sectors classified as knowledge intensive.[22] Interestingly, a great portion of knowledge migrants is employed in tradable sectors, which provides supportive evidence to the claim that geographical concentration mainly concerns tradable industries. In addition, the vast majority of knowledge migrants is young, which confirms the stylised facts presented in section 3.

If we observe the spatial distribution of knowledge workers (Figure 1), we notice an overall increase over the period considered, with many LLMs reaching 15% or more of knowledge employment over the total. However, they seem to concentrate in space, mainly in the centre-North. Moreover, considerable variability exists within regions, with neighbouring LLMs displaying very different percentages.

Similarly, looking at net migrations (Figure 2), we note that most of the country displays outflows of workers over the whole period observed. If we then focus on

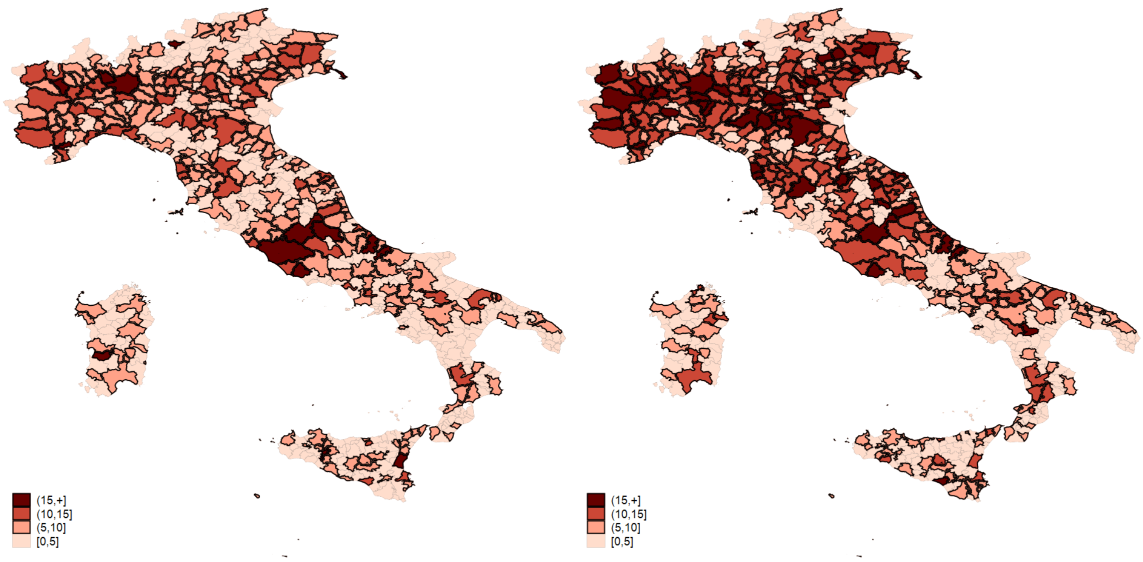
[20]For further details on the construction of *Sistemi Locali del Lavoro*, see https://www.istat.it/en/labour-market-areas. We employ the 2011 definition, since that seems the most representative description of local labour markets in our period of analysis (2005-2019).

[21]As explained in the previous section, these are workers active in tradable and knowledge-intensive sectors. Workers employed in tradable sectors are around 40% of overall 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.

[22]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 the knowledge sector can partially motivate this finding, as well as the possibility for highly educated migrants to find qualified occupations in non-knowledge-intensive sectors.

Figure 1: %jobs in the knowledge sector

2005 2019



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

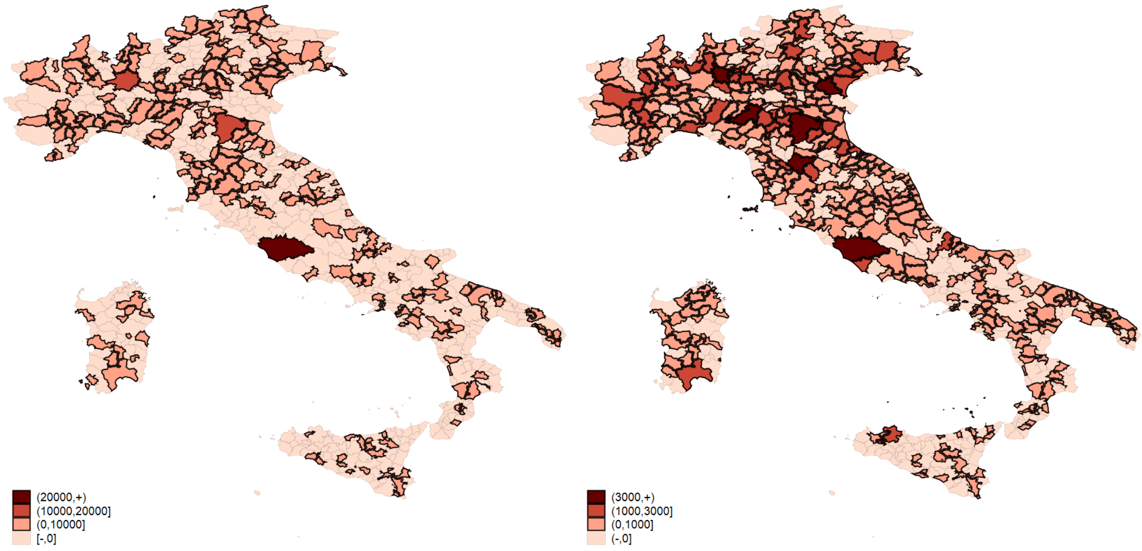
knowledge workers, more LLMs display positive net migrations, but a large part of them received less than 1000 knowledge migrants over 15 years. Here, some highly dynamic LLMs stand out for a high number of incoming workers, such as Rome, Bologna, Florence, and Padua. Moreover, in the islands, LLMs with regional administrative centres display rather high inflows, confirming that the dynamics are largely intra-regional.

As a descriptive investigation, we test whether these internal migrations are related to better labour opportunities in the destination area, that is if workers 'move to opportunities'. We regress individual (annual) wage growth on a set of worker characteristics and fixed effects (see Figure 3).[23] These estimates suggest that migrants experience a significantly higher increase in wages compared to stayers, which supports the claim that internal migrations are likely due to the search for better job

[23]In Figure A.3 of the Appendix, we do a similar exercise using as dependent variable the dummy for migration. In this way, we check which individual characteristics are associated with a higher probability of migrating. Working in the knowledge sector positively correlates with migration, even if the point estimate is sightly non significant. Temporal jobs are clearly associated with a higher likelihood of moving.

Figure 2: 2005-2019 net migrations

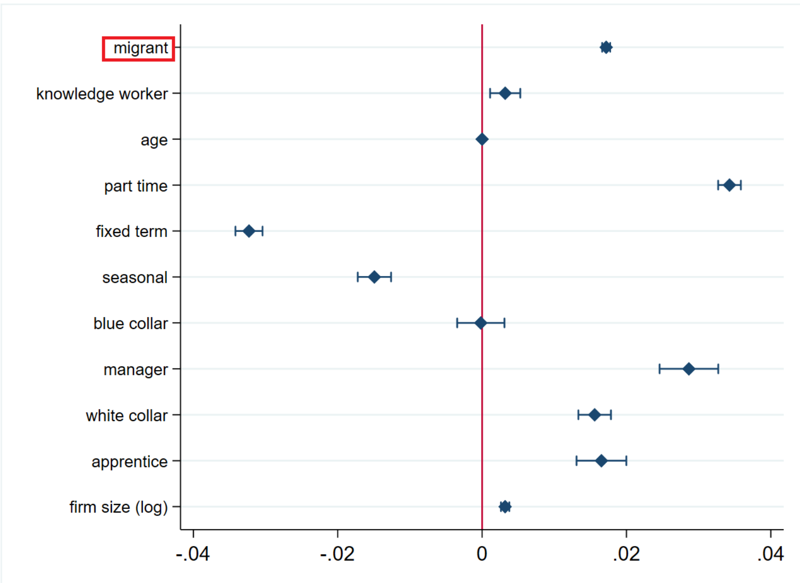
(a) all (b) knowledge workers



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 knowledge sector.

opportunities.

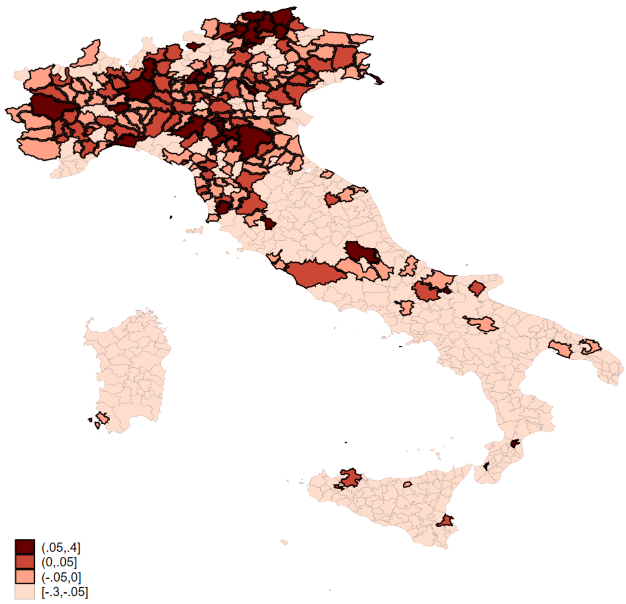
Figure 3: Expected wage growth by worker characteristics



The graph reports the estimated coefficients from a regression of annual wage growth on a set of individual characteristics (2005-2019). We also include in the specification individual and LLM-year fixed effects, and 2-digits sector fixed effects.

Focusing on the knowledge sector, we further check how the wage premium to work in those industries varies across space. The map in Figure 4 displays the local wage premium as of 2005, estimated from a regression of (log) individual wages on time fixed effects and the interactions between area and knowledge-sector dummies. The map reports estimates of these interaction terms, which can be interpreted as the wage premium to work in the knowledge sector in a given area in 2005. Most of the country displays negative wage premium, up to -30 log points. Conversely, a positive premium is visible around Rome and, mostly, in the North, with the LLMs of Bologna, Milan, Turin, and the Bolzano province standing out for the highest wage premium (up to 40 log points).

Figure 4: Wage premium to work in the knowledge sector (2005)

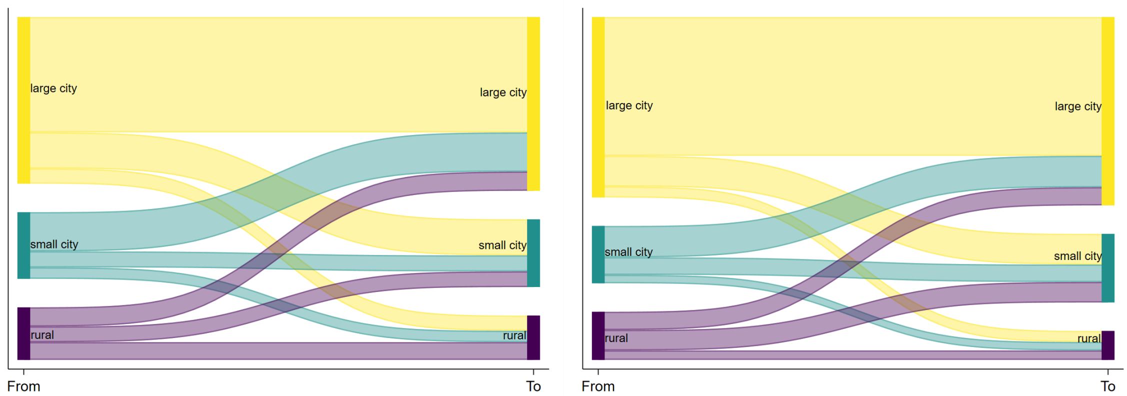


The map plots the estimated coefficient - for 2005 - from a regression of (log) wage on time fixed effects and the interaction between area and knowledge sector dummies. The plotted coefficient refers to that interaction term, which we interpret as the wage premium to work in the knowledge sector in a given area in 2005.

For an overview of mobility patterns, we also classify LLMs by initial population density and compute average origin-destination flows over 2005-2019. We do so either looking at overall migrations (Panel a of Figure 5) or focusing on migrants in the knowledge sectors (Panel b).[24] In both panels, the greater flows concerning large cities are likely due to a size effect, since these are the most densely populated areas. The interesting fact is that most migrants from those areas move to other large cities, so as the larger fraction of movers from small cities. Flows from large to small cities or rural areas are much more limited. This pattern is even more marked when looking at knowledge migrants (Panel b). For workers in the knowledge sector, large cities represent the most common destination of internal migration, while rural areas are mostly places of outmigration.

Figure 5: Mobility patterns (average flows over 2005-2019)

(a) all migrants (b) knowledge-sector migrants



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 knowledge sector.

To investigate the spatial dispersion of knowledge workers over time, in Figure 6 we plot kernel distributions of percentages of knowledge workers across LLMs in 2005, 2010, 2015, 2019. The distribution slightly shifts to the right, due to the overall increase in knowledge sector employment. Moreover, it becomes less peaked around the mean, with increased weight on the right tail of the distribution. This

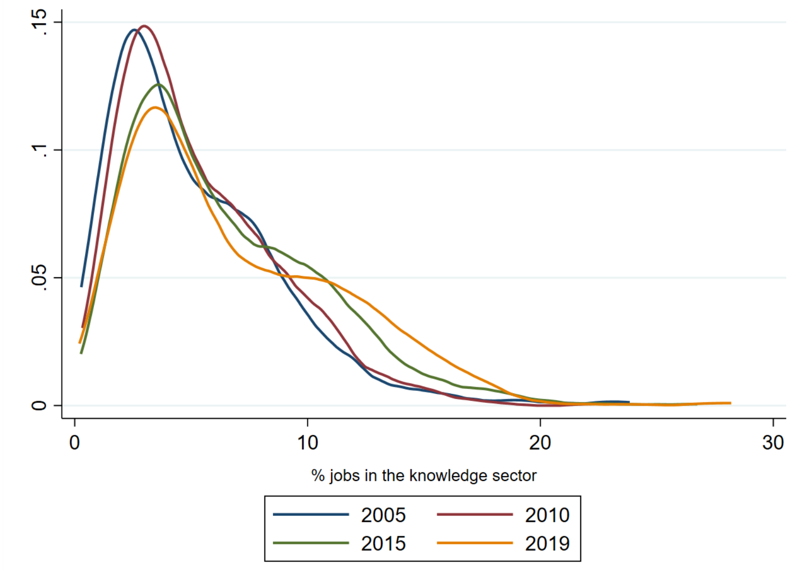
[24] Specifically, areas are classified as 'large city' if they belong to the 4th quartile of the population density distribution in 2006, 'small city' if to the 3th quartile, 'rural' if to the 1st or 2nd quartile.

feature can be interpreted as some LLMs pulling ahead of the country average, which is consistent with our hypothesis of few LLMs benefiting from the rise of knowledge economy.

We also look at the kernel distributions of two of our key outcome variables, namely wage and employment of local workers. The plots in Figure 7 refer to the distribution of average (log) daily wage and days worked per year in local sectors across LLMs. We clearly see an overall increase in wages, up until 2015. As in the previous graph, since the 2010 the distribution flattens, showing increased variance in average wage across LLMs. Regarding days worked, there progressively emerge two peaks, around 170 and 230 days per year. Here the interpretation is less straightforward, but it could suggest a polarisation of LLMs between low and high work intensive.[25]

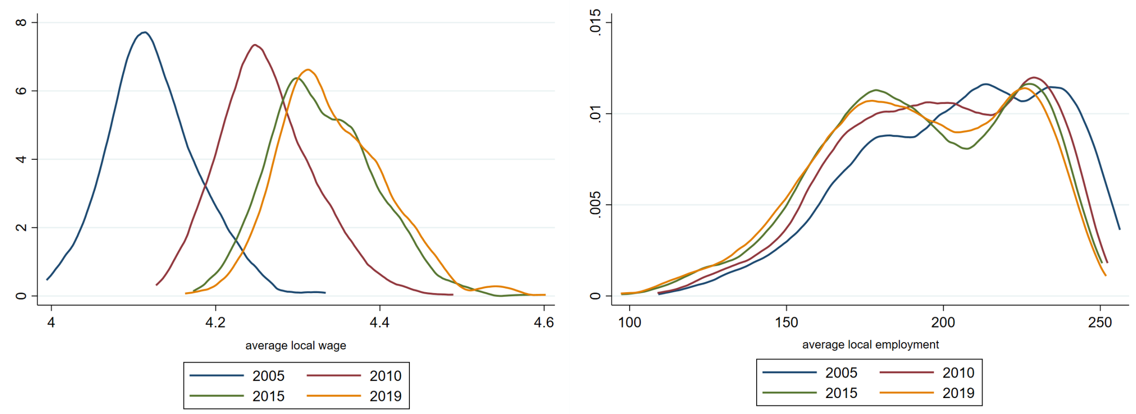
[25] The two peaks observed could be driven by different working patterns across North and South Italy. We checked the geographical distribution of LLMs below or above 200 days worked in year 2019. Such number of days worked corresponds to the bottom between the two peaks observed. Among low intensive working areas (below 200), the largest amount is concentrated in the South (75%); while among high intensive working LLM (above 200), geographical distribution is more balanced (55% in the Centre-North and 45% in the South). Therefore, those peaks only partially reflect the traditional Italian North-South divide. Among low work intensive areas, there exists some geographical variation. Concerning high work intensive LLMs, they almost evenly distribute across North and South Italy.

Figure 6: Dispersion of knowledge workers across LLMs



The graph reports the kernel distributions of the percentages of workers in the knowledge sector across LLMs in 2005, 2010, 2015, 2019.

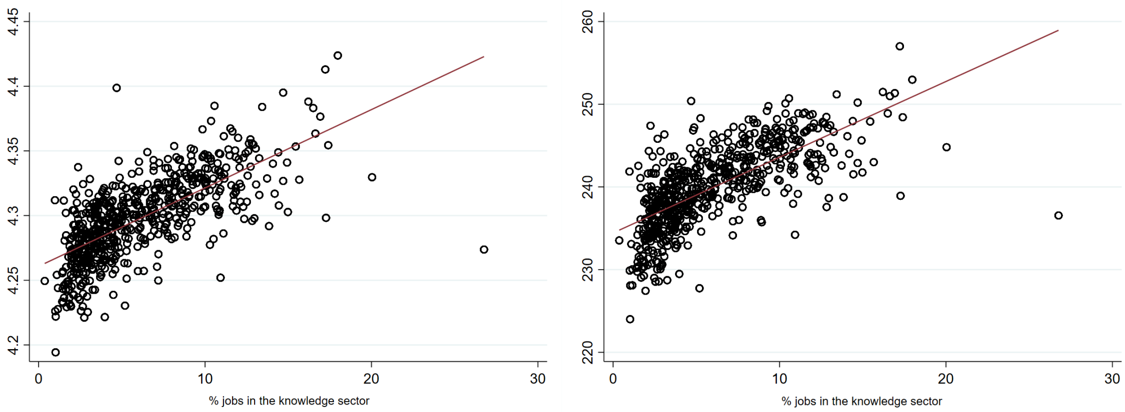
Figure 7: Dispersion of average wage and employment of local workers across LLMs



The graphs report the kernel distributions of average (log) daily wage (Panel a) and days worked (Panel b) across LLMs in 2005, 2010, 2015, 2019.

Finally, we provide some basic correlation analysis to start investigating the relation between percentages of knowledge workers and labour outcomes of local employees. To that aim, in Figure 8 we plot average daily wage and days worked at LLM level against percentages of knowledge workers. The average labour outcomes are computed from individual adjusted wages and days worked, predicted through a regression including sex, age, year of entrance in the labour market and a set of occupational dummies. In Figure 8, variables are expressed in levels and observations refer to a given LLM-year combination. Correlations are clearly positive, which provides preliminary evidence of a positive relationship between employment growth in the knowledge sector and labour outcomes.

Figure 8: Correlation between adjusted local wage/employment and % jobs in the knowledge sector



The graphs report the correlation between local adjusted daily wage (Panel a) and days worked (Panel b) at LLM level, and the percentages of knowledge 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.

6 Empirical strategy

Our aim is to identify the labour market impact of relative employment growth in the knowledge sector, either as a whole or deriving from net migrations of knowledge workers from other LLMs.

In estimating such relationships, we face two main identification issues. First, local workers may sort according to some unobservable characteristics (e.g. ability) in a way that is correlated with the presence of knowledge workers. In other words, it can be the case that local workers inherently display better labour outcomes in LLMs with increased percentages of knowledge workers. Second, unobserved idiosyncratic shocks to labour outcomes correlated with the local shares of knowledge workers may bias our estimates. Specifically, in case of unobserved local demand (supply) shocks, our estimates would be upward (downward) biased. To address these concerns, we combine a two-step estimation (Combes et al., 2008) with a shift-share instrument. The two-step estimation allows us to account for individual sorting; while the shift-share instrument mitigates possible concerns about unobserved idiosyncratic shocks at LLM level. More generally, the instrumental variable strategy should address any problem of time varying unobservables which influence local labour outcomes and correlate with the increased presence of knowledge workers.

6.1 Two-step model

First of all, we run an individual level estimation in which we regress (1) individual log daily wage, (2) log employment - proxied by the number of days worked per year - and (3) a dummy defining the (out)migrant status of a worker in the following year, on a set of worker and firm characteristics: indicators for whether the worker has a part-time, fixed-term, seasonal job, occupational dummies (white/blue collar, manager, apprentice), log firm size. We also include employment sector dummies (2-digit ateco), worker and LLM-year fixed effects.

Formally, in the 1st-step we estimate:

$$y_{it} = \alpha + \beta_1 X_{it} + \beta_2 Y_{j(it)t} + \gamma_i + \delta_{c(it)t} + \epsilon_{it}, \tag{1}$$

where y_{it} is the individual outcome of local worker i in year t; X_{it} and $Y_{j(it)t}$ are, respectively, time-varying worker and firm characteristics, with j relating to the firm where worker i is employed at time t; 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.

The fitted values of the term $\delta_{c(it)t}$ can be interpreted as the labour outcome premium to work in LLM c in year t (Combes et al., 2008, 2010). These become the dependent variable of the 2nd-step estimation, a LLM-level regression. In this equation, the main explanatory variable is one of our two $KW_{ct} \in \{KW1_{ct}, KW2_{ct}\}$ treatments of interest: (1) the percentage of workers within the knowledge sector in a given LLM, or (2) the net inflow of knowledge workers. We also add year and LLM fixed effects, and include analytical weights for the number of observations contributing to the 1st-step estimation, in order to control for the different precision in area-year estimates. We apply that correction to deal with the sampling errors possibly contained in the area-year estimates employed as dependent variable in the 2nd-step (Combes et al., 2008). "This weighted two-step procedure gives rise to estimates that are consistent although asymptotically less efficient than optimally weighted two-step estimates, which are numerically equal to one-step estimates. The two-step procedure yields standard errors that account for the grouped structure of the data" (Moretti, 2004a). Moreover, both in the 1st and in the 2nd-step estimation (equations 1 and 2), we cluster standard errors at the local level, i.e. LLM.

Our model is estimated in long-differences form, where variations refer to the whole 2005-2019 period, using observations for 2005 and 2019:

Formally, the 2nd-step equation is:

$$\hat{\delta}_{ct} = \zeta + \eta\, KW_{ct} + \theta_t + \lambda_c + \phi_{ct} \qquad t = 2005, 2019. \tag{2}$$

This two-step estimation allows us to control for a wide range of individual characteristics which can influence labour outcomes and, more importantly, to clean out unobserved individual heterogeneity through worker fixed effects. In this way, we avoid that our coefficient of interest η is biased by ability sorting. Compared to a one-step estimation, this specification allows to include - in the 1st step - LLM-time fixed effects and, therefore, separately identify the effects of individual versus area time-varying characteristics. These area-year effects, indeed, are our outcomes of interest when it comes to estimate treatment effects at LLM level.[26]

In the 2nd-step, we include year fixed effects to control for any possible business cycle dynamics influencing labour market outcomes. Moreover, since our aim is to estimate the effects of knowledge-employment relative *growth*, we add LLM fixed effects, in order to first differentiate regression variables. By doing so, η only captures the labour market impact of *variations* in our treatments, which are specified either as the percentage of knowledge workers over the total workforce in that LLM-year or as the net (cumulative) inflows of knowledge migrants from 2005 up to year t, discounted by the 2005 number of knowledge workers in that LLM.[27] More formally, our treatments are defined as follows:

$$KW1_{ct} = \frac{K_{ct}}{N_{ct}} \cdot 100 \tag{4}$$

[26]The two-step approach is discussed in details by Combes et al. (2008) and Combes et al. (2010). 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 and therefore avoids to estimate the LLM fixed effects only from movers, which represent a highly selected sample of the population. Finally, working at LLM level in the 2nd-step, we avoid the 'shock bias' (Combes et al., 2010) deriving from non-zero covariance between the treatment and individual error term. As a robustness check, we also estimate the above specification in one step. Formally:

$$y_{it} = \alpha + \beta_0 \, KW_{ct} + \beta_1 X_{it} + \beta_2 Y_{j(it)t} + \gamma_i + \delta_{c(it)} + \eta_t + \epsilon_{it}. \tag{3}$$

One-step estimates - available upon request - substantially confirm our main results. Wage and employment coefficients are equally signed and significant compared to two-step estimates. As for outmigration, 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). More importantly, in the two-step estimation we compute standard errors of *means*, i.e. area-year estimates; while here we deal with the original individual outcome, which displays larger variance.

[27]We borrow that specification for net inflows from Anelli et al. (2023). Discounting for the initial number of knowledge workers in the LLM serves to account for the different sizes of the sector among LLMs at the beginning of the period.

$$KW2_{ct} = \frac{\Sigma_{05}^{t} m_{ct}}{K_{c,05}} \cdot 100 \tag{5}$$

where K_{ct} and N_{ct} are, respectively, the total number of knowledge and overall workers in LLM c, year t; m_{ct} is the net inflow of knowledge migrants to LLM c in year t and $K_{c,2005}$ is the total number of knowledge workers in LLM c in 2005. Note that for LLMs with greater outflows than inflows, $KW2_{ct}$ will have negative sign.

Therefore, when employing treatment $KW1_{ct}$, we can interpret η as the percentage variation in the outcome - daily wage, days worked, or outmigration probability premium - due to a 1% increase in employment in the knowledge sector. When, instead, we use $KW2_{ct}$, η can be read as the percentage outcome variation deriving from a 1% increase in incoming knowledge workers with respect to their initial presence.

6.2 Shift-share instrumental variable strategy

Equation 2 does not account for the possibility that labour market shocks at local level could bias our coefficients. In other words, there could be time varying unobservables that influence local labour outcomes and correlate with the treatment, creating a problem of omitted variables. To correct for this, we employ a shift-share (Bartik, 1991) instrumental variable strategy, following the implementation in first-differences adopted by Moretti (2004a). The purpose of this IV strategy is to isolate the exogenous shift in the demand for labour in the knowledge sector. Essentially, we construct our instrument interacting historical local shares of each 4-digit sector code in our knowledge classification with the overall percentage of that specific sector at national level in the period considered. Formally,

$$Instrument_{ct} = \Sigma_s \, w_{c,95}^{s} \cdot \%S_t, \tag{6}$$

where

$$w^s_{c,95} = \frac{S_{c,95}}{N_{c,95}} \cdot 100 \tag{7}$$

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

$$\%S_t = \frac{S_t}{N_t} \cdot 100 \tag{8}$$

is the overall share of employment in sector s at national level, over the period observed. Therefore, we can interpret the instrument as a LLM-specific weighted average of national changes in the employment shares of knowledge industries. We take historical shares at 1995, ten years before the beginning of our period of analysis.[28]. This is done to mitigate the potential concerns about shares exogeneity: shares are themselves LM equilibrium outcomes and therefore can correlate with fundamentals directly related to subsequent LLM outcomes (Jaeger et al., 2018, Goldsmith-Pinkham et al., 2020).

In fact, the literature has developed two alternative approaches to the validity of shift-share instruments, either based on the exogeneity of the shares or shift component of the instrument. According to the 'shares approach' (Goldsmith-Pinkham et al., 2020), Bartik-type instruments mainly derive identification from differing initial industry composition across LLMs, which result in differential exposures to common shocks. Alternatively, the instrument isolates the shift in local labour demand only coming from national changes, provided that neither past industrial composition nor unobservables correlated with it directly predict the outcome of interest conditional on controls (Baum-Snow and Ferreira, 2015). Instead, following the 'shift approach' (Borusyak et al., 2018), shares exogeneity is not a necessary condition for the identification of causal effects. It is sufficient that shares are not correlated with the differential changes associated with the national shock itself.

[28] Note that, to construct the historical shares, we had to refer to the municipality where the employer was located, since before 2005 we do not have data on individuals' workplace location.

This approach perfectly applies to settings characterised by quasi-experimental exogenous shocks (e.g. Autor et al., 2013, Peri et al., 2015). However, it can still be appropriate 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 knowledge sector, deriving from the global technological change. Since we cannot directly observe those aggregate demand changes, we have to estimate them from national employment variations, introducing mechanical bias. Borusyak et al. (2018) asymptotic result is that "if one is willing to assume quasi-random assignment of the underlying industry demand shocks and that the regional supply shocks are spatially-uncorrelated, one can interpret the uncorrected [shift-share] estimator as leveraging demand variation in large samples".[29]

We believe that - in our setting - the orthogonality condition required by the 'shares approach' seems more plausible. Indeed, we employ initial shares specific to knowledge industries as instrument for equally specific treatment (i.e. only concerning the knowledge sector), which makes quite unlikely that unobservable industry shocks enter the error term in a way that is correlated with past shares.[30] Moreover, as already said, we take initial shares ten years before the measurement of any other variable in the estimation. If, instead, we took the 'shift perspective', for the asymptotic validity result to apply we would need to assume that regional supply shocks are spatially uncorrelated or, alternatively, to employ split sample methods, as those estimating shocks from distant regions. Since this is not straightforward in

[29]With the term 'uncorrected', Borusyak et al. (2018) refer to the Leave-Out-Option (LOO) correction. In that contribution, the authors show that in large samples that correction is irrelevant, since the risk that a single unit is driving national employment changes is negligible. Here, since we have a high number of geographical units in our sample, i.e. 611 LLM_s, we do not apply any LOO correction.

[30]In the words of Borusyak et al. (2018), "share exogeneity may be a more plausible approach in the case when the exposure shares are 'tailored' to the specific economic question, and to the particular endogenous variable included in the model. In this case, the scenario considered [..] that there are unobserved shocks which enter [the error term] through the shares may be less of a concern."

our context, we stick to the 'shares approach' and related identifying assumption, which appears reasonably plausible in our setting.

We use the instrument in equation 6 for both our treatments. $KW1$ is the employment-growth treatment commonly used in the local multipliers literature. $KW2$ can be viewed as the component of $KW1$ due to internal migrations. In other words, $KW2$ is itself a margin of adjustment to the demand shock underlying $KW1$, which can thus produce its own labour market effects. Therefore, in principle the same exclusion restriction should hold in both cases.[31]

6.2.1 Shift-share diagnostics

Our instrument combines the cross-sectional variation in past industry shares as of 1995 ('the share' component) with the industry employment growth at the national level over 2005-2019 ('the shift' component). If one takes the 'share' approach to instrument exogeneity, the validity of the IV relies on the assumption that "neither past industrial composition nor unobservables correlated with it directly predict the outcome of interest conditional on controls" (Goldsmith-Pinkham et al., 2020). To test that assumption, Goldsmith-Pinkham et al. (2020) propose some diagnostic tests. Firstly, they suggest to compute the weights that the instrument attributes to each share (the so-called Rotemberg weights): higher weight means greater importance in the identifying variation. Then, for the five industries receiving highest weight, they advise to check the correlation between past shares and pre-treatment characteristics of the local labour market.

We follow these suggestions and run the above tests for our treatment $KW1$, i.e. the variation in the percentage of knowledge workers. Table A.3 report few diagnostics on Rotemberg weights.[32] Panel A shows the shares of Rotemberg weights

[31]In Bound and Holzer (2000), the authors also apply the same Bartik instrument both to the overall demand shock and to the induced supply shift, of which they investigate the wage effect.

[32]To obtain these results, we employ the stata command *bartik_weight* by Goldsmith-Pinkham.

(α_s) that are positive and negative. Almost all of them are positive meaning that individual shares positively correlates with the IV. This suggests that our instrument is a convex combination of the industry-specific estimated β coefficients and does not show signs of mis-specification. Panel B reports correlations among the components of the IV ($\%S$ and $w_{s,95}$ - see equation 6), the Rotemberg weights (α_s), the power of the IV (F_s) and the estimated coefficients of equation 2 with - respectively - wage (Panel B.1), employment (Panel B.2), and outmigration probability (Panel B.3) as dependent variable.

From Panel B of Table A.3 we can note that we are mostly leveraging variation from the share component of the instrument, as Rotemberg weights α_s show a higher correlation with the shares $w_{s,95}$ than with the shifts $\%S$: 0.376 versus 0.215. A larger correlation implies a higher relevance of that IV component in generating the identifying variation. Panel C reports the five industries receiving the highest weight with related industry-specific estimates of equation 2, respectively using wage (Panel C.1), employment (Panel C.2), or outmigration probability (Panel C.3) as dependent variable. Firstly, notice that none of the top-5 Rotemberg weight industries generates more than 26.3% (Reinsurance) of the total instrument variation. This is reassuring, since it implies that we are not relying only on few industry-specific variations for our estimation. Moreover, the related β_s estimates are mostly equally signed, similar in size and largely comparable to the estimated coefficients of the main analysis.[33]

We have verified that - in our setting - identifying variation mostly derives from the share component of the IV. Therefore, it is important to check that past industry shares are not correlated with LLM characteristics prior to the treatment period. Significant correlations would cast doubts on the exogeneity of past industry

See https://github.com/paulgp/bartik-weight.

[33]These just-identified coefficients must be considered with some caution, since it was not possible to define the weak instrument robust confidence intervals using the method from Chernozhukov and Hansen (2008).

shares. Unfortunately, we cannot observe the evolution of our outcomes before 2005, since we do not have information on individual workplace prior to that date. For this reason, we cannot check for parallel trends before 2005, nor investigate the correlation of past industry shares with LLM outcomes over pre-treatment periods. However, we can observe whether past industry shares (as of 1995) correlate with changes in LLM characteristics over the years preceding our period of analysis. We consider past industry shares of the top 5 Rotemberg weight industries. Then, we regress those shares on the 2001-2004 variation in the number of local firms, the births of new firms, and the growth rate in local employees. Table A.4 reports the related results. Essentially no coefficient appears significant, providing some confidence about shares exogeneity. Specifically, 1995 industry shares seem not to predict the local changes in labour market conditions over the three years preceding the period of interest.[34]

6.3 Spatial clustering

Our units of analysis are the Italian *Sistemi Locali del Lavoro*, which represent the most accurate measure of LLMs. Their definition is based on actual commuting flows, which mostly occur within their boundaries.[35] However, some residual commuting takes place also across LLM borders: in 2011, an average 6% of the LLM population used to commute across LLM borders for work.[36] Despite cross-LLM commuting concerns only a small fraction of the population, we could be overestimating internal migrations, since we count as migrants individuals that start new jobs in neighbouring LLMs without changing residence. Moreover, cross-LLM commuters (changing job or not) are likely to spend their income in the LLM of

[34]The number of observations is reduced to 604 because we are excluding the 7 LLMs that in 1995 had no knowledge worker, as suggested in the replication files for the bartik-weight command. In the main estimation, for those LLMs the shift-share instrument takes value zero. However, our main estimates are not affected by the exclusion of those LLMs.

[35]For more details on the definition of *Sistemi Locali del Lavoro*, see the data section.

[36]We compute these statistics using data on cross-LLM commuting flows in 2011 provided by ISTAT through the application BTFlussi (https://gisportal.istat.it/bt.flussi/).

residence more than in the LLM they work in. Therefore, they mostly contribute to labour outcomes of the LLM of residence. In addition, the rise of the knowledge economy in one LLM can spill-over neighbouring areas, in the form of multiplier or displacement effects. All this can generate spatial correlation in the standard errors of neighbouring LLMs.

To check that spatial correlation is not driving our results, as a robustness we cluster standard errors using the method proposed by Conley (1999). This procedure does not restrict the choice about the level of clustering to administrative boundaries; conversely, it allows to define buffers of different radius around a given point, and use them for spatial clustering. As a reference point, we take the centroid of the LLM, and we re-estimate our long-difference IV specification (equation 2 with KW_{ct} instrumented with the shift share in 6) clustering standard errors at buffer-level. We adopt buffers of radius 10, 20, and 30 kilometres.[37] We chose these distances considering the median land area of LLMs, which is slightly below 400 square kilometres.[38]

[37]This is done with the STATA command *acreg*, which allows to specify the geographical coordinates of a given point and set the distance cutoff in kilometres beyond which the correlation between error term of two observations is assumed to be zero.

[38]Assuming a circle surface, the corresponding radius is around 11 kilometres. Thus, a cutoff distance of 10 kilometres is almost equivalent to cluster at LLM level, for LLMs of median size; while with 30 kilometres, we are including in the clustering the entire neighbouring LLMs (assuming again median size LLMs).

7 Results

7.1 OLS estimates

We start by reporting the results of the individual-level estimations (equation 1), where our outcomes are regressed on a set of worker and firm characteristics. Among regressors, we include: indicators for whether the worker has a part-time, fixed-term, seasonal job; occupational dummies (blue/white collar, manager, apprentice); and log firm size. Moreover, we add fixed effects for employment sector (2-digit ateco), together with worker and LLM-year fixed effects. Table 1 shows the correlation of these characteristics with log daily wage, log days worked, and outmigration probability of local workers.

Table 1: Individual level estimation

	Wage	Employment	Outmigration
Part time job	0.040***	-0.384***	-0.005***
	(0.0027)	(0.0029)	(0.0006)
Fixed term job	-0.043***	-0.369***	0.028***
	(0.0030)	(0.0030)	(0.0017)
Seasonal job	-0.011***	-0.409***	0.038***
	(0.0029)	(0.0070)	(0.0013)
Blue collar	-0.019**	-0.027***	0.004
	(0.0063)	(0.0041)	(0.0033)
White collar	0.020***	0.028***	-0.005*
	(0.0034)	(0.0040)	(0.0030)
Manager	0.202***	0.007**	-0.013***
	(0.0082)	(0.0043)	(0.0028)
Apprentice	-0.178***	-0.074***	-0.007*
	(0.0062)	(0.0049)	(0.0032)
Firm's size	0.011***	0.034***	-0.0003*
	(0.0002)	(0.0017)	(0.0002)
2-digit sector fe	✓	✓	✓
individual fe	✓	✓	✓
LLM-year fe	✓	✓	✓
N	103,350,759	103,350,759	103,350,759

Standard errors clustered at LLM level * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The Table reports estimated coefficients from the 1^{st}-step regression at the individual level (equation 1), where we regress (log) wage, (log) employment and outmigration probability on a set of time-varying individual characteristics and fixed effects. The sample includes all local workers.

Next, we move on to the LLM-level estimations, employing as dependent variables the LLM-year fixed effects estimated from equation 1. We begin by presenting the

OLS results of equation 2 in Table 2, where KW_{ct} corresponds either to the share of knowledge workers in the LLM or to net migrations of knowledge workers. We estimate this equation in long-differences, employing observations in the initial (2005) and final (2019) period and including LLMs fixed effects to first-differentiate regression variables.

Table 2 reports - for both our treatments - positive wage effects, while no significant impact is detected on employment and outmigration probability. However, these results may be biased, since they do not account for the likely idiosyncratic shocks to labour outcomes correlated with the treatment variables. To address this empirical concern, we refer to the IV estimation, where both treatments are instrumented by the shift-share measure of equation 6.

Table 2: OLS estimation

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	0.003***	-0.002	-0.0001			
	(0.0013)	(0.0010)	(0.0003)			
% knowledge migrants				0.00003**	-0.00001	-0.000001
				(0.00001)	(0.00001)	(0.00001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

Standard errors clustered at LLM level * p<0.10, ** p<0.05, *** p<0.01. The Table reports the estimated coefficients from the OLS regression of the 2^{nd}-step specification (equation 2). The outcome variables are the area-year effects predicted from equation 1. We regress these area-year estimates for 2005 and 2019 on our treatment variables (equation 4) or 5), area and year fixed effects. We also include as weights the number of local workers in the LLM, to account for different precision in 1^{st}-step estimates.

7.2 IV estimates

In Table 3 we report estimates for the first stage regressions, where we regress both treatments on the shift-share instrument. The F-statistics is above the conventional level of 10 for both estimations, showing the instrument's relevance. To provide a visual intuition of the predictive power of the instrument, in the Appendix (Figures

A.4 and A.5), we report the maps for actual and predicted percentages of knowledge workers by LLM, respectively in 2005 and 2019.

Table 3: IV estimation, first stage results

	% knowledge workers	% knowledge migrants
Bartik instrument	2.090***	24.125***
	(0.5938)	(4.7083)
year fe	✓	✓
LLM fe	✓	✓
F test	12.38	26.26
N	1,222	1,222

Standard errors clustered at LLM level * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The Table reports the coefficients for the first stage estimations in which we separately regress our treatment variables (equation 4 or 5) in 2005 and 2019 on the shift-share measure in equation 6, together with area and year fixed effects.

In Table 4, we report the second stage results of the instrumented versions of equation 2. Both Tables 3 and 4 refer to long-differences estimations, over the entire period 2005-2019. In Tables from A.5 to A.7 of the Appendix, we repeat the estimation clustering standard errors as suggested by Conley (1999). In this way, we verify that spatial correlation among neighbouring LLMs is not driving our results. Our main estimates are robust to different levels of spatial clustering, with buffers around the LLM's centroid of radius from 10 to 30 kilometres.

Comparing OLS to IV estimates, we can notice an increase in the employment coefficient and a decrease in the outmigration one, both becoming significant. We interpret these shifts in coefficients as evidence of a labour supply bias in the OLS estimates, which can be explained in terms of better amenities in areas with higher presence and/or inflow of knowledge workers. It is plausible that places growing in knowledge employment also improve on life quality, in the form of cultural initiatives and better services; a dynamics consistent with the theory of endogenous amenities described by Diamond (2016). Conversely, estimates of the impact of knowledge workers on wage premium return insignificant coefficients, differently from the positive ones of OLS estimates. This change is likely to derive from the definition of the outcome variable. Daily wage is the ratio between yearly labour income and days worked, which is also our proxy for employment. Therefore, these findings suggest that the positive effect on wages in the OLS estimation was only due to a downward bias in our measure for employment.

In sum, increases in the stock and inflow of knowledge workers determine a multiplicative effects on local employment, and a decrease in outmigration probability, whereas wages do not respond to these changes. Looking at the coefficients' size, an increase of 10 in the share of knowledge workers in the area rises local employment by 6% and reduces outmigration probability by 2%. The effect of knowledge migrations is smaller in magnitude, but significant and equally signed. These findings confirm our prior that migration responses are only one component of the overall effect of the rise in knowledge employment. Moreover, our results are consistent with the theoretical prediction of decreased outmigration, and support the claim of a local multiplier effect of knowledge employment, which - in our context - seems to dominate possible displacement effects. The insignificant effect on wages, instead, is quite interesting, considering that there is no institutional upward constraint to wages.

Looking for international comparisons, the What Works Centre for Local Economic Growth has published a toolkit on multiplier effects where they summarise empirical results obtained for various OECD countries.[39] 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, largely comparable to our findings, is considerably lower that the 1.88 average across OECD countries.[40] Furthermore, Auricchio (2015) does not

[39]The toolkit is publicly available at https://whatworksgrowth.org/resource-library/toolkit-local-multipliers/

[40]Our analysis is in relative terms. We find a 6% increase in non-tradable employment for a 10

find any significant effect for employment growth in generic tradable-industries, which confirms previous findings by De Blasio and Menon (2011). In other words, in Italy multiplicative effects on employment are smaller than in other countries. This plausibly relates to institutional factors, such as labour mobility and wage setting mechanisms, and thus to the dynamics on sorting and nominal *versus* real wages that we explore more deeply in the following sections.

Table 4: IV estimation, second stage results

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	-0.009 (0.0069)	0.006** (0.0031)	-0.002*** (0.0008)			
% knowledge migrants				-0.001 (0.0005)	0.001** (0.0003)	-0.0002** (0.0001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

Standard errors clustered at LLM level * p<0.10, ** p<0.05, *** p<0.01. The Table reports the coefficients for the first stage estimations in which we separately regress our treatment variables (equation 4 or 5) in 2005 and 2019 on the shift-share measure in equation 6, together with area and year fixed effects.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 equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are the area-year effects predicted from equation 1. 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 local workers in the LLM, to account for different precision in 1^{st}-step estimates.

7.3 The role of sorting

So far, we have treated sorting as an identification issue for our analysis. Not accounting for individual unobserved heterogeneity can bias the results if more productive workers self-select into areas with a higher presence or inflow of knowledge workers (Combes et al., 2008). However, it is worth investigating the relative contribution of sorting and cross-sector spillovers to the whole effect on labour outcomes. It could be the case that local workers increasingly sort in areas where the

points increase in the percentage of knowledge workers in the area. This result is on the intensive margin of employment, and the classifications of high-tech/knowledge workers may not perfectly overlap; still the magnitude of the effect seems very similar.

knowledge sector is growing more. Such a pattern would be part of the overall dynamics we aim to describe.

Therefore, we re-estimate the 1st-step regressions (equation 1) without individual fixed effects, and run the instrumented 2nd-step estimation employing as dependent variables the newly-computed area-year effects. Table 5 reports the second stage results of the IV estimation not accounting for sorting. The coefficient on employment is comparable to the one obtained with the inclusion of individual fixed effects. However, here we find a positive effect on wage which was absent in our main results (see Table 4). Moreover, the outmigration estimate appears insignificant when we do not account for individual sorting. These findings point to a self-selection of more productive and more mobile local workers into areas characterised by an increased presence of knowledge workers. Said differently, workers who are intrinsically more likely to migrate and to earn higher wages increasingly concentrate into 'knowledge-intensive' areas. This is consistent with an overall positive dynamics induced by the knowledge sector growth: it generates new labour opportunities, making the labour market more prosperous and dynamic, and thus more appealing to workers with higher expected wages and propensity to move.

Table 5: IV estimation, not accounting for sorting

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	0.008***	0.008***	-0.0010			
	(0.0015)	(0.0019)	(0.0009)			
% knowledge migrants				0.001***	0.001***	-0.0001
				(0.0002)	(0.0002)	(0.0001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

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 equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are the area-year effects predicted from equation 1,*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 local workers in the LLM, to account for different precision in 1^{st}-step estimates.

7.4 Nominal vs real wages

In the main analysis we focus on nominal wages. In this section, we aim to observe the impact on real living conditions in the area, and thus we investigate also the effect on real wages. If the employment growth in the knowledge sector increases the local cost of living, we could even observe a negative effect on real wages. This is particularly likely in our setting since *nominal* wages seem not to respond to the positive shock once we account for individual sorting.

To proxy for the cost of living at local level, we employ average house prices in the LLM.[41] Firstly, we employ house prices as a further dependent variable, to check the impact on the cost of living of employment growth in the knowledge sector. Secondly, we use them as a discounting factor for the area-year effects estimated in the 1st-step regression (equation 1) for wages. Since both the area-year effects and house prices are expressed in logs, we take the difference between those variables. We interpret that difference as real wage premium to work in the area.[42] We run all these estimations at the LLM level and instrument our treatments with the usual shift-share instrument. Table 6 reports IV estimates for regressions using as dependent variable minimum, maximum, and average (log) house prices in the LLM. For all these outcomes, we see a positive effect of employment growth in the knowledge sector. Therefore, areas attracting more knowledge workers become more expensive. This is consistent with an increased demand to reside in these areas, due to more and better labour opportunities locally available. Then, we con-

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

[42] For the properties of logarithms,

$$ln(\text{nominal wage}_{ct}) - ln(\text{house price}_{ct}) = ln\left(\frac{\text{nominal wage}_{ct}}{\text{house price}_{ct}}\right). \tag{9}$$

sider real wages as the difference between area-year estimates for (log) nominal wages and the (log) average house prices, and employ such difference as dependent variable. Table 7 displays the related results. We find a negative impact on real wages of employment growth in the knowledge sector: the cost of living increases, while nominal wages do not adjust accordingly.

Table 6: IV estimation: impact on house prices

	Local housing prices					
	Minimum	Maximum	Average	Minimum	Maximum	Average
% knowledge workers	0.026**	0.016*	0.020**			
	(0.0106)	(0.0085)	(0.0088)			
% knowledge migrants				0.002**	0.001	0.002**
				(0.0010)	(0.0008)	(0.0008)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,132	1,132	1,132	1,132	1,132	1,132

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 equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are minimum, maximum, and average house prices at the local level. Variables refer to 2005 and 2019, to estimate the model in long-differences. Regressors are our treatment variables (instrumented), area and year fixed effects.

Table 7: IV estimation, impact on real wages

	Real wages	
% knowledge workers	-0.029**	
	(0.0107)	
% knowledge migrants		-0.003**
		(0.0009)
year fe	✓	✓
LLM fe	✓	✓
N	1,132	1,132

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 equation 2, where the treatment variable is instrumented by the shift-share measure of equation 6. The outcome variable is the area-year effect predicted from equation 1 referring to wage, discounted by local housing prices. 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 local workers in the LLM, to account for different precision in 1^{st}-step estimates.

This pattern is consistent with previous evidence on the responsiveness of nominal and real wages in the Italian context. Belloc et al. (2023), for example, estimate the urban wage premium for Italy using INPS data. In nominal terms they do not find any significant premium, while in real terms the premium is actually negative.[43] These findings suggest that in the Italian context local prices are more reactive than nominal wages to local shocks. Therefore, real wage variations are negatively correlated with positive local demand shocks.

To provide some international comparisons, Moretti (2004a) 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. Looking at sector-specific shocks, Dix-Carneiro and Kovak (2019) highlight a negative wage impact of trade liberalisation on non-tradable workers in Brazil. Again, Marchand (2012) find a positive wage impact of energy booms for non-energy workers in Canada. Looking at the effect of immigration on natives wages in Germany, Ottaviano and Peri (2010) highlight that labour market rigidities influence the extent to which shocks translate into wage or employment effects. Not all these works account for the role of sorting, possibly overestimating wage responsiveness to local shocks. Still, it seems that in other institutional settings wages are more reactive to local conditions than in Italy. National-level wage bargaining could partially explain the non-significant effect on wages. However, the Italian wage-setting mechanism does not impose any upward limit to wage determination. In fact, when we do not account for unobserved individual heterogeneity, we find a positive impact on nominal wages. Such evidence suggests that nominal wages have some upward flexibility, but this goes to attracting inherently better workers to the local labour market, and does not translate into a proper wage effect. In other words, the positive labour demand shock creates better labour opportunities which are filled by more productive workers, so that we do not observe an increase in nominal wages

[43]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 the spatial variation in the local cost of living. Moreover, according to the theoretical framework proposed by Rosen-Roback, in equilibrium any shock to the local demand or supply of labour is fully capitalised into house prices (Roback, 1982). Therefore, we just focus on housing price indexes to compute real wages.

when accounting for individual fixed effects.

8 Concluding remarks

In this paper, we investigate the effect of employment growth in knowledge-intensive activities on the labour outcomes of local workers. Specifically, we look at wage, employment and outmigration probability of other workers in non-tradable sectors. We separately investigate the impact due to the change in the percentage of knowledge-sector employment, and to inflows of workers in this sector. In this way, we disentangle the effect's component attributable to internal migrations of knowledge-sector workers. Moreover, thanks to the richness of our panel data, we are able to distinguish the role played by individual sorting from that of local spillovers. We study the Italian context, between 2005 and 2019. Our analysis provides a number of results.

First of all, we find no effect on *nominal* wage induced by the increase in employment in knowledge-intensive activities. This is consistent with the expectation of wages being not particularly reactive to local labour conditions, in a context characterised by industry-level national bargaining. Instead, living costs (proxied by house prices) positively respond to the employment growth in the knowledge sector, resulting in a negative impact on local *real* wages. Secondly, we find evidence of multiplicative employment effects, which implies that displacement of non-tradable workers from their sectors is not a dominant force in this context. Conversely, our results are consistent with the hypothesis of a local multiplier effect. This may act through an increase in consumer demand for local services, intermediate service demand by local firms, productivity spillovers, or a combination of such mechanisms. In this work, we are not able to disentangle the effect component due to each specific channel. Our findings refer to the aggregate effect, while we leave for future investigation the estimation of channel-specific effects. Thirdly, the evidence of decreased outmigration probability is perfectly in line with the theoretical predictions of an increased labour demand in non-tradable sectors induced by the growth in knowledge workers, thus reducing incentives to migrate. In other words, the positive demand shock brought by the rise of the knowledge economy increases the attractiveness of the LLM, and fosters agglomeration processes. The reduction in real wages may partly counterbalance that overall positive dynamics. Specifically, if wages were more flexible – and thus adjusted to rising living costs -, the impact in terms of internal migrations would probably be even larger.

Those findings hold for both our treatments, the percentage variation in knowledge workers and their net migration rate. The effects are smaller in size in the case of knowledge workers migrations, consistent with our prior of migration being only a component of the overall adjustment process to labour demand shocks.

The above results are cleaned by the confounding dynamics of workers sorting based on unobservables. However, this latter mechanism is part of the overall process that we aim to describe. Comparing estimates that do or do not account for unobserved individual heterogeneity, we can identify the role of sorting in labour market changes. We detect a self-selection of more productive and more mobile workers in areas with an increased presence of knowledge workers. This is consistent with an overall positive dynamics induced by the knowledge sector growth: it generates new labour opportunities, making the labour market more prosperous and dynamic, and thus more appealing to workers with higher expected wages and a propensity to move.

If we combine those results with the evidence of a rise in the knowledge economy which is not uniform across space, we get a picture that resembles 'the great divergence' process described by Moretti (2012). *Some* LLMs benefit from the technological change, attract qualified workers and experience positive multiplicative effects in other local sectors. The rest of the country, instead, lags behind, losing human capital and suffering from negative circular dynamics at the local level. Therefore, our findings seem to support the claim that the uneven growth of the knowledge economy with its related internal migrations contributes to spatial inequalities. We do not investigate whether these dynamics generate aggregate gains at National level or they are simply a zero sum game among local labour markets. In either case, enlarging spatial inequalities can represent a relevant policy issue. For example, some workers may face mobility constraints preventing them from relocating closer to economic opportunities. Alternatively, some people may have strong idiosyncratic preferences for living in areas 'left behind' by the economic change, and be forced to move by the lack of qualified labour demand in those places. This internal 'brain drain' contributes to the decline of these areas, leaving untapped their economic potential. Finally, it is not obvious that more dynamic areas are prepared to host workers re-locating from places with few job opportunities. These internal migrations - if not properly addressed by policymakers - can lead to congestion and worsened living conditions in the destination areas. Assuming that decision-makers care about territorial disparities, our results entail relevant policy implications. The analysis provides evidence of the external effects induced by government policies affecting the local decision of knowledge-intensive industries. If we wish to contain regional divergence, public intervention should be directed to mitigate the economic disadvantages of left-behind places and their inhabitants, who cannot or will not move. This may imply different and complementary policies, including the promotion of alternative sector-specialisation or facilitating the spreading of the benefits of the knowledge economy to less attractive areas.

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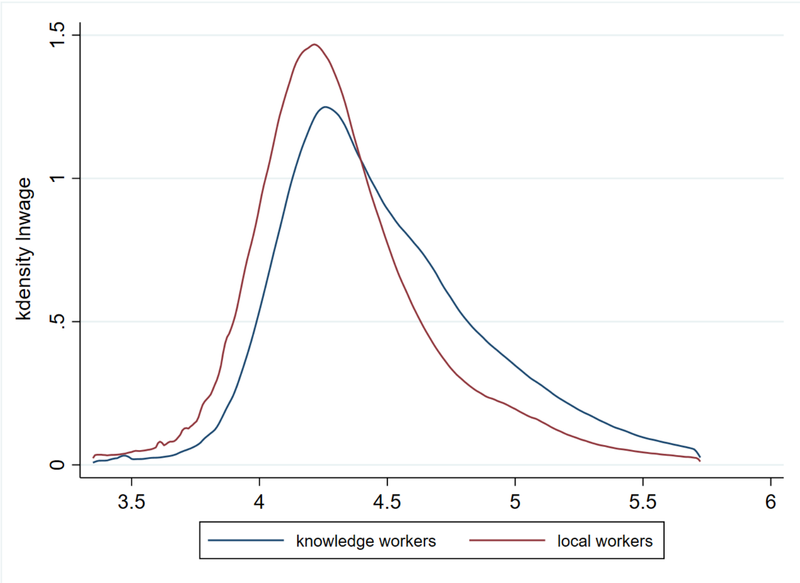
Appendix

Table A.1: Distribution of (non-)knowledge-sector workers by education group and job position

	Knowledge sector	Non-Knowledge sector
Panel a. Education group		
% High-school dropouts	24.07	41.72
% High-school diploma	47.21	44.09
% College degree	25.51	12.14
% Master or PhD	3.21	2.05
Total	100	100
Panel b. Job position		
% Blue collar workers	27.98	57.33
% White collar workers	61.42	33.56
% Managers	6.17	3.17
% Apprentices	3.43	5.64
Total	100	100

The Table reports the percentages of workers in each education group and job position inside and outside the knowledge sector. Panel a. focus on the years 2017-2019, for which the percentage of missing information is reduced to a 22%. Panel b., instead, refers to the full sample over the 2005-2019 period.

Figure A.1: (log) wage distribution of knowledge-sector and non-tradables workers



The graph visualises the (log) wage kernel distribution of knowledge-sector and non-tradable workers.

Figure A.2: The knowledge sector

		Knowledge-intensity	
		High	Low
Tradability	High	Knowledge workers	
	Low	Local workers	

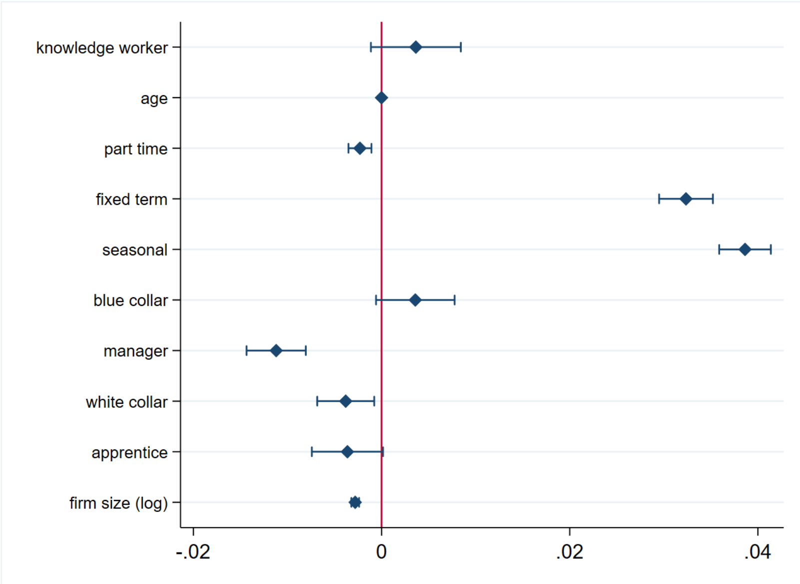
The graph visualises the definition of knowledge and local workers: respectively, workers of tradable and knowledge-intensive sectors, and workers of non-tradable industries.

Table A.2: Sector codes in the knowledge sector (4-digit)

Code	Description
910	Support activities for oil and natural gas extraction
990	Support activities for the extraction
1910	Manufacture of pitch and pitch coke
1920	Oil refineries and manufacture of refined petroleum products
2110	Manufacture of basic pharmaceutical products
2120	Manufacture of medicinal products and other pharmaceutical preparations
2612	Manufacture of assembled electronic boards
2620	Manufacture of computers and peripheral equipment
2630	Manufacture of other electrical and electronic telecommunications equipment, radio and television transmitter, anti-theft and fire protection systems
2640	Manufacture of sound and image reproducing and recording apparatus, video game consoles (excluding electronic games)
2651	Manufacture of instruments for navigation, hydrology, geophysics and meteorology, flame and combustion detectors, mine, motion detectors, pulse generators and metal detectors, other measuring and regulating apparatus, drawing instruments, meters for electricity, gas, water and other liquids
2652	Manufacture of watches
2660	Manufacture of irradiation equipment for food and milk and other irradiation instruments and other electrotherapeutic equipment
2670	Other irradiation instruments and other electrotherapeutic equipment, photographic and cinematographic equipment, optical measuring and control equipment
2680	Manufacture of magnetic and optical media
5110	Scheduled passenger air transport, non-scheduled passenger air transport; charter flights
5121	Air cargo transport
5122	Space transport
5811	Publishing of books
5812	Publication of lists
5814	Publishing of journals and periodicals
5819	Other publishing activities
5821	Edition of computer games
5829	Edition of other package software (excluding computer games)
5911	Motion picture, video and television production activities
5912	Film, video and television post-production activities
5913	Motion picture, video and television programme distribution activities
5914	Activities of film projection
5920	Printed music edition and sound recording studios and edition
6110	Fixed telecommunications
6120	Mobile telecommunications
6130	Satellite telecommunications
6201	Production of software not related to the edition
6202	Consultancy in the field of information technology
6203	Management of hardware IT facilities and equipment - housing (excluding repair)
6311	Electronic accounting data processing (excluding Tax Assistance Centres - Caf), database management, other electronic processing of data
6312	Web portals
6391	Activities of news agencies
6399	Other information services activities
6420	Activities of holding companies (holding companies)
6430	Mutual funds (open and closed, real estate, securities market), Sicav (Variable Capital Investment Company)
6491	Financial leasing
6492	Activities of credit guarantee consortia and other credit activities
6499	Brokering activities, merchant bank, factoring
6511	Life insurances
6512	Other insurance activities
6520	Reinsurance activities
6530	Pension funds

6611	Administration of financial markets
6612	Trading of securities and commodities contracts
6619	Credit card payment processing activities, money transfer, financial promoters, activities of Administrative Trustees
6621	Activities of independent insurance valuers and liquidators
6622	Insurance agents, brokers and other insurance intermediaries
6629	Central supervisory authorities for insurance and pension funds and auxiliary activities
6630	Management of mutual funds and pension funds
6910	Activities of notarial and law studios
7010	Activities of holding companies engaged in management activities
7021	Public relations and communication
7111	Activities of architectural firms
7112	Activities of engineering studies, cartography and aerophotogrammetry activities, technical activities carried out by surveyors
7211	Research and experimental development in biotechnology
7219	Research and experimental development in other natural sciences and engineering
7220	Research and experimental development in the social sciences and humanities
7311	Conducting marketing campaigns and other advertising services
7312	Activities of concessionaires and other advertising agents
7320	Market research and opinion polls
7410	Fashion design and industrial design activities, graphical and web design
7430	Translation and interpretation
7490	Consulting on safety, agriculture and other technical issues; weather forecasts; entertainment and sports agencies and agents or prosecutors; technical activities carried out by industrial experts
7810	Search, selection, placement and support services for personnel relocation
7820	Activities of temporary work agencies (temporary agency work)
7830	Other human resources supply and management activities (staff leasing)
7911	Activities of travel agencies
7912	Tour operators
8411	General planning activities and general statistical services; activities of central and local legislative and executive bodies; financial administration; regional, provincial and municipal administrations
8421	Foreign affairs
8422	National defense
8423	Justice and judicial activities
8424	Public order and national security
8559	Language courses, training and retraining courses, other educational services
8560	School counselling and guidance services
9001	Activities in the field of acting and other artistic representations
9002	Rental with operator of structures and equipment for events and shows, other support activities for artistic performances, directing
9003	Activities of independent journalists, conservation and restoration of works of art, other artistic and literary creations
9004	Management of theatres, concert halls and other artistic structures
9102	Museum activities
9103	Management of historical sites and monuments and similar attractions
9104	Activities of botanical gardens, zoos and nature reserves
9411	Activities of employers' organizations, industrial federations, commerce, craft industries and services, associations, unions, federations between institutions
9412	Activities of professional federations and councils and colleges
9420	Activities of trade unions
9492	Activities of political parties and associations
9499	Activities of organisations for international cooperation and solidarity, filanthropy, cultural organisations, organisations for human and animals rights
9900	Extraterritorial organisations and bodies

Figure A.3: Likelihood of moving by worker characteristics

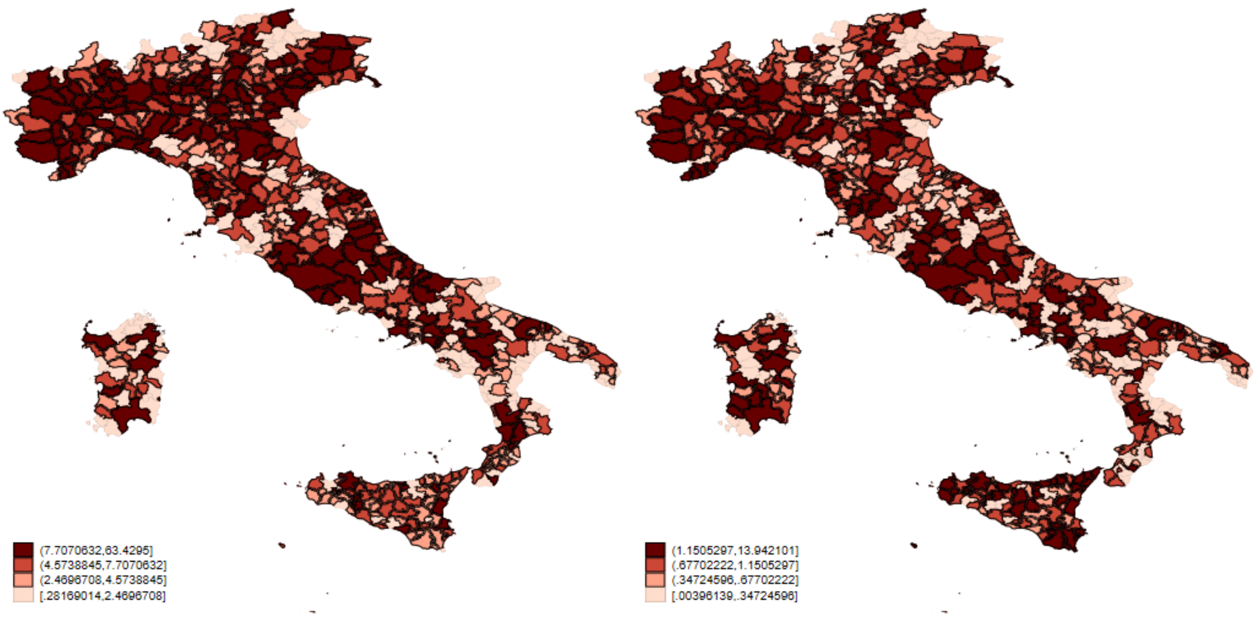


The graph reports the estimated coefficients from a regression of outmigration probability on a set of individual characteristics (2005-2019). We also include in the specification individual and LLM-year fixed effects, and 2-digits sector fixed effects.

Figure A.4: 2005 % knowledge workers

Observed

Predicted



The maps report the percentages of knowledge workers by LLM in 2005, observed (Panel a) and predicted by the instrument (Panel b).

Table A.3: Shift-share diagnostics

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.052	-0.003	0.047
Positive	1.054	0.016	0.953

Panel B.1: Correlations of Industry Aggregates _ Wage

	α_s	$\%S$	β_k	F_s	Var$(w_{s,95})$
α_k	1				
$\%S$	0.215	1			
β_s	0.048	-0.206	1		
F_s	-0.112	-0.042	0.003	1	
Var$(w_{s,95})$	0.376	-0.029	0.162	-0.123	1

Panel B.2: Correlations of Industry Aggregates _ Employment

	α_s	$\%S$	β_s	F_s	Var$(w_{s,95})$
α_s	1				
$\%S$	0.215	1			
β_s	0.048	-0.181	1		
F_s	-0.112	-0.042	0.021	1	
Var$(w_{s,95})$	0.376	-0.029	0.190	-0.123	1

Panel B.3: Correlations of Industry Aggregates _ Outmigration

	α_s	$\%S$	β_s	F_s	Var$(w_{s,95})$
α_s	1				
$\%S$	0.215	1			
β_s	0.089	-0.128	1		
F_s	-0.112	-0.042	-0.056	1	
Var$(w_{s,95})$	0.376	-0.029	0.014	-0.123	1

Panel C.1: Top 5 Rotemberg weight industries _ Wage

	$\hat{\alpha}_s$	$\%S$	$\hat{\beta}_s$	Ind Share
Law firms	0.107	0.236	0.003	43.710
Reinsurance	0.263	0.364	0.003	76.190
Staff leasing	0.076	4.855	0.003	0.947
Organisations for citizens' rights	0.069	0.393	0.010	20.122
Judicial activities	0.076	0.219	0.006	35.890

Panel C.2: Top 5 Rotemberg weight industries _ Employment

	$\hat{\alpha}_s$	$\%S$	$\hat{\beta}_s$	Ind Share
Law firms	0.107	0.236	0.004	43.710
Reinsurance	0.263	0.364	0.004	76.190
Staff leasing	0.076	4.855	0.004	0.947
Organisations for citizens' rights	0.069	0.393	0.005	20.122
Judicial activities	0.076	0.219	0.005	35.890

Panel C.3: Top 5 Rotemberg weight industries _ Outmigration

	$\hat{\alpha}_s$	$\%S$	$\hat{\beta}_s$	Ind Share
Law firms	0.107	0.236	-0.00003	43.710
Reinsurance	0.263	0.364	0.00003	76.190
Staff leasing	0.076	4.855	-0.0003	0.947
Organisations for citizens' rights	0.069	0.393	-0.0004	20.122
Judicial activities	0.076	0.219	-0.0002	35.890

The table reports the IV diagnostics as suggested by Goldsmith-Pinkham et al. (2020). Panel A reports the sum, the mean and the share of negative and positive Rotemberg weights α_s. Panel B reports correlations between the weights (α_s), the 2005-2019 industry employment shares within the knowledge sector at national level ($\%S$), the just-identified coefficients (β_s), the related first stage F-statistics (F_s) and the variance in past industry shares (Var($w_{s,95}$)). Panel C reports the top five industries according to the Rotemberg weights. The coefficients $\hat{\beta}_s$ are based on the regression of Table 4, where we regress our outcomes of interest (wage, employment and outmigration) on treatment ($KW1$), LLM and year fixed effects, and weight by the number of observations employed in the 1st-step estimation (1). We computed the Rotemberg decomposition using the *bartik_weight* Stata package.

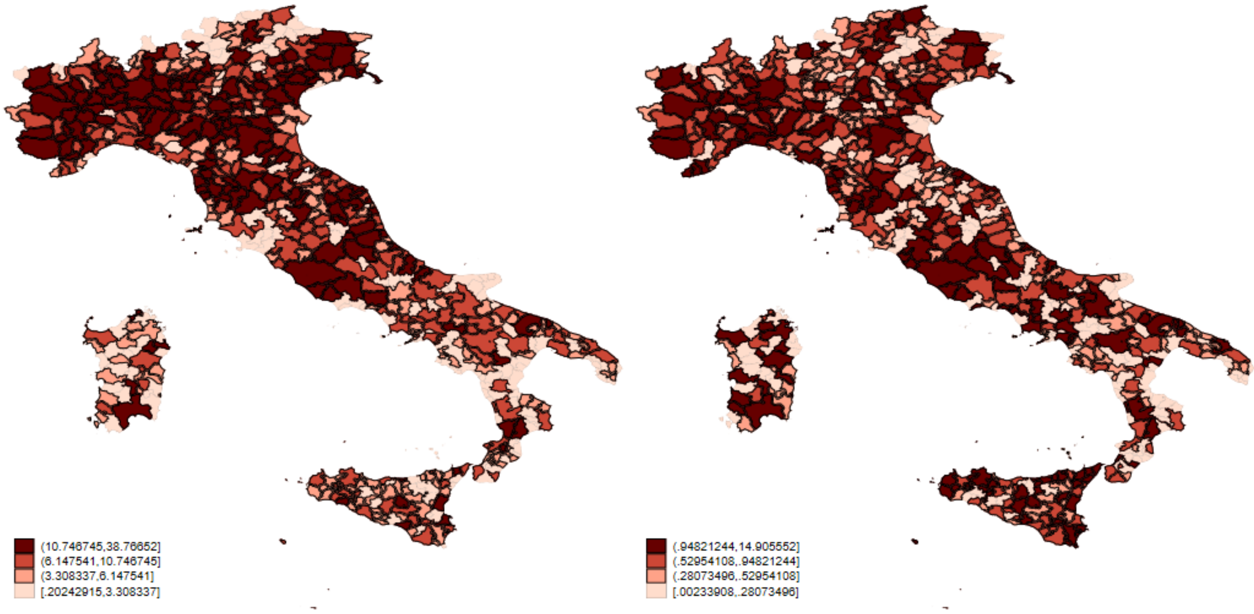
Table A.4: Correlation between Top 5 Rotemberg weight industry shares and LLM characteristics

	Law firms	Reinsurance	Staff leasing	Organisations for citizens' rights	Judicial activities
Δ numb. of firms	0.00018	-0.00036	-0.00001	0.00006	0.00055
	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0004)
Numb. of firm births	0.00001	0.00025*	0.00001	0.00002	-0.00025
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Employees growth rate	0.11872	-0.69713	0.01353	-0.05517	-4.77037
	(0.1386)	(0.4327)	(0.0153)	(0.1078)	(5.5580)
N	604	604	604	604	604

Standard errors clustered at LLM level * p<0.10, ** p<0.05, *** p<0.01. The Table reports the estimated correlation between past shares (1995) of the top 5 Rotemberg weight industries and LLM characteristics over the period 2001-2004. Regressors of the OLS estimation include the variation in the number of local firms, the number of newly created firms (births), and the growth rate of employees of local firms. Observations are reduced to 604 since we exclude the 7 LLMs that had no knowledge workers in 1995.

Figure A.5: 2019 % knowledge workers

Observed Predicted



The maps report the percentages of knowledge workers by LLM in 2019, observed (Panel a) and predicted by the instrument (Panel b).

Table A.5: IV estimation: second stage results, Conley-standard errors using buffers of 10km radius

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	-0.009 (0.0069)	0.006** (0.0031)	-0.002*** (0.0008)			
% knowledge migrants				-0.001 (0.0005)	0.001* (0.0003)	-0.0002** (0.0001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

Standard errors clustered using the method by Conley (1999) * p<0.10, ** p<0.05, *** p<0.01. Here we employ buffers of 10km around the LLM's centroid. The Table reports the estimated coefficients from the second stage regression corresponding to equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are the area-year effects predicted from equation 1. 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 local workers in the LLM, to account for different precision in 1st-step estimates.

Table A.6: IV estimation: second stage results, Conley-standard errors using buffers of 20km radius

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	-0.009	0.006*	-0.002**			
	(0.0069)	(0.0032)	(0.0008)			
% knowledge migrants				-0.001	0.001*	-0.0002**
				(0.0005)	(0.0003)	(0.0001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

Standard errors clustered using the method by Conley (1999) * p<0.10, ** p<0.05, *** p<0.01. Here we employ buffers of 20km around the LLM's centroid. The Table reports the estimated coefficients from the second stage regression corresponding to equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are the area-year effects predicted from equation 1. 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 local workers in the LLM, to account for different precision in 1st-step estimates.

Table A.7: IV estimation: second stage results, Conley-standard errors using buffers of 30km radius

	Wage	Employment	Outmigration	Wage	Employment	Outmigration
% knowledge workers	-0.009	0.006*	-0.002***			
	(0.0070)	(0.0034)	(0.0008)			
% knowledge migrants				-0.001	0.001*	-0.0002**
				(0.0005)	(0.0003)	(0.0001)
year fe	✓	✓	✓	✓	✓	✓
LLM fe	✓	✓	✓	✓	✓	✓
N	1,222	1,222	1,222	1,222	1,222	1,222

Standard errors clustered using the method by Conley (1999) * p<0.10, ** p<0.05, *** p<0.01. Here we employ buffers of 30km around the LLM's centroid. The Table reports the estimated coefficients from the second stage regression corresponding to equation 2, where the treatment variable is instrumented by the shift share measure of equation 6. The outcome variables are the area-year effects predicted from equation 1. 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 local workers in the LLM, to account for different precision in 1st-step estimates.