Returns to Experience Across and Within Cities

Donald R. Davis (Columbia University and NBER),
Eric Mengus (HEC Paris and CEPR),
Tomasz K. Michalski (HEC Paris),
Elie Vidal-Naquet (Université Paris-Dauphine)

March 26, 2026

WORK IN PROGRESS, NOT FOR CIRCULATION

Abstract

A growing literature in regional, urban, and labor economics considers the origin of urban and skill premia in wages that rises with city size and density. An area of contest has been the extent to which these premia are explained by the sorting of firms and skills versus location effects in both levels and dynamics. We argue that resolving this dispute requires a focus on the spatial resolution of the inquiry. The traditional AKM approach focuses on the commuting zone as the appropriate spatial unit, since this defines the labor market for matching. However a rich literature in urban economics focuses on spatial heterogeneity within cities, especially the role of job-dense central business districts. These may have a quite distinct character that promotes knowledge spillovers, with consequences for wages. In this paper, we pursue this insight by using geocoded French administrative data that allows us to distinguish between high and low job-density locations and so to consider both within and between city differences. We also partition jobs along an axis with high versus low analytical and interpersonal skills that may matter differently in different locations. We estimate both localized and occupation-specific returns to experience. We find that a small number of highly dense areas within large cities are at the apex of both the dynamic and static components of the urban wage premium. After ten years of experience, workers in analytical and interpersonal occupations in the 50 densest km^2 of the Paris metropolitan area earn dynamic wage gains 3.4 times higher than similar workers elsewhere in Paris (+88pp vs. +26pp), relative to workers outside large cities. Occupations involving high computer use display particularly strong gains, suggesting that task content and local job density jointly shape wage trajectories. Controlling for establishment fixed effects or the time evolution of job type wages at the area level does not qualitatively change our results.

1 Introduction

Large, dense cities pay an urban wage premium (Combes et al., 2008; Baum-Snow and Pavan, 2011; Ahlfeldt and Pietrostefani, 2019) and higher skill premia (Bacolod et al., 2009; Baum-Snow et al., 2018; Koster and Ozgen, 2021). These advantages are not only static, but also dynamic (Glaeser and Maré, 2001; de la Roca and Puga, 2017). These are central facts anchoring theory and empirics in regional and urban economics. In recent years, they have also figured more prominently in discussions of wage determination in labor economics, particularly work building on the framework of Abowd et al. (1999), as in Card et al. (2025).

Traditional theoretical models trace the productivity advantages of large cities to matching, sharing, and learning in labor and product markets because of static (Duranton and Puga, 2004) or dynamic agglomeration economies (Glaeser and Maré, 2001; de la Roca and Puga, 2017), and skill-biased interactions (Davis and Dingel, 2019).

A substantial literature estimates the magnitude of these wage premia. Denser locations have more productive firms (Combes et al., 2012) as well as stronger assortative matching between workers and firms (Dauth et al., 2022). Recent theoretical approaches have modeled how these urban advantages have synergies with heterogeneous firms and workers sorting across cities (Davis and Dingel, 2020; Gaubert, 2018). These theories have pointed out that, in the limit, synergistic sorting of workers and firms may take place in the presence of vanishingly small productivity differences across locations (Oh, 2024).

This body of research has powerfully raised the question of how much of the observed urban wage premia is due to location or city effects and how much simply to sorting of workers and firms. Insights into this question have come from two primary strands of empirical research. One investigates the microeconomic mechanisms of the productivity advantage of cities (Davis and Dingel, 2019; Lhuillier, 2023). Many of these have focused on approaches to measuring knowledge spillovers within cities, at small spatial scales, and even within buildings (Arzaghi and Henderson, 2008; Baum-Snow et al., 2024). Broadly, such studies have concluded that one can measure the nature and value of some of these spillovers in credible ways.

The second strand of recent literature has built on the AKM and related approaches to estimating the determinants of wages and wage growth. Card et al. (2025) find roughly equal roles for location effects and sorting. However, a number of recent contributions have argued that after accounting for sorting, both static and dynamic premia for larger cities may be tiny (Carry et al., 2025; Oh, 2024; Adenbaum et al., 2025).

The papers arguing that place effects are essentially null provide a fundamental challenge to the way that economists have thought about why wages differ across cities, indeed even why the size differences across cities exist. There is thus a strong tension in the two major strands of empirical literature on this question: The empirical literature on knowledge spillovers contributing to productivity is providing growing evidence of their importance, yet some of the most recent contributions to the AKM wage determination literature are arguing that these forces by contrast must be quite weak.

In these discussions, decisions about the spatial resolution of the data loom large. Research within the AKM approach has considered the ideal unit of aggregation as the commuting zone. The logic of this is straightforward. Commuting zones, defined by home-workplace flows, are viewed as the relevant geography within which firms and workers match.

Thus place effects in the AKM literature are defined as commuting zones precisely because they represent the relevant labor market. To state this is immediately to recognize its critical limitation. This geography recognizes that New York is not Denver is not Des Moines. But it fails to recognize that Manhattan is not Queens is not Staten Island. That is, it fails to recognize that even if the commuting zone is the relevant labor market, it may not be the proper spatial unit for thinking about place effects that may reflect *inter alia* knowledge spillovers.

An extensive literature within urban economics considers the heterogeneity of employment and production inside the city or commuting zone (Lucas and Rossi-Hansberg, 2002). A first observation is the tremendous concentration of employment within central business districts (Ahlfeldt et al., 2024). Outside of the AKM framework, there is evidence for the United States that some superstar zip codes feature wage growth dramatically higher than other zip codes in the same commuting zone (Acosta et al., 2024). These facts are consistent with research on within-city land values, which demonstrate steep gradients in dense areas and the fact that both the premia and gradients tend to be greater in large cities (Albouy et al., 2018).

This message is strongly reinforced when we examine the literature that considers the microeconomic mechanisms of agglomeration, particularly knowledge spillovers (Rosenthal and Strange, 2020). Early work on the advertising industry in New York City in the area of Madison Avenue, emphasizes that a measure of spillovers reaches across blocks, not miles (Arzaghi and Henderson, 2008). Research at a highly granular level, within and between buildings inside of a downtown, reinforces this conclusion (Baum-Snow et al., 2024). Similarly, research on spillovers between people from different firms emphasizes the role of serendipity, particularly available in areas of dense employment (Atkin et al., 2022; Jacobs, 1992).

Robert Lucas famously asked the question: "What can people be paying Manhattan or Downtown Chicago rents for, if not for being near other people?" (Lucas, 1988). These frontier contributions in the AKM tradition have answered that it's really about sorting into the commuting zone. But the microeconomic mechanism literature we have referenced highlights that Lucas's question is about *the dense areas of the commuting zone*. Once firms and workers have sorted into the same commuting zone, why are they then paying spectacularly high prices to be in the dense central business district of that commuting zone? Our perspective is that there can be no adequate answer that doesn't involve strong equilibrium place effects.

In this paper, our central contribution will be to change the spatial resolution with which we approach the idea of location effects. This will bring our AKM approach in line with the new literature on the importance of knowledge spillovers to productivity in cities. Specifically we will focus on employment density as defining the relevant places that matter for the AKM place effects. This is made possible by the fact that the French employer-employee data is geo-coded at the establishment level. Having changed the definition of the relevant locations for our study also invites other amendments to the AKM structure. One is to reexamine how to approach the occupations and tasks performed in different jobs. We will take a stand about the most useful way to partition the jobs in dimensions that highlight the different opportunities and outcomes.

These two dimensions of change also interact importantly. The differences across jobs may depend on where in the city those jobs are performed, in high versus low job density

locations. Our results suggest that the heterogeneity across both locations inside the city and jobs is overwhelmingly about differences in dynamic returns. Our results also emphasize that the heterogeneity within cities can be as much or even more important than the heterogeneity across cities. The magnitudes of these effects vary greatly depending on the nature of the job performed as well as where it is performed. We believe that these results, tying together heterogeneity within cities, across jobs, and across cities, should call forth a rethinking of the sources of differences across cities as well as the forces that hold together the multiple locations and job types inside of cities.

Our point of departure is an applied framework inspired by Davis and Dingel (2019) in a dynamic setting where we explicitly model worker learning and acquisition of experience by location and occupation.[1] We start by reevaluating the earlier empirical implementation of those ideas in de la Roca and Puga (2017), who found that workers in larger cities experience dynamic learning gains in the largest cities throughout their careers to a greater extent than their peers in smaller locations. Moreover these gains are partially preserved should they move to smaller cities, which the authors take as evidence of learning in large cities.[2] The implications of this are profound: passage through a large city greatly boosts an individual's productivity and wages.

We start where de la Roca and Puga (2017) stopped and revisit their findings. Are the earnings gains available to all workers in large metropolitan areas or are they available in only a few locations? Are they available to workers independent of their occupation or do they depend on the skill or task characteristics of the occupation? To what extent they reflect prior experience in specific jobs performed in particular areas? Are the gains portable when workers move out of these places, consistent with the learning hypothesis? Is the extent of portability affected by whether movers are across- or within-firm? Is portability from large, dense cities constrained by the types of jobs available in smaller, less-dense locations?

To answer these questions, we employ detailed geocoded French administrative data. We build on the prior literature to show that the productivity advantage of large cities are due to a very limited set of locations with highly concentrated economic activity. In the case of France, we show this is focused on the core areas of Paris (e.g. densest $50km^2$). Moreover, these gains are largely limited to occupations that feature both highly analytical and interpersonal tasks and at the same time require extensive computer use.[3][4] Dynamic earning gains depend on precise within-city location, a feature ignored in many studies, as for example Card et al. (2025). They are not confined to particular sectors, but rather to different types of jobs across diverse sectors. As such, neither traditional localization nor urbanization economies suffice to explain the observed wage premia of workers in the densest locations in a city. Importantly, as well, the heterogeneity and extent of dynamic experience gains across jobs is not fully captured by conventional skill measures such as college education levels or the CS1-based hierarchical classification used in French data (Caliendo et al., 2015).

[1] See also Crews (2024) for a dynamic application of the Davis and Dingel (2019) model.

[2] See also Eckert et al. (2022) for causal evidence based on refugees in Denmark.

[3] More precisely, the gains arise mainly for jobs with task intensity scores above the U.S. average in terms of non-routine analytical (reading + thinking) & non-routine interpersonal (personal interactions + guiding/coaching) plus high computer use dimensions according to the classification of Caunedo et al. (2023).

[4] Bacolod et al. (2009) document existence of urban wage premia for workers with high cognitive and people skills.

Moreover, accounting for experience specifically in highly analytical and interpersonal jobs with high computer use in dense areas is critical in understanding the evolution of urban wage premia over the life cycle. The existing literature neglects these key distinctions.

For example, in the Paris agglomeration, the 2% of locations with the highest job density, which we define as the Paris "core", contain 27% of the entire metropolitan area employment. The difference in the static and dynamic wage gains after 10 years of work experience within highly analytical and interpersonal jobs in this core in comparison to work experience in the same occupations in the rest of France excluding the largest cities is respectively 15pp and 82pp. At the same time, such gains from 10-years of work experience in the same occupations in less job-dense areas of Paris are much more modest, yielding an 9pp static and 20pp dynamic premium over the rest of France. Moreover, such premia are much lower for jobs not requiring analytical and interpersonal tasks. Furthermore, we document a rapid decay of such gains even in the densest areas with total gains after 10 years decreasing by 42pp as the place of work changes from the "hypercore", the densest 10^2 km to the remainder of the "core" – the densest $50^2 km$ in Paris. Our findings suggest experience gains are linked both with characteristics like local job density and occupation task content rather than solely job location in large MSAs.

Job density is thus an important characteristic in explaining local learning effects. Furthermore, earning profiles in dense locations are markedly different (in terms of intercept and slope) than in non-dense ones, especially for occupations that require both high interpersonal and analytical skills, requiring high computer use. We find that static premia vary modestly across locations of differing density within a city. However, dynamic premia vary greatly by density and also at small geographical scales, suggesting strong local agglomeration effects for workers (akin to what Arzaghi and Henderson (2008) find for firms in one industry - advertising). Our results survive a wide battery of robustness tests, reassuring us that the patterns we observe is not due to time-variation of wages in certain jobs due to technological changes that increase their productivity nor to the mere presence of establishments paying high wages (with high fixed effects).

Our results speak to a variety of literatures. They relate to the study of static and dynamic urban wage premia (e.g., de la Roca and Puga, 2017; Card et al., 2025; Lhuillier, 2023; Niebuhr et al., 2024); skill sorting (e.g., Eeckhout et al., 2014; Davis and Dingel, 2020; Oh, 2024); establishment and skill sorting (Carry et al., 2025); assortative matching in cities (e.g., Dauth et al., 2022; Carry et al., 2025; Adenbaum et al., 2025); within-firm labor markets (e.g., Cestone et al., 2023); and the differential benefits of location across skill types of workers (e.g., Hornbeck and Moretti, 2024). We contribute to this literature in three important dimensions. First, we explore whether these gains are available everywhere in large cities or within those cities only in the areas of greatest job density. Second, we study how these gains are attainable for occupations of different characteristics. Thus we focus our study on worker earnings throughout their careers taking into account both localized place of work and occupation task characteristics. Third, we shed light on the results of the active research (e.g., Carry et al., 2025) claiming that place effects are much weaker than previously estimated. Our focus on dynamic gains in the densest subset of locations revisits the claim that agglomeration effects are unimportant.

The role of interpersonal, social or interactive skills have been emphasized recently in multiple literatures. For example, Deming (2017) show how these skills have experienced

higher returns in the labor market. Bacolod et al. (2009) show that workers with cognitive and interpersonal skills have higher urban wage premia while Michaels et al. (2018) document the increasing specialization of cities in occupations intensive in these skills over the very long run. Our findings confirm the importance of these skills but with three important distinctions. We first give direct evidence of the importance of such skills for agglomeration gains as captured by dynamic earning gains. Second, we show that interpersonal skills are important but mainly in small subsets of locations in large cities and, third, only when they are associated with analytical skills and relatively high computer use.

Our results also matter for policy questions. If broadly large cities are more productive places, to what extent should government subsidize lower income individuals to locate there? Moretti (2012) argues in favor of mobility vouchers, speaking partly about unemployment differences across space, but also extolling the wage benefits to all locations in larger cities. Autor (2019) cites the diminution of an urban wage premium for high school graduates as a critical element in the declining fortunes of the less skilled in US cities. New York City has had an ongoing declared rent emergency since World War II, that in practice preserves in excess of 1 million low cost, low quality rental units there that act as an effective subsidy for low income workers who would want to rent in that segment. In France, the law requires communes in metropolitan areas to have a minimal share of social housing in order to reduce social segregation and minimize commuting distances within metropolitan areas; some communes such as Paris have set inclusive objectives as high as 40% of housing.[5] But if the benefits from being in the large city are restricted to those with select skills working in the densest employment centers in the city, what objective are we attaining with large subsidies to make the non-core commuting zone where these effects may be weak more accessible to the less skilled?

Thus understanding with greater richness for whom both static and dynamic benefits of being in large cities is valuable would help to inform such discussions.

2 Data

As a base we use the Panel-DADS data set constructed by the INSEE from the French social security data. This data set allows us to track all work spells of individuals through time for a 1/24 or (since 2003) 1/12 sample of the entire population. The variables employed include wages, hours worked, work experience, occupation, firm and plant place of work, employment dates at a plant, and demographic variables such as age and sex. Firm and plant details include location (commune), sector and legal status.

We can use other datasets curated by the INSEE to add information. For example, we use the LIFI data set to construct business groups to study internal firm labor markets.

[5]The "loi Solidarité et renouvellement urbain" or "loi SRU", introduced in 2000, defines a minimum share of social housing for communes with more than 3,500 inhabitants within metropolitan areas of more than 50,000 inhabitants (1,500 in the Paris area). This minimal share was initially 20% of dwellings and it was increased to 25% in 2013. In November 2022, Mairie de Paris has set an objective of 40% of public housing with 30% of social housing and 10% of publicly-owned housing with "affordable" rents.

2.1 Geography in this paper

We define as a city or MSA an urban area ("unité urbaine") in the definition and territorial assignments of the INSEE as of 2010. Such urban areas are composed of individual communes – the smallest French administrative unit.

Using these MSAs we can obtain a partition of France for the location experience is gathered, reproducing as a starting point the type of territorial split of Spain in de la Roca and Puga (2017). At the outset, we consider a division of France into three areas: (i) the largest city, Paris; (ii) a set of other large cities (Lyon, Marseille, Lille and Toulouse); (iii) the rest of France, controlling for MSA fixed effects.

We show that using such a partition misses important features of where work experience is obtained *within* cities. To move forward, we use geolocation of firm plants given by the INSEE from a firm registry to locate the place of work of individuals throughout their careers and obtain coordinates according to the Lambert conformal conic projection (the Lambert 93 version). This allows us not only to assign workers to very fine geographies, but also to compute job density for arbitrary geographic units.

We are interested in the effects of job density on the dynamic wage gains of workers. This requires choices on (i) how to measure density and (ii) over what geographic units. We experimented with different approaches that in the end all yielded qualitatively similar results (see Section 5). For our main results, we built a smoothed density measure for each 1 km^2 as the average of the total number of hours worked in the square and in the neighboring squares.[6]

It turns out that one division succinctly captures the most important contrasts in static and dynamic wages across space. We studied alternative geographical splits (e.g., ranking places by density over $1km^2$ squares in entire France), but the most dense $50km^2$ are almost always only in Paris no matter what the density measure used.

In our main regressions, we partition entire France into 4 areas ranked by density:

(i) The "core" of Paris (the most dense $50km^2$ in terms of hours worked of the Paris urban area),

(ii) Paris complement (i.e. relative to the "core" – ca. $2750km^2$),

(iii) other large French cities (Lyon, Marseille, Lille, and Toulouse),

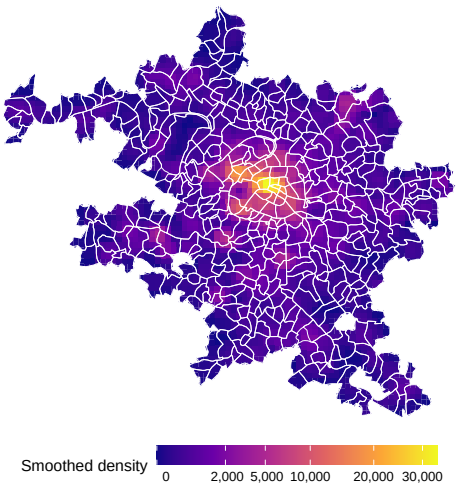
(iv) the rest of France.

The last area serves as the reference group for variables defined by area or by both area and job characteristics. We use the average of the fixed effects of 10 cities around the median city size above 40,000 (threshold as in de la Roca and Puga (2017)) for the interpretation of the static wage premia.

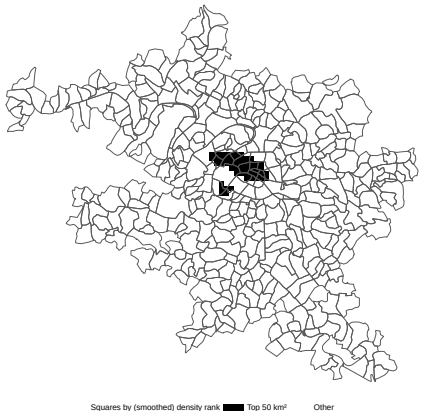
Employment density is highly concentrated in the Paris region, mainly in the western part of inner Paris and in La Défense, as shown in Figure 1a. We therefore define the 'core' area of Paris as the 50 most densely populated square kilometers, which are shown in 1b with summary statistics of most important variables across the studied areas in Table 3. The

[6]The partition of MSAs was obtained in the following way. The urban area was inscribed into a rectangle that then was divided into 1 km^2 squares starting from the North-West corner.

"core" area of Paris includes in particular the central business district (parts of the 2nd, 8th and 9th arrondissements) and parts of the La Defense and Boulogne-Billancourt business districts. Many intra-muros areas of Paris do not exhibit high job densities and are hence a part of the "complement" to the core.



(a) Smoothed Density Paris MSA



(b) Paris "core", top 50 km^2 density of Paris superimposed on Paris UU borders

Figure 1: Smoothed Employment density in Paris Urban Unit

2.2 Occupations

Job data in the Panel-DADS is given according to the PCS 2003 classification.[7] This distinguishes 516 occupations at a 4-digit level. We can characterize these occupations according to hierarchy (based on finer details of the PCS classification) and their cosine distance in terms of tasks to other occupations.[8]

2.3 Occupation types

To analyze worker-level heterogeneity of experience gains in large cities using fine geographies, we distinguish different groups of occupations depending on the capacity to learn on the job from other workers in the vicinity. In this we follow the path of Bacolod et al. (2009).

Our central approach groups occupations based on task-based indices matched with 4-digit level PCS job classification using the extension of Caunedo et al. (2023) of the Autor et al. (2003) measures.[9] We use two broad measures of available job task characteristics –

[7]The PCS 2003 classification is roughly similar to the previous PCS 1982 classification at the 2-digit level.

[8]We use the ESCO classification at the ISCO 2008 level to obtain job task characteristics. We then compute cosine distances between the ISCO occupations and use them to calculate distances between individual 4-digit PCS jobs.

[9]These measures are available for several countries, including France and United States. They are based on data from the period 2006-2015 (that includes the years of our study) and so are up-to-date in comparison to the RTI measures used by Autor et al. (2003) that come from the 1970s. These scores are standardized

their non-routine analytical (NRA) and non-routine interpersonal (NRI) scores. The first measures cognitive intensity of a job. The second measures the extent to which the job requires interactions with others. High scores in both categories suggest the need to constantly exchange ideas, learn on the job from others, or manage people. Workers with such characteristics would benefit from being surrounded with similar individuals in dense areas. In contrast, jobs with low cognitive intensity or that lack the need to collaborate with coworkers likely benefit less from density.

This gives us a partition of occupations into 4 groups that we call respectively "learning", "nerds", "sales" and "manual and routine". The "learning" group that ranks relatively highly on both non-routine analytical (NRA) and non-routine interpersonal (NRI) scores (both $>$ 0) will be of particular interest. Table 1 gives a summary of our partition, with examples of occupations in each category.

		Analytical	
		Low	*High*
Interpersonal	*Low*	**Manual and Routine** Office clerks, drivers, industrial workers	**Nerds** Lawyers, R&D or software engineers
	High	**Sales** Vendors, retail	**Learning** Executives / consultants in finance, accounting, advertising or marketing

Table 1: Typology of jobs

For estimation, while groups are built up based on the occupation held at the time of estimation, we account for accumulated individual experience in different occupations. Given that we are able to track occupations at the 4-digit level only since 2003, we cap the experience in different occupations at 10 years.[10]

We also explore different classifications for robustness. First, we consider jobs in the business services sector as in Eckert et al. (2025) (see Section 4.4.1). However, many workers in this sector do not belong to the high-skilled category of "cadres" nor are necessarily including jobs with high cognitive and interpersonal content. Second, we partition jobs according to whether they are high in the hierarchy or not (CS 23 – CEOs and CS 3 – all "cadres"), which does not take into account differential task content (Section 4.4.2). Those jobs are high-paid and require typically college degrees. We also examine dynamic returns for college versus non-college graduates (available upon request).

for the United States, and the scores for other countries (France in our case) should be evaluated relative to the U.S. benchmark.

[10]Looking over a longer horizon would have required using the 2-digit occupation level, for which there is a near perfect correspondence between PCS 1982 and PCS 2003 classifications. However the latter partition of occupations is too coarse to allow us to compare their task content. Card et al. (2025) similarly cap worker city experience at 10 years due to data limitations. We stress that we cap only experience in performing a particular type of job; we can observe full worker histories, thus total work experience by location tier.

2.4 Main sample

Data availability constrains our choice of sample years. For overall work experience, we use the entire available panel-DADS data set going back to 1976. Accounting for experience in particular types of jobs (e.g. learning or not), can be done from 2003 onward as a new job classification is introduced at a 4-digit level. At the time of writing, the last year for which the panel-DADS data set is available is 2021.[11] We thus divide the period 2003-2021 as follows. Over the period 2003-2012 we compute work experience by job type within the geographical areas considered, capping experience in a particular job type & area at 10 years. We then use 2013-2021 as the estimation period.

Our base sample includes men between 18-55 years as of 2013 for which we can observe their entire career.[12] We keep only those for whom we can geolocate all employment spells (this excludes any workers employed by temporary work agencies as these jobs for short term hire cannot be localized) and that always worked in the private sector (excluding agriculture).[13]

Summary statistics as of 2013 are given in Tables 2 and 3. Workers in our sample have on average 30.7 years of age, with a mean experience of 9.35 years. Our sample is thus tilted to younger workers given that the panel doubles in 2003. Only 9% of jobs are highly analytical and interpersonal ("learning") while 15% are classified as "nerds". Most jobs in the sample are "manual and routine" – characterized by scores both below the U.S. mean in terms of analytical and interpersonal traits. Business services, the sector that according to Eckert et al. (2025) was particularly responsible for the great urban divergence in the U.S. constitutes 12% of employment. Across the different areas considered, workers in the "core" are on average one year younger than in the rest of France, with 2.8 years shorter work experience and considerably higher average hourly wages. Job composition in the core is very different: 25% and 29% of jobs are "learning" and "nerd" in the core while only 6% and 10% in France outside the largest cities. Business service jobs are 25% of the total while only 9% in the rest of France, where manufacturing remains a sizeable sector (25% of jobs).

[11] There is currently typically 3-4 of lag in provision of this data by the INSEE.

[12] This means their work experience is zero when they appear the first time in the panel. This an important restriction as we want to precisely measure work experience that accrues to individuals, especially at the beginning of their careers. From 2003 onward, the fraction of individuals for whom we can track the entire work history doubles, but many have non-zero experience. Hence our sample is relatively skewed to younger individuals in the 18-55 range.

[13] In the 1990s, we can geolocate approximately 90% of workplaces, and thereafter the matches improve.

	Mean	Std. dev	Min	Max
	Individual characteristic			
Age	30.70	8.41	18.00	55.00
Hourly Wage (Euros)	17.45	11.78	2.01	1381.01
Main Job (dummy)	0.96		0.00	1.00
Half time job (dummy)	0.09		0.00	1.00
Experience (years)	9.35	7.23	0.00	39.92
Tenure at firm (years)	4.70	5.03	0.00	37.92
	Job type			
Learning	0.09		0.00	1.00
Nerds	0.15		0.00	1.00
Sales	0.07		0.00	1.00
Routine non interpersonal	0.69		0.00	1.00
	Sectors			
Business services	0.12		0.00	1.00
Manufacturing	0.21		0.00	1.00

Table 2: Summary statistics as of 2013

	(1) Paris Core				(2) Paris Complement				(3) Other Big cities				(4) Rest of France			
	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max	Mean	Std. devsd	Min	Max
	Individual characteristics															
Age	29.87	6.91	18.00	55.00	30.33	7.74	18.00	55.00	30.69	7.93	18.00	55.00	30.89	8.80	18.00	55.00
Hourly Wage (Euros)	24.08	21.22	2.20	838.79	19.96	12.55	2.07	721.94	18.24	13.56	2.09	1381.01	15.88	9.10	2.01	687.45
Main Job (dummy)	0.94		0.00	1.00	0.95		0.00	1.00	0.95		0.00	1.00	0.97		0.00	1.00
Half time job (dummy)	0.13		0.00	1.00	0.11		0.00	1.00	0.10		0.00	1.00	0.08		0.00	1.00
Experience (years)	7.11	5.65	0.00	36.78	8.41	6.46	0.00	38.70	8.79	6.75	0.00	39.04	9.95	7.58	0.00	39.92
Tenure in firm (years)	2.96	3.42	0.00	32.41	4.06	4.35	0.00	37.09	4.26	4.55	0.00	37.14	5.14	5.37	0.00	37.92
	Job type															
Learning	0.25		0.00	1.00	0.14		0.00	1.00	0.11		0.00	1.00	0.06		0.00	1.00
Nerds	0.29		0.00	1.00	0.21		0.00	1.00	0.20		0.00	1.00	0.10		0.00	1.00
Sales	0.07		0.00	1.00	0.08		0.00	1.00	0.07		0.00	1.00	0.07		0.00	1.00
Routine non interpersonal	0.39		0.00	1.00	0.57		0.00	1.00	0.62		0.00	1.00	0.77		0.00	1.00
	Sectors															
Business services	0.25		0.00	1.00	0.15		0.00	1.00	0.16		0.00	1.00	0.09		0.00	1.00
Manufacturing	0.04		0.00	1.00	0.13		0.00	1.00	0.18		0.00	1.00	0.25		0.00	1.00
Employment density (full time equivalent by $1km^2$)	18,235.80				3,170				3,916				1,40			

Table 3: Summary statistics as of 2013 by area tier

3 Conceptual framework

In this section, we lay out a conceptual framework that allows us to incorporate returns to experience across locations and occupations in an Abowd et al. (1999) (AKM) type of a wage equation framework. We revert to a class of models started by Davis and Dingel (2019) where agglomeration gains of cities stem from ideas exchange. The original model is static in nature, but it is amenable to adding a dynamic accumulation of human capital in the spirit of Ben-Porath (1967) with additional local external effects. We show that such models yield in general additional dynamic terms to the ones from traditional AKM-approaches that are a function of worker job experience across space and occupations.

3.1 A model of history-dependent human capital.

Time is discrete and indexed by $t \in \{0, 1, ...\}$. The economy consists of a set of individuals $\mathcal{I}$ working in a set of locations $\mathcal{L}$ and occupations $\mathcal{O}$.

The wage of a worker i in occupation o and location l is:

$$W_{it} = \exp\left(\alpha_i \psi_l \Gamma_o z_{t,l,o}(h_i^t)\right) \tag{1}$$

with α_i a worker fixed effect, ψ_l a location fixed effect and Γ_o is an occupation fixed effect. $z_{t,l,o}(h_i^t)$ is worker i's human capital at date t to work in location l and in occupation o after a history of working experiences h_i^t.

The history of working experiences of worker i, h_i^t is a spell of occupations and locations with $h_i^t = \left\{\{o_{t,i}, l_{t,i}\}, h_i^{t-1}\right\}$, where $o_{t,i}$ and $l_{t,i}$ denote the occupation and the location of worker i at date t. The career of worker i starts at date t_0^i so that $h_i^{t_0^i - 1} = \emptyset$.

We posit that the history of working experience affects current human capital in the following way:

$$z_{t,l,o}(h_i^t) = \sum_{t_0^i \leq t' < t} \gamma^{o,l,t}_{o_{t',i}, l_{t',i}} B_{o_{t',i}} Z_{l_{t',i}} \tag{2}$$

The human capital acquired in a period t' in occupation $o_{t',i}$ and location $l_{t',i}$ is the product of an occupation-specific term $B_{o_{t',i}}$ with the local index of human capital $Z_{l_{t',i}}$. As a result, human capital acquired in a period depends both on the occupation and the location: it may be more critical for workers in some occupations to spend some specific periods of a career in a given location. In addition, $\gamma^{o,l,t}_{o_{t',i}, l_{t',i}}$ measures whether the resulting experience is relevant for the human capital for the current occupation o and location l.

Taking together equations (1) and (2), we obtain that the logarithm of the wage that we denote w_{ijlt} satisfies:

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \sum_{t_0^i \leq t' < t} \gamma^{o,l,t}_{o_{t',i}, l_{t',i}} B_{o_{t',i}} Z_{l_{t',i}}$$

By reorganizing the terms in the sum, we can elicit the effect of an experience in a given location and occupation:

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \sum_{l' \in \mathcal{L}, o' \in \mathcal{O}} \gamma^{o,l,t}_{o',l'} B_{o'} Z_{l'} Exp_{i,o',l',t} \tag{3}$$

with $Exp_{i,o,l,t}$ the experience – or time spent – of worker i in occupation o and location l.

Equation (3) allows to highlight the two components of the effect of the worker's experience on its current log-wage.

On the one hand, each past experience of this worker allows for the accumulation of human capital. For instance, the human capital accumulated in a given location l' and occupation o' depends on intensity of learning in that occupation $B_{o'}$ and in this location as measured by the local index of human capital Z'_l but also on the time spent in this location and occupation $Exp_{i,o',t'}$.

On the other hand, $\gamma^{o,l,t}_{o',l'}$ measures this extent to which such accumulated human capital is relevant for the worker's current job, characterized by an occupation and a location.

3.2 The role of history dependence.

Introducing history-dependent terms in the wage equation allows us to think about the effect of experience, the effect of experience in a given location as in de la Roca and Puga (2017), portability of experience and how dynamic gains may be age/experience dependent.

The effect of experience. To start with, the formulation allows to think about the effect of experience on human capital. To see this, let us abstract from occupation and location fixed effects ($B_o Z_l = \kappa$ for all o and l) and let us assume that $\gamma^{o,l,t}_{o',l'} = 1$. In this minimal model, we obtain that

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \kappa Exp_t.$$

Furthermore, the model allows for a more complex dependence with respect to past experience. For example, suppose that $\gamma^{o,l,t}_{o',l'} = 1 + \eta Exp_t$. In this case:

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \kappa Exp_t + \kappa\eta Exp_t^2.$$

Log wage is then a quadratic function of past experience.

The effect of experience in a given location. We now illustrate how the formulation allows to capture the effects of experience in a given location. We still assume that $B_o = \kappa$ for all occupations o but the index of human capital is now different across locations l. For simplicity, we start with $\gamma^{o,l,t}_{o',l'} = 1$. In this case, we obtain:

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \sum_{l' \in \mathcal{L}} \kappa Z'_l Exp_{i,l',t.}$$

In this situation, the log wage is a function of the time spent in each location weighted by the local index of human capital.

The value of accumulated human capital may depend on the current location of a worker. The way to capture this in our model is through $\gamma^{o,l,t}_{o',l'}$. Suppose, for example, that $\gamma^{o,l,t}_{o',l'} = \lambda_{l,l'}$ with $\{\lambda_{l,l'}\}_{l,l' \in mathcalL}$ a matrix of positive real numbers. In this case, we obtain

$$w_{it} = \alpha_i + \psi_l + \Gamma_0 + \sum_{l' \in \mathcal{L}} \lambda_{l,l'} \kappa Z'_l Exp_{i,l',t.}$$

Log wage is, in this situation, a function of the time spent in each individual location weighted both by the local index of human capital and by the relevance of such accumulated human capital for the worker's current location.

Shifting from one location/occupation to another. We now investigate how our framework allows to capture potential portability of experience from one location and/or occupation to another.

Shifting from a job in location l and occupation o to a job in location l' and occupation o' leads to a log wage change:

$$\Delta w = \psi_{l'} - \psi_l + \Gamma_{o'} - \Gamma_o + \sum_{k \in \mathcal{L}, j \in \mathcal{O}} \left(\gamma_{j,k}^{o',l',t} - \gamma_{j,k}^{o,l,t} \right) B_j Z_k Exp_{i,j,k,t}$$

The variation of the wage is the sum of three components. The first two terms stem from the variations of the occupation and location fixed effects. The third term results from the relevance of the history of working experience for the worker's current job.

In particular, note that this third term is absent of models in which location and/or occupation have effects only on human capital accumulation but not on the adequacy of such human capital with the current location and/or occupation of the current job. This is, for example the case, of the models of Crews (2024) – in which case z is accumulated as a function of the local index of human capital – or Aguilar (2025) – in which case z is accumulated as a function of location, individual fixed effects and age.

Dynamic learning gains are age/experience dependent. Finally, let us illustrate that our framework allows from potential dependence of accumulation of human capital as a function of age and/or experience.

When occupying the same occupation in the same location, the wage evolution of worker i is:

$$w_{it+1} - w_{it} = \gamma_{o,l}^{o,l,t+1} B_o Z_l \delta_{t+1} + \sum_{l' \in \mathcal{L}, o' \in \mathcal{O}} \left(\gamma_{o',l'}^{o,l,t+1} - \gamma_{o',l'}^{o,l,t} \right) B_{o'} Z_{l'} Exp_{i,o',l',t}$$

The evolution of the wage from one period to another is the sum of two components. The first component is the direct effect of having spent an additional year in location l and occupation o. The second component is the indirect effect through the value of the worker's past experience.

3.3 Mapping the wage equation to the data.

We now map the wage equation to the types of regressions conducted in de la Roca and Puga (2017) as well as our baseline regressions.

De La Roca and Puga. To obtain the formulation in De La Roca-Puga, one needs to assume that:

$$\gamma_{o',l'}^{o,l,t} = 1 + \lambda_{l,l'} + \eta Exp_t + \mu_{l,l'} Exp_t, \text{ and } B_o = 1 \text{ for all } o, l, l', t.$$

This assumption implies that past experiences are relevant for today human capital depending on the current location of the worker relative to past locations ($\{\lambda_{l,l'}\}_{l'\in\mathcal{L}}$ and $\{\mu_{l,l'}\}_{l'\in\mathcal{L}}$) and as a function of the worker's experience.

In this case, the logarithm of the wage can be written as follows:

$$\begin{aligned} w_{it} &= \alpha_i + \psi_l + \Gamma_o + \cdots \\ &\cdots + \sum_{l'\in\mathcal{L}} Z_{l'}Exp_{i,l',t} + \lambda_{l,l'}Z_{l'}Exp_{i,l',t} + \eta Exp_{i,t}Z_{l'}Exp_{i,l',t} + \mu_{l,l'}Exp_{i,t}Z_{l'}Exp_{i,l',t} \end{aligned} \tag{4}$$

The term $Z_{l'}Exp_{i,l',t}$ is the effect of experience in location l'. The term $\lambda_{l,l'}Z_{l'}Exp_{i,l',t}$ leads this effect to depend on the current location l. $\eta Exp_t Z_{l'}Exp_{i,l',t}$ and $\mu_{l,l'}Exp_t Z_{l'}Exp_{i,l',t}$ modulate these effects as a function of the total experience of the worker i $Exp_{i,t}$.

To estimate the wage equation (4), one needs to run the following regression:

$$\begin{aligned} w_{it} =& \tilde{\alpha}_i + \tilde{\psi}_l + \tilde{\Gamma}_o + \cdots \\ &\cdots + \sum_{l'\in\mathcal{L}} \left[\tilde{b}_{l,l'}1_l Exp_{i,t}Exp_{i,l',t} + \tilde{b}_{l'}Exp_{i,t}Exp_{i,l',t} + \tilde{c}_{l,l'}1_l Exp_{i,l',t} + \tilde{c}_{l'}Exp_{i,l',t}\right] + \varepsilon_{ijlt} \end{aligned} \tag{5}$$

Several comments are in order. First, as noted in the previous subsection, such a formulation allows to think about portability effects: $\gamma^{o,l,t}_{o',l'}$ depends both on the current location l and the location where the experience was accumulated l'. As a result, a change in location does not translate only into a variation in the location fixed effect ϕ_l (or, if it also involves a change in occupation, in the occupation fixed effect) but it also leads to a change to the value of past experiences.

Second, such formulation allows benefits of the experience in a given location to be not uniform with time. The net effect of additional experience is the sum of two terms: a term linear in experience ($Z_{l'}Exp_{i,l',t}$) and a quadratic one ($\eta Exp_{i,t}Z_{l'}Exp_{i,l',t}$). In particular, a positive linear term associated with a negative quadratric term would lead experience to be very valuable early on, but with declining benefits over time.[14]

Baseline regression. In our baseline regression, as for the formulation of de la Roca and Puga (2017), we assume that:

$$\gamma^{o,l,t}_{o',l'} = 1 + \lambda_{l,l'} + \eta Exp_t + \mu_{l,l'}Exp_t \text{ for all } o,l,l',t.$$

but we make no restrictions on the role of occupations, not only for in terms of static effects Γ_o but also for dynamic effects B_o. The wage equation now reads:

$$\begin{aligned} w_{it} =& \alpha_i + \psi_l + \Gamma_o + \cdots \\ &\cdots + \sum_{l'\in\mathcal{L},o'\in\mathcal{O}} B_{o'}Z_{l'}Exp_{i,o',l',t} + B_{o'}Z_{l'}Exp_{i,o',l',t}\lambda_{l,l'} + cdots \\ &\cdots + \sum_{l'\in\mathcal{L},o'\in\mathcal{O}} \eta B_{o'}Z_{l'}Exp_{i,o',l',t}Exp_{i,t} + \mu_{l,l'}B_{o'}Z_{l'}Exp_{i,o',l',t}Exp_{i,t} \end{aligned} \tag{6}$$

[14] Note that the exact formulation in de la Roca and Puga (2017) also includes terms that, on top of linear and quadratic terms depending on locations, depend only on experience ($Exp_{i,t}$) and experience squared ($Exp^2_{i,t}$). Here, we omit these terms to keep simple formulas. Note that it is possible to obtain these terms when the local index of human capital is of the form $Z_l = Z + \zeta_l$ where Z is a constant.

To estimate this equation in the data, we need to run the following type of regression:

$$
\begin{aligned}
w_{it} = \tilde{\alpha}_i + \tilde{\psi}_l + \tilde{\Gamma}_o + \cdots \\
\cdots + \sum_{l' \in \mathcal{L}, o' \in \mathcal{O}} \tilde{b}_{l,o',l'} 1_l Exp_{i,t} Exp_{i,l',t} + \tilde{b}_{o',l'} Exp_{i,t} Exp_{i,o',l',t} + \cdots \\
\cdots + \sum_{l' \in \mathcal{L}, o' \in \mathcal{O}} \tilde{c}_{l,o',l'} 1_l Exp_{i,o',l',t} + \tilde{c}_{o',l'} Exp_{i,o',l',t} \cdots \\
\cdots + \varepsilon_{ijlt}
\end{aligned} \tag{7}
$$

where $\tilde{\alpha}_i$, $\tilde{\psi}_l$ and $\tilde{\Gamma}_o$ are, respectively, an individual, a location and an occupation fixed effects. Finally, ε_{ijlt} is an error term.

Mapping the wage equation (6) to the regression (7) yields the following correspondences:

$$\tilde{b}_{l,o',l'} = \mu_{l,l'} B_{o'} Z_{l'},\ \tilde{b}_{o',l'} = \eta B_{o'} Z_{l'},\ \tilde{c}_{l,o',l'} = \lambda_{l,l'} B_{o'} Z_{l'}, \text{ and } \tilde{c}_{o',l'} = B_{o'} Z_{l'}$$

Estimating these terms thus allows to obtain the human capital accumulation terms $B_{o'}$ and $Z_{l'}$ as well as how this human capital is relevant for the current location λ_l.

Equipped with this framework and the type of regressions that this framework implies, we now turn to estimating dynamic gains as a function of location and occupation.

4 Dynamic gains in large cities

Our empirical effort proceeds then in five steps. We take the dynamic learning approach of de la Roca and Puga (2017) focused on Spanish cities as a starting point. Thus we would like to verify that the shift to French data, a different period for estimation, and modest changes in sample choice don't greatly alter outcomes. Second, a fundamental addition that we are making to the literature is to consider variation *within* the city in the availability of learning opportunities. Specifically, we investigate whether the availability of these dynamic gains is independent of where one works within a metro or whether this is quite different in the densest employment areas, which in our case are nearly exclusively located in what we will term the core of Paris. Third, we investigate whether the value of the experience accumulated depends also on the currently held type of job. Fourth, we explore whether these dynamic gains also depend not only on worker current job and historical location but also on which types of jobs were held while accumulating work experience. Finally, we assess how accounting for establishment mobility as in Carry et al. (2025) affects our results, and draw conclusions on the nature of agglomeration gains.[15] In ongoing work (not in the current version), we characterize the patterns portability of experience in learning jobs (e.g. whether it is higher for jobs prevalent in the core of Paris) and the role of within-firm labor markets.

4.1 Replicating the de la Roca and Puga (2017) results

We start by estimating the static and dynamic wage benefits of large cities with a rich set of controls as in equation (1) of de la Roca and Puga (2017). Importantly, we first partition

[15] We evaluate the validity of the base specification with tests suggested by Card et al. (2025) the Appendix.

France into Paris, other large cities, and the rest of France for computing experience acquired while working in a particular city class and controlling for its use.[16]

That is, we estimate the following equation of the log of the wage of worker i in location l at time t, w_{it}:

$$w_{it} = \tilde{\alpha}_i + \tilde{\psi}_l + \sum_{l'=1}^{\mathcal{L}} Exp_{i,l',t}\delta_{l',l} + \mathbf{x}'_{it}\beta + \eta_t + \varepsilon_{ict} \tag{8}$$

This equation is close to Equation (5) in the previous section but with additional time- and individual-specific controls.

More precisely, $\tilde{\psi}_l$ is the current location – either city or area place of work – fixed effect, $\tilde{\alpha}_i$ is a worker fixed effect, $Exp_{i,l',t}$ is the vector of experience obtained by worker i in city type l' up until time t (also with quadratic terms and interactions of where it was obtained and where it is used) – these terms are similar as in (5) –, $\mathbf{x}$ contains the vector of worker or occupation characteristics controls described below, η_t is a set of time fixed effects (year, month), δ and β are parameters while ε_{ict} is the error term.

Worker-specific variables include age and overall work experience (all also with quadratic terms). Occupation characteristics consist of 2-digit PCS occupation controls, 2-digit NACE sector and sector-by-city (MSA) fixed effects. Worker-job attributes include tenure at the current job (with quadratic terms), main job dummy, contract type and whether the work is less than half of the full-time equivalent. We also include variables relating to job change, such as the cosine distance (in terms of tasks) to previous job or hierarchical change between job moves.

Results are shown in the Appendix Table (B.1). These are illustrated with a series of figures depicting earning profiles of workers with different career trajectories. In Figure 2 we contrast the earnings premia of working in Paris and Lyon[17] in comparison with 10 median-sized cities in France.[18] We observe results that are qualitatively similar but quantitatively somewhat smaller than those of de la Roca and Puga (2017). We estimate that a worker who has spent 10 years in a job in the Paris MSA obtains on average 24% higher wages than a similar worker in a typical median sized city. This is composed of a 5.5% static and an 18.5% dynamic premium. For a worker in Lyon, the gains are strikingly lower: no static premium and roughly a 3% dynamic gain in wages after 10 years.[19] This contrast in the static and dynamic wage gains in Paris versus France's second largest MSA, Lyon, are stark and demonstrate the absolutely central role of Paris in the country.

[16] In de la Roca and Puga (2017) Madrid and Barcelona are grouped together as the largest cities, as population differences between the two are approximately 20%, with a sizeable gap relative to the third largest city in Spain (Valencia). In France, Paris is approximately 7 times larger than the second largest city, Lyon. Hence, we take Paris as being the largest city and the only one in that category, and form the second group with 4 other large cities above 1 million of inhabitants – Lyon, Marseille, Lille and Toulouse.

[17] For Lyon, we exhibit the dynamic gains estimated commonly for the group of four large cities — Lyon, Marseille, Lille and Toulouse but with a static fixed effect specific to Lyon.

[18] In their paper, de la Roca and Puga (2017) use one median sized city among cities above 40,000. We include here an average of city fixed effects of 10 MSAs around the median (cities in the range 60-70k) among cities above 40,000 to reduce dispersion of the static premia.

[19] Card et al. (2025) also find small dynamic wage premia for large cities in their data; however they cap work experience to 10 years due to data limitations.



Figure 2: Earning profiles: reproducing de la Roca and Puga (2017).

The base category reflects the evolution of wage profiles in the rest of France.

4.2 Adding within-city density

We now want to add within-MSA differences in density. The existing literature on the dynamics of wages due to working in large cities ignores differences within MSAs. Likely this is due to data limitations. A large literature in urban economics focuses precisely on the special nature of high employment density central business districts (Lucas and Rossi-Hansberg, 2002; Fujita and Thisse, 2002; Ahlfeldt et al., 2015; Duranton and Puga, 2015; Couture et al., 2024; Ahlfeldt et al., 2024). Thus it is natural to explore whether the nature of wage dynamics differs in large cities according to the employment density of a location within the MSA.

To examine whether this is the case for dynamic learning gains, we now add a finer *within-city* dimension by splitting Paris into two areas where workers can obtain experience: the densest $50km^2$ "core" area; and what we term "Paris complement," as described in Section 2.1. We still estimate equation (8). We compute now experience in one of four areas: the Paris "core"; Paris complement; other large cities (pooled Lyon, Marseille, Lille, or Toulouse); or in the remainder in France.

We show the resulting earning profiles in Figure 3. It is immediately clear that most of the dynamic earnings gains are driven by worker experience in the Paris core. An average employee that spent 10 years working in the Paris core enjoys a 45% higher wage than an individual having a career outside of the largest French cities. This consists of an 8% static premium and a 37% dynamic premium. In contrast, working in Paris outside the densest $50km^2$ for 10 years creates much smaller gains: a 5% static and 8% dynamic premium for a

13% higher wage over the rest of France in total. Ignoring within-city density heterogeneity distorts the dynamic gain estimates: in our case, these are more than four times as high in the Paris core as in the Paris complement, and more than twice the over all Paris average estimated when ignoring the split between job-dense and non-job-dense areas (see section 4.1).

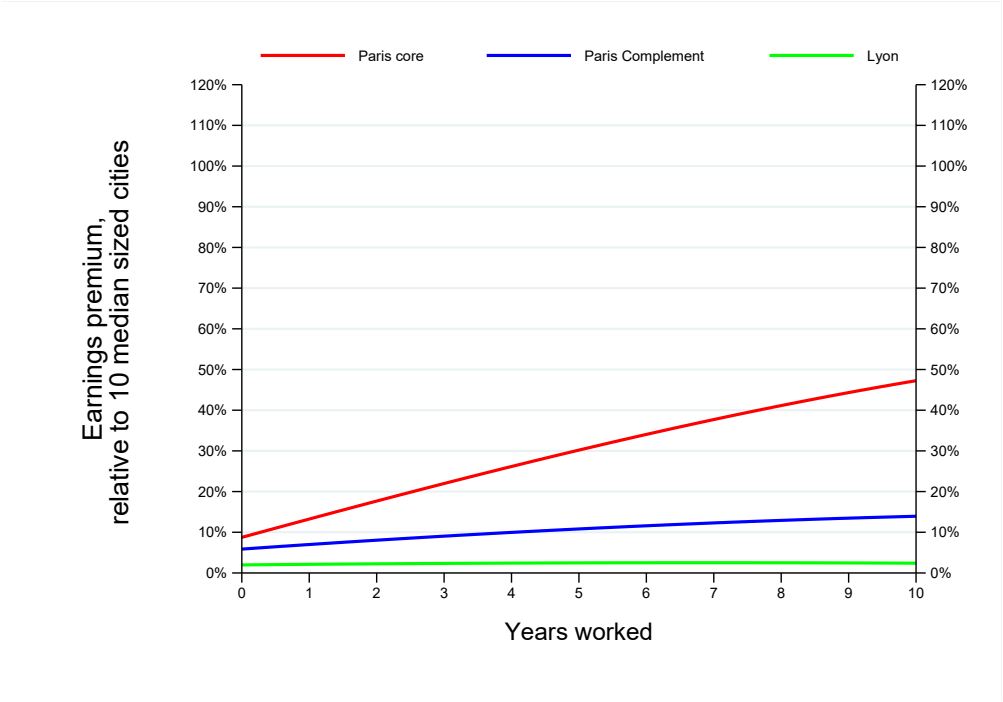


Figure 3: Earning profiles: adding within-Paris core vs. complement distinction.

The base category reflects the evolution of wage profiles in the rest of France.

4.3 Dynamic gains as a function of density and current job type

As we have noted, jobs in the city center may be different in nature from those outside the core. This suggests that the dynamic gains exhibited in the previous section may accrue to workers in only some jobs with particular characteristics. We now estimate equation (8) continuing with a split of the Paris area into the core and complement and partition our base sample into four current job types (described in section 2.3).

We give the static and dynamic premia by area for each job type in Table 4, the earning profiles for each of the four job types in Figure B.1 while the regression results for learning jobs are given in Table B.1.

We observe that dynamic gains accrue not only to individuals working in the "core" but predominantly to those in "learning" occupations, that is those exercising jobs with high cognitive *and* interpersonal task content. Learning jobs in the core offer on average a 56% wage premium in comparison to learning jobs in median-sized cities after 10 years of work experience. Out of this, 52,6% constitutes the dynamic gains from experience of working in the core. The gains of working in the Paris complement are much lower, however. While

learning workers in the complement enjoy the same static premium as those in the core of Paris (4%) the dynamic gains are much more modest at only 13%. This contrast in dynamic gains in the core is much smaller for other occupations, as e.g. among those in the low cognitive but high interpersonal sales occupations (7%).

Table 4: Earnings Premium by job type

	Paris (core)		Paris complement		Lyon	
	Static	Dynamic (10y)	Static	Dynamic (10y)	Static	Dynamic (10y)
All workers	8.7%	38.5%	5.9%	8.1%	2.0%	0.4%
"Learners"	8.5%	56.2%	7.0%	12.8%	3.6%	3.7%
"Nerds"	4.6%	1.7%	5.0%	-0.1%	-2.4%	1.3%
"Sales"	4.6%	1.7%	5.0%	-0.1%	-2.4%	1.3%
"Manual and Routine"	5.6%	7.3%	3.9%	0.8%	1.5%	-1.8%

Notes: This table presents the static and dynamic returns estimated from equation 8 across different occupational groups. The base category reflects the evolution of wage profiles in each category in the rest of France. For example, in the row "Learners" the wage gains of workers in learning jobs are compared in three areas versus the gains in the rest of France. The column "Lyon" represents the static gains in Lyon and dynamic ones in Lyon, Marseille, Lille and Toulouse.

4.4 Dynamic gains and experience by job type and area

The preceding section demonstrated that dynamic urban wage premia depend on both the place of work and also the type of job currently exercised. However, our measure of work experience has only focused on *where* a worker obtained that experience but not on *the type of job* performed.

We now add to our specification (8) variables related to experience in particular job types and location to be able to track e.g. how long a given individual worked as a nerd in a large city like Lyon before moving to a learning job in the Paris complement. A part of the experience vector $\mathbf{e}_{ijkt}$ contains now also experience by worker i obtained in location tier j in job type k until time t.[20] For parsimony, and given that most dynamic wage gains we obtain are for the "learning" jobs category we will consider only two job types in these regressions – those in the "learning" group (high NRA and NRI scores) and those that are not. Our modified regression is:

$$w_{it} = \sigma_c + \mu_i + \sum_{j=1}^{C}\sum_{k=1}^{K} \mathbf{e}'_{ijkt}\delta_{kjc} + \mathbf{x}'_{it}\beta + \eta_t + \varepsilon_{ict} \tag{9}$$

We run equation (9) on our full sample. For parsimony, we show selected earning profiles in Figures 4 and 5 where we show the evolution of wages in comparison to non-learning jobs in the rest of France. The constructed earning profiles now exhibit both the effects of up to 10 years experience in a particular area and on the (learning or non-learning) job type.

In Figure 4 we observe that both static and dynamic earnings gains increase with area density. Outside of Paris and the largest French cities, there is an 18% static and a 7%

[20]We cap – given data availability – the maximum experience in a particular jobXarea at 10 years. We still compute the full extent of work experience by area and overall.

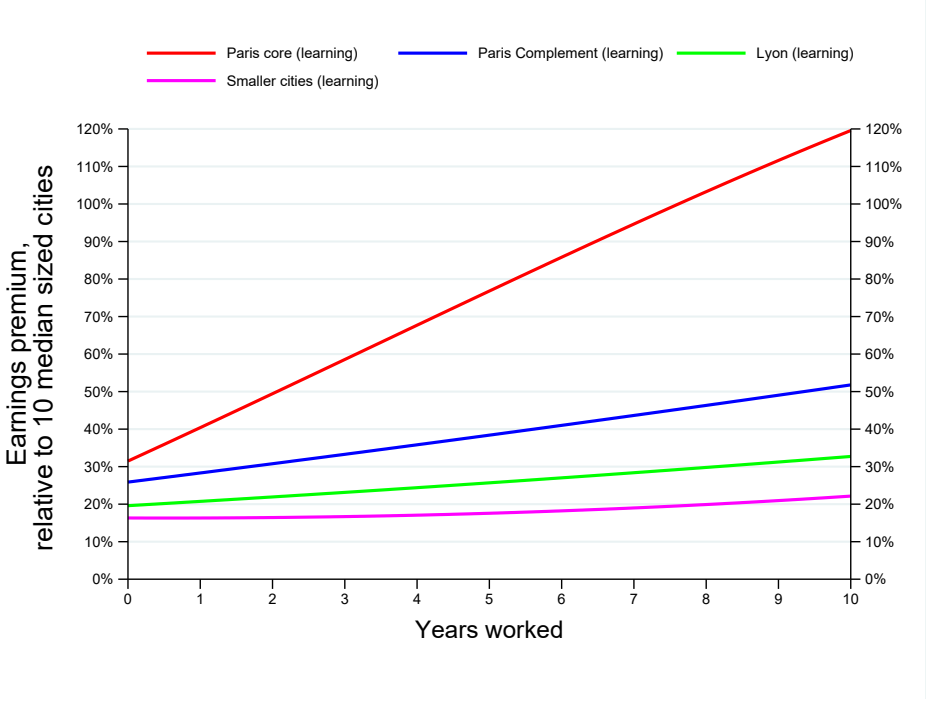


Figure 4: Earning profiles: accounting for job by area experience. Profiles for learning occupations.

This figure shows earning profiles obtained from regression (9). The base category reflects the evolution of wage profiles in non-learning jobs in the rest of France. The profile for "Lyon" represents the static gains in Lyon and dynamic ones in Lyon, Marseille, Lille and Toulouse.

dynamic (after 10 years) premium of working in a learning rather than non-learning occupation. These premia rise to respectively 32% and 86% (after 10 years) for the Paris core. The difference in the static and dynamic gains after 10 years within the learning occupations is respectively 14pp and 79pp between the Parisian core and rest of France excluding the largest cities. The differences remain sizable also within the Paris MSA: working outside the core in the complement in a learning job gives only a 26% static premium and a 23% dynamic gain after 10 years, substantially lower than for the Paris core.

We move next to the static and dynamic gains for non-learning jobs (Figure 5). First, they are much lower than for learning jobs in the same area tier. For example, the static and dynamic (after 10 years) gains from working in the Paris core in comparison to France outside of largest cities is respectively only 7% and 23%. For cities like Lyon or Marseille the static premium is 2% while there are no dynamic gains.

4.4.1 Is the evolution of gains an artifact of specific shocks to jobs in some areas?

Eckert et al. (2025) discuss how the technological bias of the developing information and communication technologies (ICT) favored the rise of productivity of business services in the largest U.S. cities since 1980s. Although our sample does not span such a long period, we

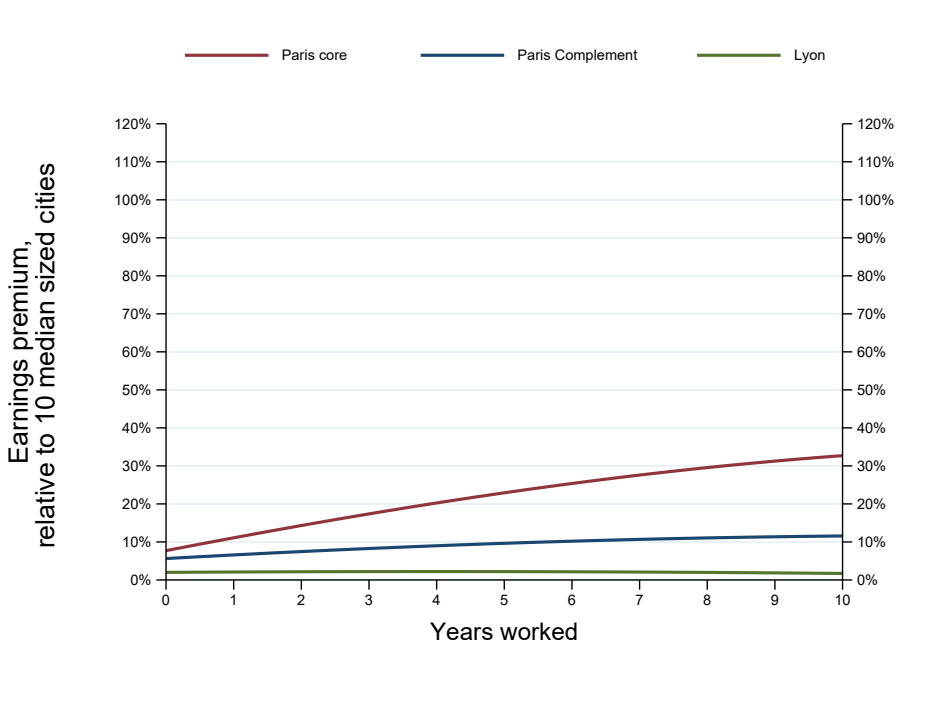


Figure 5: Earning profiles: accounting for job by area experience. Profiles for non-learning occupations. The profile for "Lyon" represents the static gains in Lyon and dynamic ones in Lyon, Marseille, Lille and Toulouse.

This figure shows earning profiles obtained from regression (9). The base category reflects the evolution of wage profiles in non-learning jobs in the rest of France.

would like to control for any technological changes or shocks that may benefit only some types of jobs in large cities or specifically the core that could confound our results. We control now for sector-year, sector-year-area and job-year-area fixed effects to see how much our results are potentially driven by changes in particular sectors or jobs that locate e.g. in the Paris core. These fixed effects can capture composition effects (e.g. dispersion or concentration of industries, stronger sorting of individuals) or technological change that affects particular occupations/sectors in some areas (e.g. ICT for business services jobs). They are conservative in nature as e.g. stronger composition effects – stronger sorting of individuals into dense job areas may be additionally reinforcing agglomeration gains for highest-skilled individuals.

In Table 5 we exhibit static and 10 year premia with these additional controls (lines two to seven) in comparison to our baseline. We conclude that we still capture sizeable gains even if we control for very demanding specifications with job by area by year fixed effects. It is true, however, that the dynamic experience gains are due to learning occupations with relatively high computer use (fifth row of Table 5). Our findings suggest that the types of jobs that exhibit highest dynamic gains in densest ares are characterized by high cognitive, interpersonal *and* computer use.

Area Premium	Paris core (static)	Paris core (10y dynamic)	Paris complement (static)	Paris complement (10y dynamic)	Lyon (static)	Lyon (10y dynamic)	Small cities (static)	Small cities (10y dynamic)
Baseline	31.5%	88.1%	25.9%	25.9%	19.6%	13.1%	16.3%	5.8%
Adding Industry x Year FE	33.5%	78.2%	26.4%	22.6%	19.9%	10.5%	19.7%	4.7%
Industry x Area x Year FE	44.2%	51.7%	33.4%	15.9%	25.7%	9.9%	18.4%	5.4%
Job type x Area x Year FE	37.5%	46.5%	31.0%	12.6%	23.3%	10.0%	17.4%	5.4%
Learners with low computer use	19.9%	39.8%	25.9%	2.3%	1.2%	23.8%	24.6%	-18.7%
Without Business services	28.2%	73.7%	23.3%	20.9%	15.3%	10.7%	12.5%	7.0%
Industry-specific gains from exp.	40.2%	87.8%	32.3%	24.8%	26.9%	13.2%	20.1%	4.8%
Including establishment FE	19.6%	66.9%	17.5%	23.7%	12.7%	13.2%	12.0%	7.5%

Table 5: Static and dynamic premia for learning jobs with added controls for sector-year, sector-area-year, job-area-year effects and for computer use.

Notes: This table presents the static and dynamic premia for learning jobs estimated from different variants of the baseline specification in equation 9. The first row reports the estimates from the baseline specification. "Adding Industry × Year FE" augments the baseline with a full set of 2 digit NACE industry-by-year fixed effects, absorbing common sectoral shocks over time. "Industry × Area × Year FE" further includes industry-by-area-by-year fixed effects, allowing sector-specific shocks to differ across local labour markets where "area" refers to one of the four partitions we consider (Paris; Paris complement; Lyon, Marseille, Lille and Toulouse; small cities). "Job type × Area × Year FE" instead adds occupation-by-area-by-year fixed effects, controlling for local occupation-specific trends. Job type is one of the four occupation groupings in our typology of jobs. "Learners with low computer use" restricts the sample to learners employed in jobs characterized by low computer use. "Without Business services" re-estimates the baseline after excluding establishments in the business services sector from the sample. "Industry-specific gains from exp." control for industry specific the returns to experience by interacting experience terms with industry dummies. Finally, "Including establishment FE" adds establishment fixed effects, following Carry et al. (2025). All premia are expressed in percentage points; static premia refer to the contemporaneous effect and 10-year dynamic premia to the cumulated gain ten years after entering a learning job net of the static premia. The base category reflects the evolution of wage profiles in non-learning jobs in the rest of France. The profile for "Lyon" represents the static gains in Lyon and dynamic ones in Lyon, Marseille, Lille and Toulouse.

4.4.2 Comparison with the standard occupation classification

We now want to assess to what extent the dynamic gains are different when we define learners as workers in highly analytical and interpersonal occupations rather than if — what is standard in the literature – as those with two 2-digit occupation categories (managers and engineers, CS 37 and 38 respectively). We then compare the results of the estimation of equation 9 for these two distinct definitions of learners. To allow for comparison, the reference group is the same in both regressions: workers who are not defined as learners with either of the two definitions (occupation characteristics or 2-digit classification). [21]
Table 6 shows that dynamic gains are significantly higher for learners relative to managers in the core of Paris (+14.9pp) and Lyon (+5.4pp). This finding suggests that occupational classifications based on task characteristics (interpersonal and analytical) are more effective at identifying groups that benefit from prime locations than conventional 2-digit classifications. The third row indicates that managers and engineers in non-interpersonal occupations experience dynamic location gains in the core of Paris that are less than half those of workers in analytical and interpersonal roles. These results indicate that within highly analytical occupations, interpersonal tasks appear to be a critical mechanism for leveraging gains from employment density.

[21] There are multiple occupations that belong to the CS 37 or 38 category but have low interpersonal task scores: e.g. Retail store operations managers, Electrical and electronic R&D engineers and managers, Mechanical and metalworking R&D engineers and managers, IT research and development engineers and managers, IT administration, IT project managers and IT department heads. Several engineer or manager occupations have low interpersonal or analytical scores: e.g Specialized technical educators, workshop supervisors, Restaurant supervisors: establishment management, CEO).

Area Premium	Paris core (static)	Paris core (10y dynamic)	Paris complement (static)	Paris complement (10y dynamic)	Lyon (static)	Lyon (10y dynamic)	Small cities (static)	Small cities (10y dynamic)
Occupation highly analytical and interpersonal	34.5%	82.6%	28.2%	21.4%	20.9%	9.9%	19.0%	3.7%
Engineers and Managers	31.3%	68.6%	26.3%	20.3%	18.2%	4.3%	15.4%	2.2%
Engineers and Managers not interpersonal	30.1%	51.9%	26.0%	20.6%	17.2%	1.4%	14.7%	-0.8%

Table 6: Static and dynamic premia for interpersonal and analytical occupations vs engineer and manager ones.

Notes: This table presents the static and dynamic returns estimated from equation 9 across different occupational groups. The group "Highly analytical and interpersonal occupations" refers to the classification defined in Section 2.3. Engineers and Managers correspond to the two-digit occupational codes 38 (Ingénieurs et cadres techniques d'entreprise) and 37 (Cadres administratifs et commerciaux d'entreprise). In both regressions, the reference group consists of workers in occupations that are neither classified as highly analytical and interpersonal nor fall under CS codes 37 or 38. In the first regression, workers in highly analytical and interpersonal occupations as well as those in occupations 37 or 38 are excluded. In the second regression, only Engineers and Managers (codes 37 and 38) are excluded, along with workers in highly analytical and interpersonal occupations. The third raw represents the static and dynamic gains for workers in an occupation in the manager or engineer category with a low interpersonnal score.

4.4.3 Adding the comparison with the Lyon core

So far we have only considered the within-city dimension of Paris. We now add the densest area of the second-largest city, Lyon. We take the most dense 2% of area of the Lyon MSA as the "Lyon core" and reestimate our regressions (8) and (9) with this additional location. We show results in Figure 6. In the simple regression from (8) as in de la Roca and Puga (2017) a comparison of the Lyon core and Paris complement reveal economically trivial differences in static or dynamic gains. The center of Lyon has an occupational composition that is more skewed to business service jobs than the Paris complement. Nonetheless, when we focus on learning jobs (Figure 6a) the dynamic gains in a learning job in Lyon are 4 pp lower than in the Paris complement. When we compute the portability of experience[22] between the Paris core and Lyon core (Figure 6b) we see that the dynamic wage gains are nearly preserved except for the immediate loss of a core urban premium. Movers from the Lyon core to the Paris core enjoy an immediate bump due to the static premium and then follow a very similar trajectory of dynamic gains with time as those who spent their entire career in Paris.

This suggests that the most dense area in Paris offers very different life-time wage schedules from that of the second-largest French city.

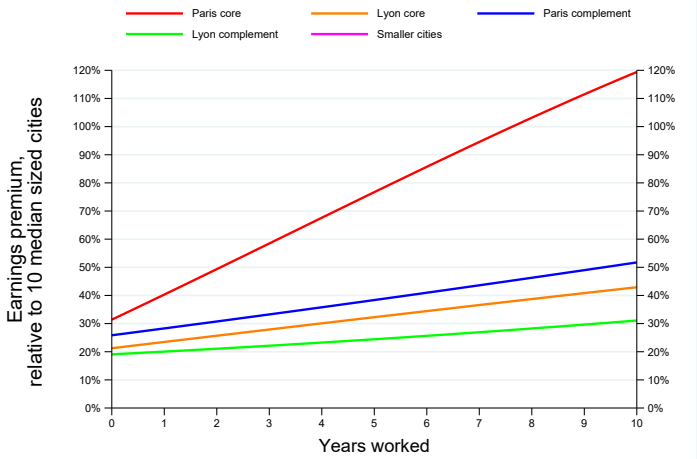
4.5 Accounting for establishment fixed effects

Carry et al. (2025), leveraging on the strengths of French administrative data, include establishment fixed effects in AKM regressions and control for changing locations of establishments. They find that estimated place effects are much lower than typically estimated in the literature and question the role of agglomeration in generating city productivity gains.

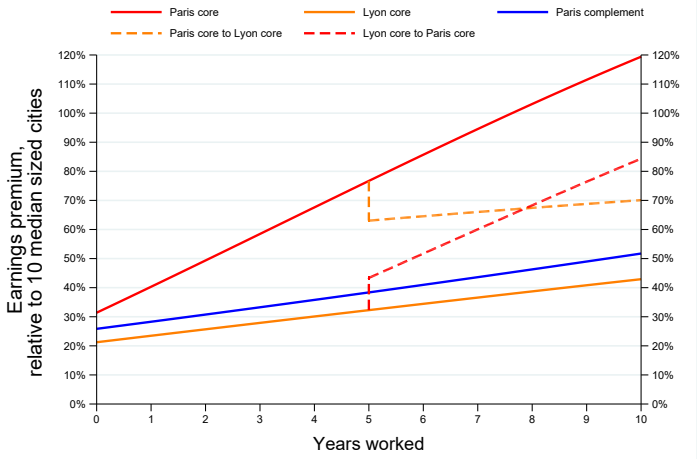
Given that we have access to similar data, we revisit our baseline regression to include such establishment fixed effects. We follow the approach in Carry et al. (2025), who rely on the *Register of Establishment Relocation* built from the French business register (SIRENE).[23] This information allows the same establishment to be tracked over time even when administrative identifiers change after a move. In practice, we reconstruct longitudinal trajectories by chaining successive identifiers that correspond to the same relocation event and we create a stable, unique establishment identifier shared by all its observations before and after relocation. This step collapses identifier changes induced by moves and enables specifications with establishment fixed effects while allowing the establishment's location to vary over time, so that the identification of location effects partially leverages within-establishment moves across areas.

[22] We construct this from our estimates earning profiles of individuals that work 5 years in one area and then switch to another learning job in the other area.

[23] Relocations are reported through the M2 form and recorded as a matched pair of the former and new addresses, providing an explicit link between the destination establishment identifier and its initial location.



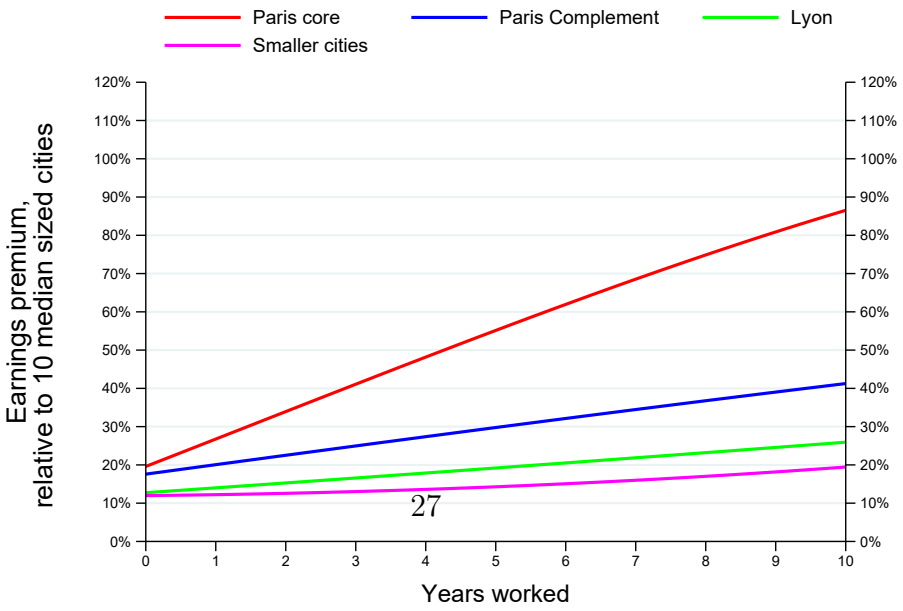
(a) Earning profiles: accounting for job by area experience. Profiles for learning occupations



(b) Earning schedules for movers between the Paris core and Lyon core

Figure 6: Earning profiles: adding the within-city dimension for Lyon

These figures revisits earning profiles with additional "core" area for Lyon for Figure 4 and exhbits earning schedules of movers between the Paris and Lyon cores. The base category reflects the evolution of wage profiles in non-learning jobs in the rest of France.



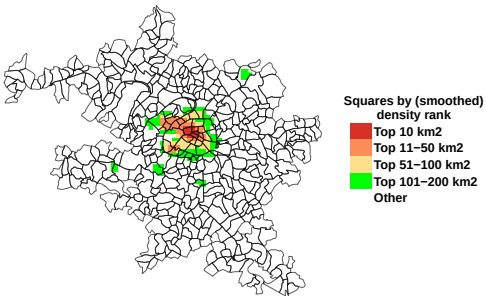
As in Section 4.4 we relate the static and dynamic premia of learners to those in non-learning jobs working in the rest of France. Adding establishment fixed effects (see Figure 7) reduces static premia, in particular the Paris-core premium, consistent with the work of Carry et al. (2025).[24] The gap in static premia between Paris core and the complement shrinks from about 12pp (32% vs. 20%) to about 8pp (25% vs. 17%), indicating that the static premia for working in the core after accounting for establishment FE and firm-induced moves are negligible. However, the bulk of our dynamic gains in the Paris core remain: at 10 years of experience they stay at 86% (i.e. a fall of about 32pp from the baseline, partially driven by a 12pp drop in the static premium).

Static place effects may be hence low even for high job density areas. However, it does not mean that there are no gains from agglomeration. First, we still observe dynamic wage gains for workers in jobs that require face to face exchange of ideas and hence should benefit from job density. These dynamic wage gains suggest there may be a dynamic role for spatial agglomeration even if there is selection of workers and firms at play. Second, while there may be nothing particularly favorable in terms of productivity enhancement for learning jobs about the 3 arrondissements that principally form the Paris core, there may be a need for one location in a country like France where such specific task activity agglomerates.

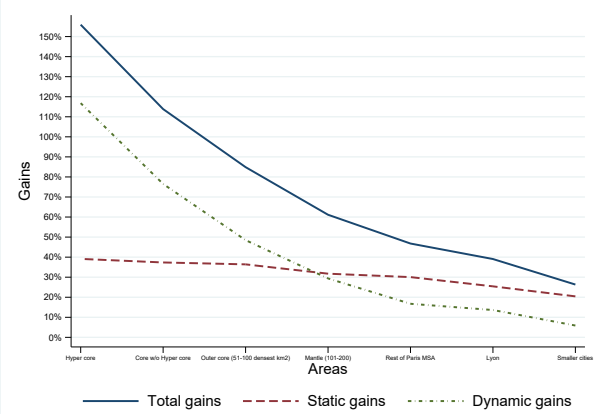
5 Granularity and spatial concentration of dynamic gains

We have found that the highest dynamic gains occurred in areas in Paris we defined as the "core" – the most dense 50 km^2 in terms of private employment. This choice was somewhat arbitrary, and we analyze now a wider array of locations with highest locations in Paris. Another important question is to what extent these dense areas – and the ones with highest dynamic returns – are strongly agglomerated within the city.

[24]There are substantial differences in the samples and approaches we use. Notably, the unit of interest in the Carry et al. (2025) are commuting zones that cover exclusively the entire country while we focus on cities and the within-city dimension. We also principally are interested in the learning jobs while they do not make a distinction between occupations. Finally, they are not primarily focused on dynamic gains.



(a) Most job dense areas in Paris: 4 categories



(b) Static, Dynamic and Total gains

Figure 8: Most job dense areas in Paris

Panel (a) maps the 1km × 1km squares of the Paris metropolitan area by categories of smoothed employment density. Smoothed density is defined as the average employment density in a square and in its adjacent squares. The four categories correspond to the 10 densest km^2, the next 40 densest km^2, squares ranked 51 to 100, and squares ranked 101 to 200. Panel (b) reports the estimated total, static, and dynamic gains for learning jobs across these areas, together with the rest of the Paris metropolitan area, Lyon, and smaller cities. The estimates are obtained from eq. (9). The dynamic component is defined as the difference between total gains after 10 years and static gains.

We next compute the static and dynamic gains for learning jobs after estimating eq. (9), again distinguishing several areas within Paris on the basis of employment density. Figure 8b reports three distinct curves corresponding to total gains (in blue), static gains (in dashed red), and dynamic gains (in dotted green) in comparison to the evolution of wage profiles in non-learning jobs in the rest of France. We first document a positive relationship between dynamic gains and density within the 200 densest km^2. This pattern is driven primarily by the dynamic component rather than by differences in static gains. Static gains are positive in all areas and increase only gradually with density, from about 20pp in smaller cities to about 39pp in the hyper core. By contrast, dynamic gains vary much more sharply across locations: they are only about 6pp in smaller cities, 14pp in Lyon, and 17pp in the rest of the Paris MSA, but rise to 29pp in the mantle, 49pp in the outer core, 77pp in the core excluding the hyper core, and 117pp in the 10 densest km^2. Overall, the figure points to substantial heterogeneity within the top 50 km^2 of Paris, with the hyper core generating markedly larger dynamic gains than the rest of the core despite only limited differences in static gains.

In Figure B.2 we exhibit the estimation of returns when we use smaller base units (0.25 km^2) and job density based only on learning jobs. We conclude that qualitatively and quantitatively the estimated gains remain similar. The corresponding geographical areas to each categorization within Paris are shown in maps in Figure B.3.

As robustness, in ongoing work we study wage premia when we divide the entire territory of France by density and not urban areas. The 50 km^2 with highest job density are in the Paris core as in our base area division.

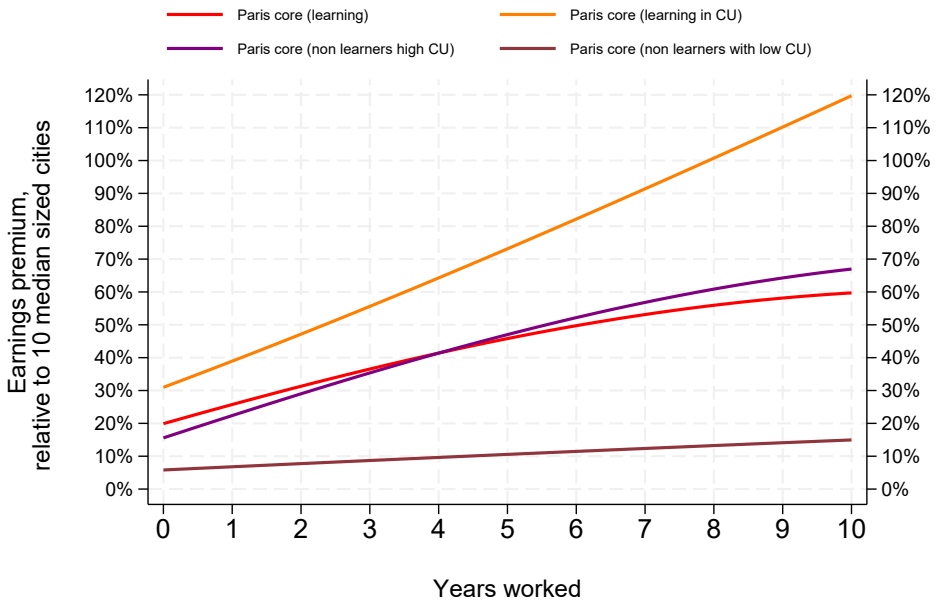


Figure 9: Earning profiles: adding high computer use in occupations.

6 Conclusions

We conclude that city size where work experience is gathered does matter for dynamic earning gains but only for individuals working in particular jobs that involve performing highly cognitive and interpersonal tasks, "learning" jobs.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Acosta, C., Eckert, F., and Liang, J. (2024). Superstar zip codes. Technical report.

Adenbaum, J., Babalievsky, F., and Jungerman, W. (2025). There's nothing in the air. Technical report.

Aguilar, E. (2025). Credit constraints, learning, and spatial misallocation. mimeo.

Ahlfeldt, G. M., Albers, T. N., and Behrens, K. (2024). Prime locations. *American Economic Review: Insights (forthcoming)*.

Ahlfeldt, G. M. and Pietrostefani, E. (2019). The economic effects of density: A synthesis. *Journal of Urban Economics*, 111:93–107.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The Economics of Density: Evidence From the Berlin Wall. *Econometrica*, 83(6):2127–2189.

Albouy, D., Ehrlich, G., and Shin, M. (2018). Metropolitan land values. *The Review of Economics and Statistics*, 100(3):454–466.

Arzaghi, M. and Henderson, J. V. (2008). Networking off Madison avenue. *The Review of Economic Studies*, 75(4):1011–1038.

Atkin, D., Chen, M. K., and Popov, A. (2022). The returns to face-to-face interactions: Knowledge spillovers in silicon valley. Technical report, National Bureau of Economic Research.

Autor, D., Levy, F., and Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4).

Autor, D. H. (2019). Work of the past, work of the future. *AEA Papers and Proceedings*, 109:1–32.

Bacolod, M., Blum, B. S., and Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics*, 65(2):136–153.

Baum-Snow, N., Freedman, M., and Pavan, R. (2018). Why has urban inequality increased? *American Economic Journal: Applied Economics*, 10(4):1–42.

Baum-Snow, N., Gendron-Carrier, N., and Pavan, R. (2024). Local productivity spillovers. *American Economic Review*, 114(4):1030–1069.

Baum-Snow, N. and Pavan, R. (2011). Understanding the city size wage gap. *The Review of Economic Studies*, 79(1):88–127.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 75(4):352–365.

Bonhomme, S., Lamadon, T., and Manresa, E. (2019). A distributional framework for matched employer employee data. *Econometrica*, 87(3):699–739.

Caliendo, L., Monte, F., and Rossi-Hansberg, E. (2015). The Anatomy of French Production Hierarchies. *Journal of Political Economy*, 123(4):809–852.

Card, D., Rothstein, J., and Yi, M. (2025). Location, location, location. *American Economic Journal: Applied Economics*, 17(1):297–336.

Carry, P., Kleinman, B., and Nimier-David, E. (2025). Location effects or sorting? evidence from firm relocation. Technical report, National Bureau of Economic Research.

Caunedo, J., Keller, E., and Shin, Y. (2023). Technology and the Task Content of Jobs across the Development Spectrum. *The World Bank Economic Review*, 37(3):479–493.

Cestone, G., Fumagalli, C., Kramarz, F., and Pica, G. (2023). Exploiting growth opportunities: The role of internal labour markets. *The Review of Economic Studies*, 91(5):2676–2716.

Combes, P.-P., Duranton, G., and Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63(2):723–742.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D., and Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, 80(6):2543–2594.

Couture, V., Gaubert, C., Handbury, J., and Hurst, E. (2024). Income growth and the distributional effects of urban spatial sorting. *Review of Economic Studies*, 91(2):858–898.

Crews, L. (2024). A dynamic spatial knowledge economy. Technical report.

Dauth, W., Findeisen, S., Moretti, E., and Suedekum, J. (2022). Matching in cities. *Journal of the European Economic Association*, 20(4):1478–1521.

Davis, D. R. and Dingel, J. I. (2019). A spatial knowledge economy. *American Economic Review*, 109(1):153–70.

Davis, D. R. and Dingel, J. I. (2020). The comparative advantage of cities. *Journal of International Economics*, 123:103291.

de la Roca, J. and Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1):106–142.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640.

Duranton, G. and Puga, D. (2004). Chapter 48 - micro-foundations of urban agglomeration economies. In Henderson, J. V. and Thisse, J.-F., editors, *Cities and Geography*, volume 4 of *Handbook of Regional and Urban Economics*, pages 2063–2117. Elsevier.

Duranton, G. and Puga, D. (2015). Urban land use. In *Handbook of regional and urban economics*, volume 5, pages 467–560. Elsevier.

Eckert, F., Ganapati, S., and Walsh, C. (2025). Urban-biased growth: A macroeconomic analysis. Technical report.

Eckert, F., Hejlesen, M., and Walsh, C. (2022). The return to big-city experience: Evidence from refugees in denmark. *Journal of Urban Economics*, 130:103454.

Eeckhout, J., Pinheiro, R., and Schmidheiny, K. (2014). Spatial Sorting. *Journal of Political Economy*, 122(3):554–620.

Fujita, M. and Thisse, J.-F. (2002). *Economics of Agglomeration: Cities, Industrial Location, and Regional Growth*. Cambridge University Press.

Gaubert, C. (2018). Firm sorting and agglomeration. *American Economic Review*, 108(11):3117–3153.

Glaeser, E. L. and Maré, D. C. (2001). Cities and skills. *Journal of Labor Economics*, 19(2):316–342.

Hornbeck, R. and Moretti, E. (2024). Estimating who benefits from productivity growth: Local and distant effects of city productivity growth on wages, rents, and inequality. *The Review of Economics and Statistics*, 106(3):587–607.

Jacobs, J. (1992). *The death and life of great American cities*. Vintage.

Koster, H. R. and Ozgen, C. (2021). Cities and tasks. *Journal of Urban Economics*, 126:103386.

Lhuillier, H. (2023). Should i stay or should i grow? Technical report, mimeo.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1):3–42.

Lucas, R. E. and Rossi-Hansberg, E. (2002). On the internal structure of cities. *Econometrica*, 70(4):1445–1476.

Michaels, G., Rauch, F., and Redding, S. J. (2018). Task Specialization in U.S. Cities from 1880 to 2000. *Journal of the European Economic Association*, 17(3):754–798.

Moretti, E. (2012). *The New Geography of Jobs*. Houghton Mifflin Harcourt.

Niebuhr, A., Peters, J. C., and Roth, D. H. (2024). Dynamic agglomeration effects of foreigners and natives – the role of experience in high-quality sectors, tasks and establishments. *Regional Science and Urban Economics*, 108:104040.

Oh, R. (2024). Spatial Sorting of Workers and Firms. mimeo.

Rosenthal, S. S. and Strange, W. C. (2020). How close is close? the spatial reach of agglomeration economies. *Journal of Economic Perspectives*, 34(3):27–49.

A Validating the base specification

We present here tests to evaluate the restrictions of the specification in equation 9 about the exogenous mobility with respect to the error term, and additive separability of the worker and urban unit effects along the lines suggested by Card et al. (2025).[25] We note that our base framework is not of the typical AKM type, and instead of firm fixed effects we have urban unit fixed effects. Our use of urban unit fixed effects instead of firm fixed effects as in the typical AKM framework may be viewed as a way to assuage concerns about limited mobility bias (Bonhomme et al., 2019) in our non-exhaustive DADS panel data.

Figure A.1 shows mean adjusted wages by month relative to the month of the move for workers grouped by origin and destination urban-unit quartiles, where quartiles are defined based on the urban-unit premia. Under exogenous mobility, there should be no strong differential trends before the move across origin-destination groups. The figure also shows that mean wages evolve in the expected direction depending on the size and sign of the jump in the urban-unit distribution: moves from low- to high-quartile urban units (e.g., Q1 to Q4) are associated with clear upward shifts in wages, whereas moves from high- to low-quartile urban units (e.g., Q4 to Q1) are followed by declines, with smaller adjustments for moves across closer quartiles. Overall, pre-move trends are fairly limited, while the main adjustment occurs around month 0, which is consistent with destination-related wage effects rather than strong anticipatory shocks.

Figure A.2 presents mean residuals by the decile of worker effects and urban unit effects. Under additive separability, average residuals should be close to zero in all worker-effect and urban-unit-effect decile cells, with no systematic patterns across the heatmap. The figure does not show a simple monotonic gradient across worker and urban unit deciles that would suggest assortative matching. Instead, residuals are positive in parts of the upper-left and lower-right of the matrix, while the most negative values appear among low worker/low urban unit cells and around urban unit decile 9 for mid-to-high worker deciles. This pattern suggests localized departures from additive separability rather than a uniform interaction between worker and urban unit effects.

[25] The study of residuals from the estimating equation prior to moves across urban areas is available upon request.

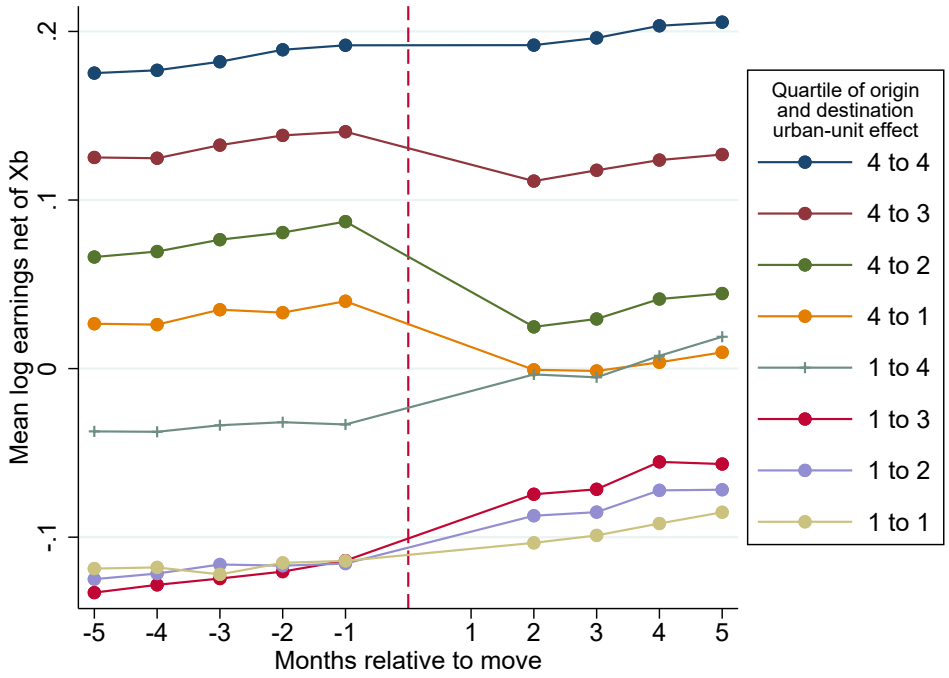


Figure A.1: Mean earnings before and after the move across firms

Notes: This figure reports event-time averages of residualized wages for workers moving across urban units, separately by quartiles of the origin and destination urban units' earnings premiums. Residualized wages are obtained after netting out the controls included in the specification as well as month-year fixed effects. The month of the move and the adjacent months are excluded. The sample is restricted to workers observed within the event window, and the outcome is averaged by event month and origin-destination quartile group.

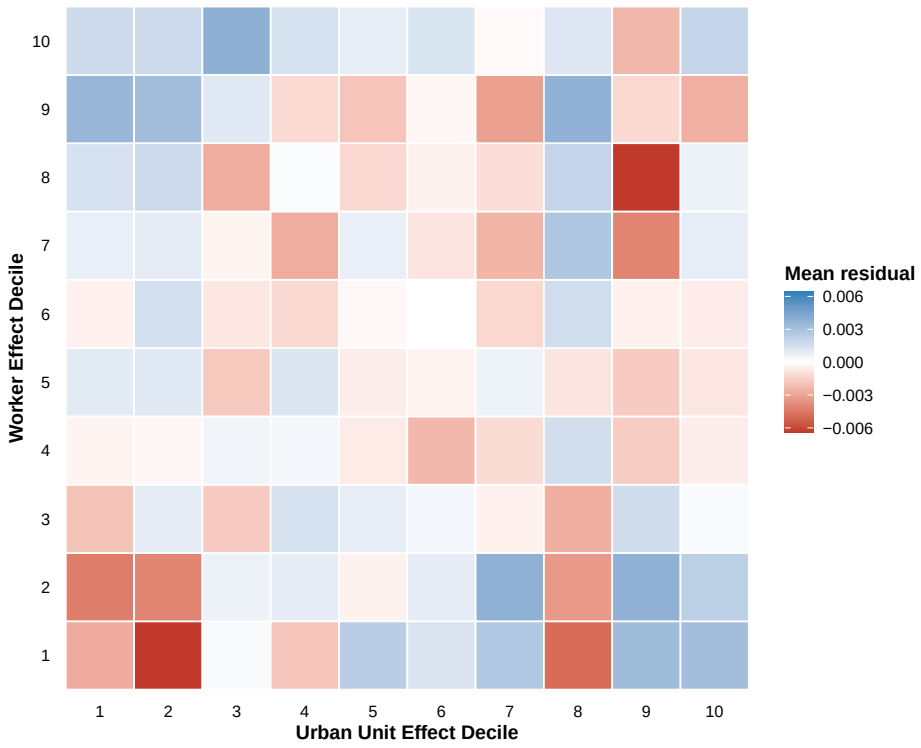


Figure A.2: Heatmap of mean of residuals by decile of person effect and urban unit/industry effect

Notes: This heatmap shows mean residuals from the AKM specification by decile of the estimated person effects and urban unit/industry effects. Each cell reports the average residual for workers located in a given combination of person-effect decile and urban unit/industry-effect decile. Darker shades indicate larger values of the mean residual.

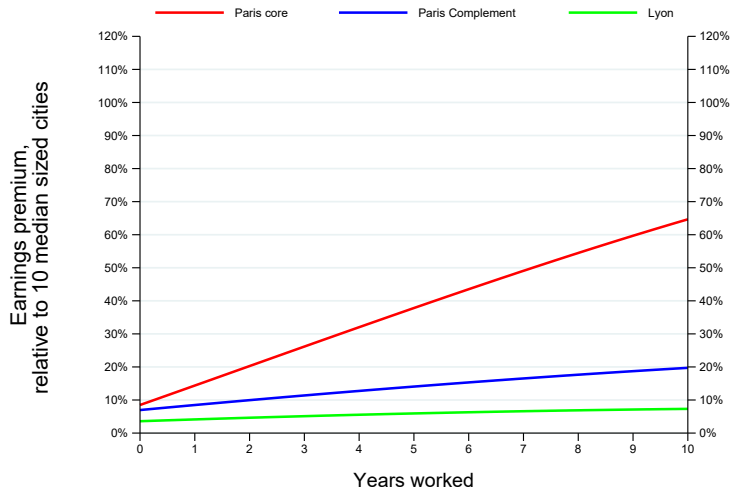
B Additional Tables and Figures

Table B.1: Regression results: dynamic gains

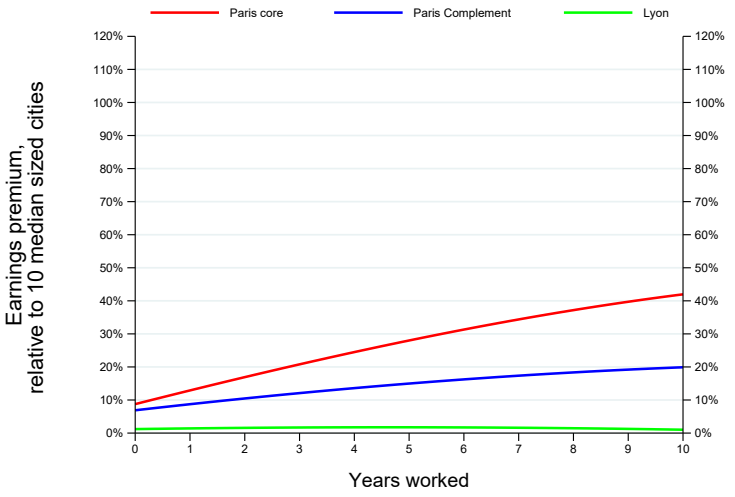
	(1) Experience by job type All sample	(2) Dynamic gains and Within city density All sample	(3) Learning occupations
Experience	0.0545***	0.0552***	0.0373***
	(325.99)	(332.07)	(44.07)
Experience (square)	-0.00146***	-0.00144***	-0.000813***
	(-531.95)	(-538.93)	(-76.30)
Experience in Paris (core)	0.0265***	0.0297***	0.0401***
	(44.21)	(56.17)	(28.31)
Experience in Paris (Complement)	0.00643***	0.00791***	0.00901***
	(20.63)	(27.38)	(9.78)
Experience in second to fifth biggest cities	0.00379***	0.00323***	0.0109***
	(11.21)	(10.10)	(10.25)
Exp*Experience in Paris (core)	-0.00123***	-0.000881***	-0.000436***
	(-35.89)	(-29.11)	(-5.50)
Exp*Experience in Paris (Complement)	-0.000290***	-0.000217***	-0.0000488
	(-18.86)	(-15.54)	(-1.19)
Exp*Experience in second to fifth biggest cities	-0.000359***	-0.000243***	-0.000219***
	(-17.81)	(-16.02)	(-4.54)
Experience in second to fifth biggest cities in a learning occupation	0.00905***		
	(6.72)		
Experience in a smaller city in a learning occupation	0.000377		
	(1.06)		
Exp*Experience in Paris (core) in a learning occupation	0.00133***		
	(14.16)		
Exp*Experience in Paris (complement) in a learning occupation	0.0000660		
	(1.16)		
Exp*Experience in second to fifth biggest cities in a learning occupation	0.000546***		
	(7.46)		
Exp*Experience in a smaller city in a learning occupation	0.000520***		
	(28.63)		
Experience in Paris (core) in a learning occupation	0.00698***		
	(4.62)		
Experience in Paris (complement) in a learning occupation	0.0181***		
	(8.15)		
Experience in Paris (core)*now in a big city	0.00326***	0.0102***	0.0130***
	(5.56)	(19.61)	(9.23)
Experience in Paris (complement)*now in a big city	0.00378***	0.00338***	0.00568***
	(12.73)	(12.28)	(6.30)
Experience in second to fifth biggest cities*now in a big city	-0.00184***	-0.00103***	-0.000448
	(-5.69)	(-3.38)	(-0.43)
Experience in smaller cities*now in a big city	-0.00104***	-0.00235***	0.00123
	(-4.85)	(-11.49)	(1.77)
Exp*Experience in Paris (core)*now in a big city	0.000221***	-0.000177***	-0.000776***
	(6.41)	(-5.86)	(-9.77)
Exp*Experience in Paris (complement)*now in a big city	-0.000142***	-0.000160***	-0.000280***
	(-9.37)	(-11.67)	(-6.98)
Exp*Experience in second to fifth biggest cities*now in a big city	0.000186***	0.000104***	-0.0000815
	(11.53)	(6.97)	(-1.69)
Exp*Experience in smaller cities*now in a big city	0.0000224*	0.000105***	-0.0000550*
	(2.27)	(11.30)	(-1.99)
Experience in Paris (core) in a learning occupation*now in a big city	0.0272***		
	(18.12)		
Experience in Paris (complement) in a learning occupation*now in a big city	-0.0112***		
	(-11.16)		
Experience in second to fifth biggest cities in a learning occupation*now in a big city	-0.00313*		
	(-2.37)		
Experience in a smaller city in a learning occupation*now in a big city	-0.00881***		
	(-10.56)		
Exp*Experience in Paris (core) in a learning occupation*now in a big city	-0.00167***		
	(-17.80)		
Exp*Experience in Paris (complement) in a learning occupation*now in a big city	0.000353***		
	(6.24)		
Exp*Experience in second to fifth biggest cities in a learning occupation*now in a big city	-0.0000941		
	(-1.30)		
Exp*Experience in a smaller city in a learning occupation*now in a big city	0.000320***		
	(6.91)		
Observations	12966349	12966351	1395436
R^2	0.860	0.859	0.877

t statistics in parentheses

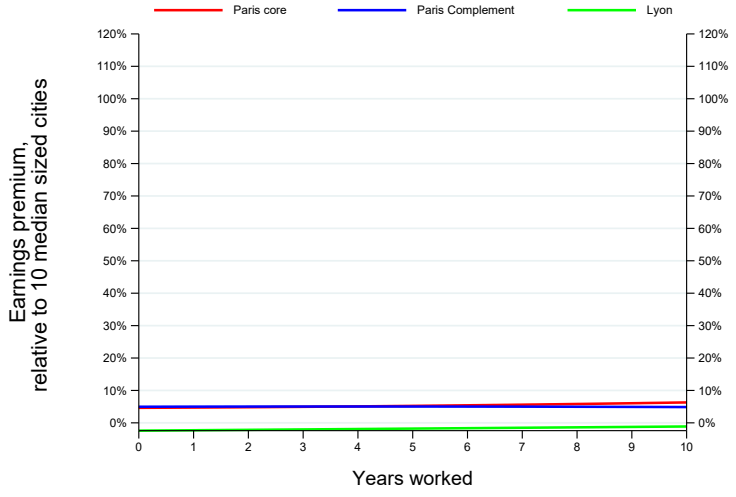
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



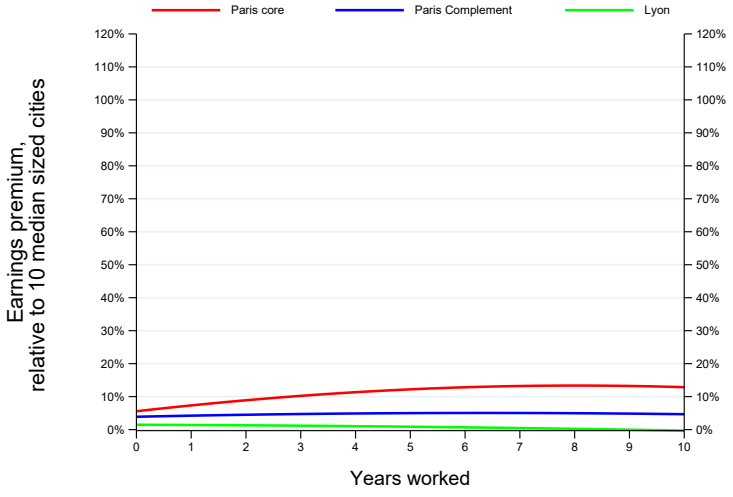
(a) "Learning"



(b) "Nerds"



(c) "Sales"



(d) "Manual and Routine"

Figure B.1: Earning profiles by job type

Table B.2: Top occupation Nationally

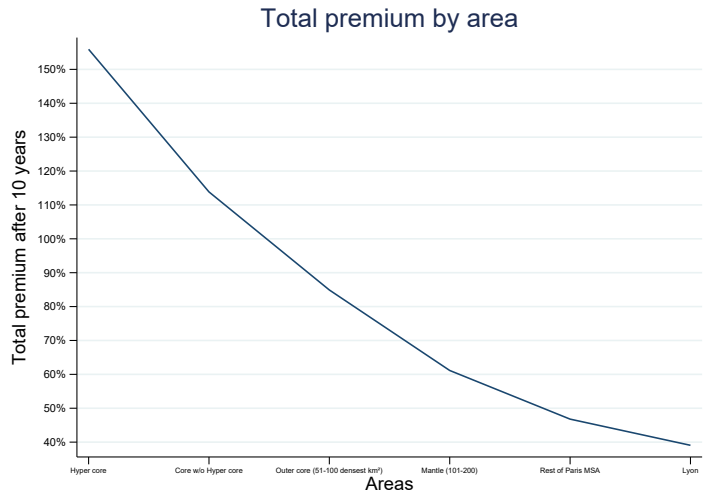
Rank	Occupation	Share (in %)
1	IT Engineers in R&D	2.65
2	Retail employees and storekeepers	2.62
3	Automotive mechanics	2.50
4	Kitchen assistants	2.37
5	Truck drivers	1.97

Table B.3: Top learning occupations in Paris: Core vs Complement

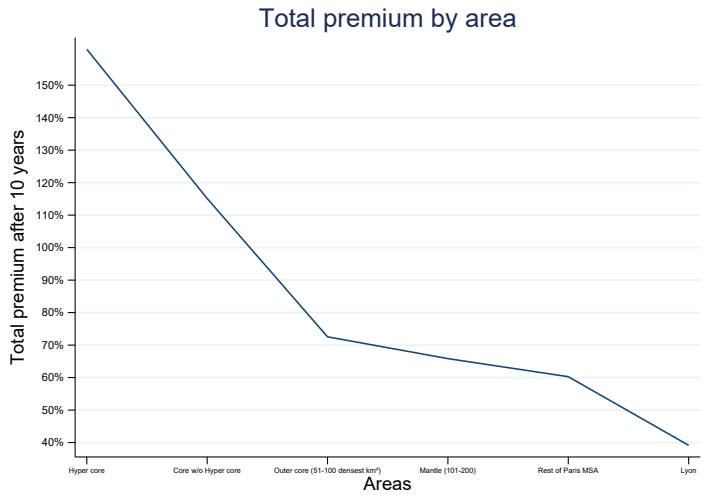
Rank	Paris Core Occupation	Share (%)	Paris Complement Occupation	Share (%)
1	Managers of administrative and financial services	11.980	Commercial managers of small and medium-sized enterprises	12.164
2	Managers in finance	10.459	Engineers in building and public works	7.867
3	Commercial managers of small and medium-sized firms	10.355	Commercial managers of large firms	6.900
4	Financial or accounting managers of small and medium-sized firms	6.654	Managers of administrative and financial services	5.649
5	Managers of other administrative services of small and medium-sized firms	6.549	Managers in finance	5.111

Table B.4: Top occupations by city category

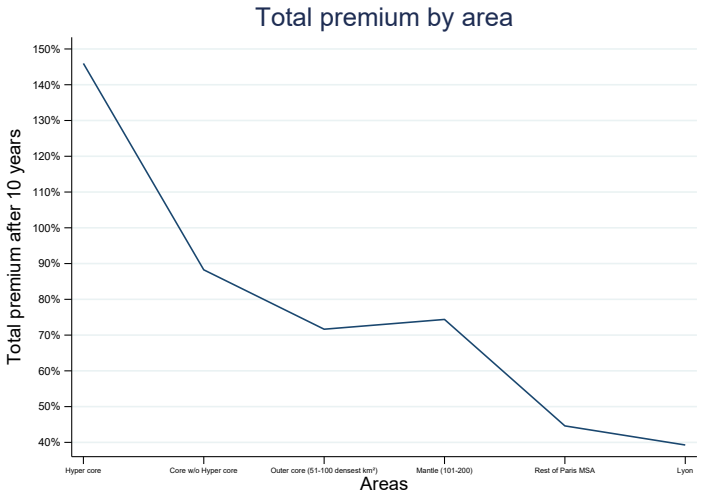
	Paris Core		Paris Complement		Other Big cities		Smaller cities	
Rank	Occupation	Share (in %)	Occupation	Share (in %)	Occupation	Share (in %)	Occupation	Share (in %)
1	IT engineers and managers in research and development (computing)	9.747	IT engineers and managers in research and development (computing)	3.903	IT engineers and managers in research and development (computing)	5.102	Skilled mechanics in maintenance, repair: automotive	3.144
2	IT project managers, IT managers	3.830	Self-service retail employees and warehouse workers	2.137	Production methods engineers and managers	2.456	Self-service retail employees and warehouse workers	3.016
3	(Code 561b)	3.451	Kitchen assistants	2.132	Kitchen assistants	2.382	Kitchen assistants	2.463
4	HR and recruitment specialist managers	3.331	Commercial managers in small and medium-sized enterprises	1.884	Self-service retail employees and warehouse workers	2.146	Truck drivers	2.460
5	Managers in economic, financial, and commercial studies	2.908	IT project managers, IT managers	1.756	Cooks	1.690	Cooks	1.993



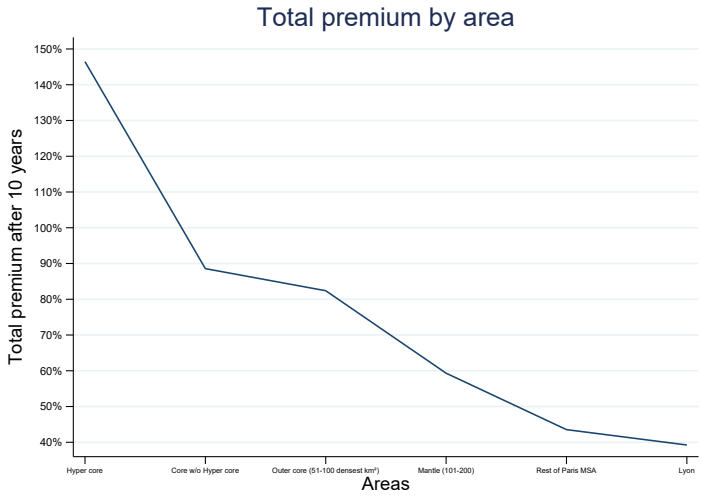
(a) Smooth density: all jobs, $1km^2$ squares



(b) Smooth density: learning jobs only, $1km^2$ squares



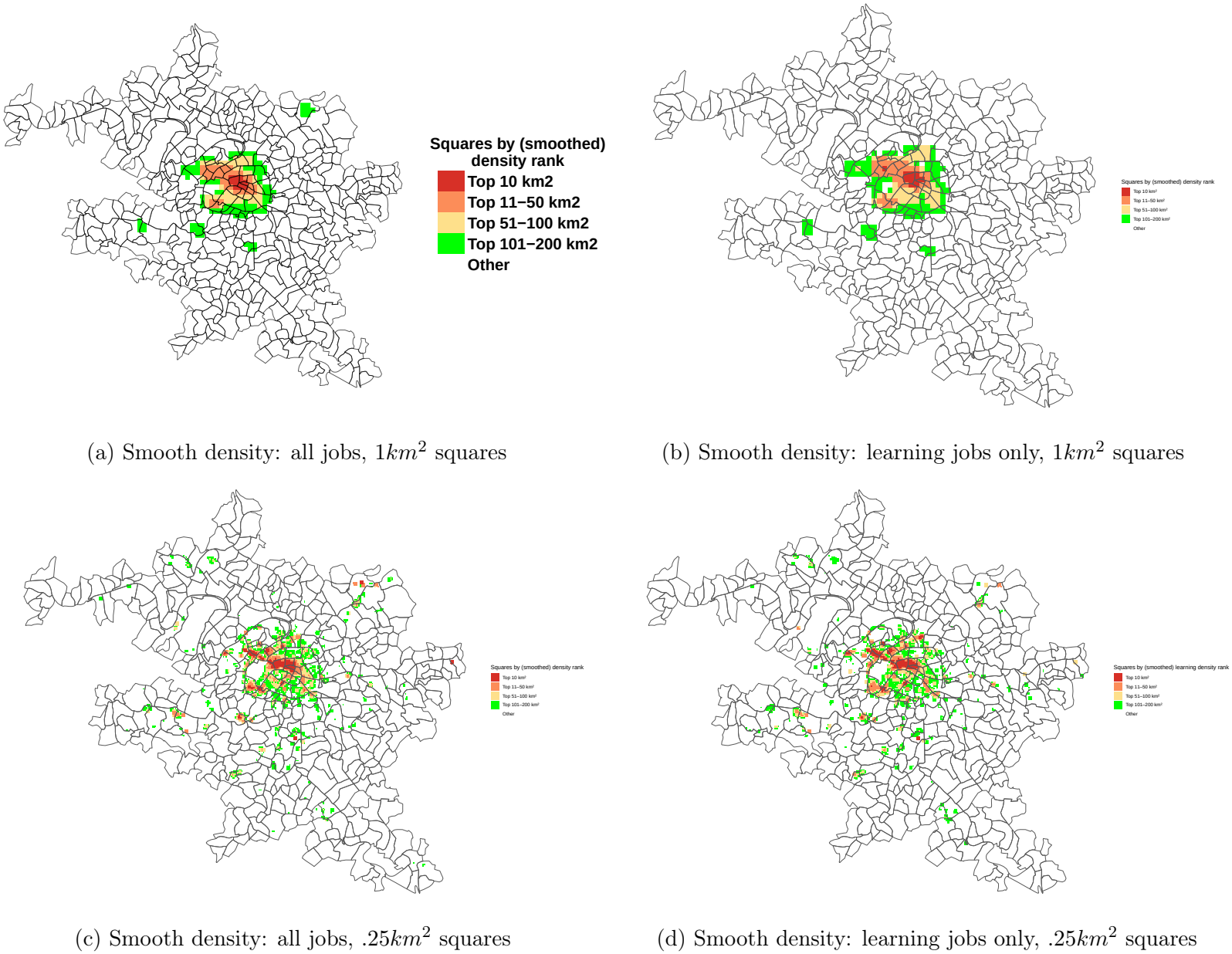
(c) Smooth density: all jobs, $.25km^2$ squares



(d) Smooth density: learning jobs only, $.25km^2$ squares

Figure B.2: Dynamic returns in learning jobs by area.

This figure shows the dynamic returns in different areas in Paris by job density, based on different definitions and granularity. The hype core area corresponds in all figures to the densest 10 km^2, the core to the 11 to 50 densest km^2, the outer core to 50 the 51 to the 100 densest km^2, and the Outer core to the 101 to 200 densest km^2.



(a) Smooth density: all jobs, $1km^2$ squares

(b) Smooth density: learning jobs only, $1km^2$ squares

(c) Smooth density: all jobs, $.25km^2$ squares

(d) Smooth density: learning jobs only, $.25km^2$ squares

Figure B.3: Most job dense areas in Paris

This figure shows the areas in Paris with highest job densities, based on different definitions and granularity.