Occupational Coherence and the Geography of Unemployment

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Abstract

Why do labor markets in some regions perform better than in others? This paper studies how the occupational coherence of local labor markets shapes regional unemployment dynamics. Using matched employer–employee data for France, we develop a network of inter-occupational relatedness based on worker mobility. By mapping local occupational structures onto this occupation space, we derive a measure of occupational coherence for 304 commuting zones in France. Occupational coherence captures the ease with which workers can switch jobs locally. Using a shift-share instrument that exploits exogenous trade shocks to other developed countries, we find that local labor markets with higher occupational coherence experience significantly lower unemployment. This effect operates mainly through within-firm reallocation: workers in more coherent labor markets are more likely to adjust by moving internally to other occupations. Our findings highlight the importance of occupational structure for local labor market performance and suggest that policies fostering occupational mobility can help reduce local unemployment rates.

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1 Introduction

Two types of cities are found in many countries: highly specialized cities with few occupations and diversified cities with many different occupations (Gervais et al., 2022; Duranton and Puga, 2005; Defever, 2005). Examples of these two types of cities are New York City, which attracts a large set of workers ranging from lawyers, financiers, technology workers, and artists (Eeckhout et al., 2014; Abel and Gabe, 2012), and the San Jose-Sunnyvale-Santa Clara Metropolitan Statistical Area, located in and around Silicon Valley, which is a functionally specialized cluster of computer programming and related high-technology workers. Which type of locational pattern is more advantageous for local labor market and workers' employment outcomes? Could the performance of local labor markets be dependent upon local occupational composition? Can the local skill composition contribute to explaining why the unemployment rate is persistently high in some places and low in others?

While most papers have focused on the employment impact of industrial concentration in local labor markets (e.g., Rinz, 2022; Autor et al., 2023) or on the value of skill concentration as reflected through inter-industry flows, very few have investigated the role of occupational concentration and specifically, the clustering of skill-related occupations within local labor markets (Hane-Weijman et al., 2022; Henning et al., 2025). There is a potential tradeoff between having strong ties among a small set of occupations, and a larger number of weak ties between diverse occupations. The trade-off between the two is clear. Marshallian externalities, which arise in thick labor markets, enhance economic coherence, efficiency, and performance by facilitating worker retention and re-employment—particularly for workers whose skills align with the local specialization (Neffke et al., 2018; Macaluso, 2025). In contrast, a diversified set of occupations is more likely to attract productive employers and facilitate better matches between workers and firms (Bilal, 2023; Card et al., 2023; Dauth et al., 2022, Papageorgiou, 2021, De la Roca et al., 2023). This article examines how the spatial clustering of occupations that rely on similar skill sets affects both individual and local labor market unemployment dynamics.

Our empirical approach begins by mapping a network of occupational relatedness derived from occupational mobility, using a unique French dataset that provides career paths for a representative sample of French workers. Our first step is to construct a measure of relatedness between occupations based on the frequency of job transitions between them. The underlying assumption is that an excess of mobility between two occupations indicates that they likely share similar tasks, skills, and know-how that are transferable. Mapping the proximity between all occupations in our dataset yields a network of relatedness that we refer to as the occupation space. Occupations located at the center of this space benefit from greater redeployment capabilities, while peripheral occupations are associated with more specific tasks that are less transferable across occupations. Our second step is to superimpose local occupational composition onto this occupation space to obtain a measure of occupational coherence for 304 commuting zones (CZs) in France. We define occupational coherence as the degree to which interrelated skills are locally concentrated within a CZ. The more a CZ is composed of occupations that are closely connected in the occupation space, the higher its occupational coherence. Our measure of occupational coherence is novel because it is derived from observed worker transitions across occupations, capturing the realized potential for occupational mobility within local labor markets. Unlike existing approaches, which rely on expert-defined occupational relatedness or co-location patterns (e.g., Bocquet, 2024; Muneepeerakul et al., 2013), our approach uses actual worker flows to reveal the network structure.

We are then in a position to examine the importance of local occupational coherence in explaining labor market performance. Endogeneity concerns may arise from the endogenous sorting of workers and firms across regions or from unobserved regional characteristics that influence both occupational structure and labor market outcomes. To address potential endogeneity issues, we adopt an instrumental variable approach following the methodology outlined by Autor et al. (2013). Specifically, we instrument for occupational coherence using a shift-share instrument that interacts pre-period industrial employment shares with industry-level exposure to imports from China.

We find that CZs with a one-standard-deviation higher occupational coherence have, on average, a 0.6 percentage point lower working-age unemployment rate over the five-year period from 2010 to 2015. We implement a range of robustness checks, including a two-step estimation procedure that isolates variation in regional unemployment growth and an additional specification based on the long difference in unemployment between 2010 and 2015. Finally, while we believe that our own methodology for measuring skill relatedness has several advantages, including the use of a directional network that accounts for asymmetric relationships between occupations, we also use robustness index of occupational coherence based on the work of Macaluso (2025) and Hane-Weijman et al. (2022). All of these checks confirm that local skill-related occupational structures are systematically associated with lower local unemployment rates.

To better understand the distinctiveness of our findings and to situate them within the context of existing research—which has largely emphasized the role of industrial coherence—we compare the effects of occupational coherence with those of industrial coherence. Our comparison shows that industrial coherence has a much smaller impact on unemployment over the same period. One potential explanation for why occupational coherence is more important than industrial coherence in shaping local labor market performance is that it allows for internal labor movement — that is, workers can shift occupations within firms. Industrial coherence, by contrast, cannot account for internal labor mobility, as it inherently involves a change of industry and therefore very likely a change of employer.

Building on this insight, we next examine how occupational coherence operates in practice by focusing on the specific channels through which it affects worker mobility. The final part of our study shifts the focus from local labor market adjustments to individual workers. We analyze the influence of occupational coherence on two adjustment margins: (i) the reallocation of incumbent workers within their original firm, facilitated by reassignment to other occupations; and (ii) the transition of workers to new employers. As we show later, the relationship between local occupational coherence and labor market performance appears to be primarily driven by enhanced protection against unemployment through within-firm occupational mobility, rather than by easier transitions to new employers. In particular, we find that workers in the same 2-digit occupation who are employed in regions with a one-standard-deviation higher level of occupational coherence are about 0.16 percentage points more likely to be employed on any given day. This effect is mainly driven by workers who stay with their original employer but switch to a different occupation.

This paper contributes to the literature in three ways. First, we introduce a novel, data-driven measure of occupational coherence that captures actual worker mobility patterns, extending existing concepts of industrial relatedness to the occupational dimension. Our measure improves on existing approaches by providing a directed network that allows for more granular analysis and does not rely on external or sometimes arbitrary expert-based classifications of skill similarity. Second, we provide new evidence that occupational coherence significantly reduces local unemployment, complementing prior work that focuses mainly on industrial specialization. Third, we show that this effect operates partly within firms, highlighting an important channel for local labor market adjustment. Together, these findings deepen our understanding of how labor market structure shapes regional economic performance.

The rest of the paper is organized as follows. Section 2 situates our contribution within the related literature. Section 3 outlines the theoretical mechanisms that explain the role of occupational coherence. Section 4 describes the data and cleaning procedures. Section 5 presents our methodology, including the construction of the occupation space and the measure of occupational coherence. Section 6 reports the empirical design and results on the relationship between occupational coherence and local labor market unemployment rates. Section 7 provides worker-level estimates to explore the mechanisms behind the role of occupational coherence. Section 8 concludes.

2 Related Literature

Traditionally, the literature on regional economic performance has largely focused on the role of local industrial specialization to explain large and persistent differences in unemployment across regional labor markets, often overlooking the labor skills and work tasks required as inputs. For example, Yi et al. (2024) shows that the industry mix of regions is an important determinant of reallocation probabilities of workers across sectors, and the wage losses for displaced workers is determined by the sector to which they reallocate.[1] This output-oriented perspective may lead to an incomplete understanding of regional performance, as occupational composition can also play a critical role in shaping the long-term employment prospects of both workers and regions.

This is motivated by new evidence that regions are moving from industrial specialization to functional specialization (Duranton and Puga, 2005; Defever, 2005), particularly in service-intensive regions (Diodato et al. 2018).[2] Local areas are therefore better represented by groups of occupations than by groups of industries. Building on this observation, economists have sought to demonstrate how the occupational composition of the workforce affects the economic performance of local labor markets. For example, Henning et al. (2025) develop a new approach using Swedish job postings (2019–2021) to compute a skill-relatedness matrix between jobs, based on shared skill requirements in vacancy texts. They find that job-switching is linked to better economic outcomes, even in diverse labor markets. Macaluso (2025) constructs an occupation–city level measure of skill remoteness

[1] The core argument is that locations with a variety of technology-related industries with little local input-output relationships with one another are better able to exploit new growth paths through the recombination of available technological capabilities (Balland et al. 2015; Diodato and Weterings 2015; Neffke et al. 2012, Xiao et al. 2018, Cainelli et al. 2019). Studies have measured skill-relatedness between industries using actual job transitions between industries. In other words, labor flows that cannot be explained by the characteristics of the two industries indicate skill-relatedness between those industries. If individuals can easily move from one industry to another, then it is because the production processes in the two industries likely draws upon similar skills (Neffke and Henning, 2013, Neffke, Otto and Weyh, 2017). The literature has also measured technology-relatedness. Technology-relatedness is based on the intuitive idea that the ability of a region to produce a product depends on its ability to produce other related products (Hidalgo et al., 2007). If two goods are related because they require similar institutions, infrastructure, resources, technology, or some combination thereof, they will likely be produced in tandem, whereas dissimilar goods are less likely to be produced together. Bryce and Winter (2009) count the co-occurrence of plants within firms in two different industries to measure relatedness between industries. Neffke and Henning (2008) count the number of products from different industries in the portfolios of manufacturing plants' products. Xiao et al. (2018) counts the co-occurrence of two industries in the same region.

[2] For example, innovation-related functions such as R&D are in areas with concentrations of intellectual capital. Administrative and decision-making functions are more sensitive to proximity to political or administrative institutions. Logistics and distribution functions have a propensity to locate near production activities. Gervais et al. (2021) proposes a theoretical model where, as geographic fragmentation costs fall, sector (industry) concentration and regional specialization fall for sectors and rise for functions (occupations). Their empirical analysis using US data fits this pattern as well.

using detailed O*NET-based skill profiles to measure post-layoff outcomes. Her findings, among others, show that workers laid off from skill-remote jobs experience persistently lower earnings.

By acknowledging the importance of local occupational composition, economists have increasingly used network analysis to characterize labor markets. For example, Muneepeerakul et al. (2013) construct an occupation network based on the co-location of occupations within geographic areas.[3] However, while co-occurrence may reflect task complementarity, it does not necessarily capture the ease with which workers can transition between occupations. This limitation has led subsequent research to explore job-to-job transitions and skill relatedness using network-based approaches.[4] Bocquet (2024) constructs an occupation network based on expert-defined measures of skill relatedness. He shows that labor reallocation depends not only on job availability but also on the topological structure of the skill network. This underscores the importance of bottleneck occupations in shaping adjustment dynamics and informing targeted labor policies. Fogel and Modenesi (2023) introduce a data-driven classification of workers and jobs by uncovering latent skill and task heterogeneity, applying network theory to large-scale administrative job-matching data from Brazil. Nimczik (2023) adopts a firm-level network perspective, linking firms via job-to-job transitions. He applies community detection algorithms, such as the stochastic block model, to identify 'data-driven' labor markets. We contribute to this literature by developing a novel, network-based measure of local labor markets that captures skill relatedness between occupations using observed worker transitions. Unlike Bocquet (2024), our approach does not rely on expert assessments of occupational similarity. It still constructs a directed occupational network, allowing for the possibility that transitions between occupations may be asymmetric. This asymmetry offers a comparative advantage over methods that rely on skill-similarity measures.

Our work is also related to the literature investigating the role of workers' outside options. The concept of outside options is closely linked to occupational mobility. Caldwell and Danielli (2022) construct a micro-founded index of outside employment opportunities—the Outside Options Index (OOI)—to examine the effect of outside options on wages, holding worker productivity constant. Schubert et al. (2022) incorporate within-occupation employer concentration into the analysis of outside options. Using occupational mobility

[3] They use conditional probabilities rather than traditional proximity measures, such as those in Hidalgo et al. (2007), because co-occurrence within a locality may reflect general occupation prevalence rather than meaningful relatedness. Specifically, they analyze the ratio of conditional to marginal probabilities to assess whether specialization in one occupation depends on the presence of another. Their measure is: $\epsilon_{ij} = \frac{P(LQ_i>1|LQ_j>1)}{P(LQ_i>1)P(LQ_j>1)}$, where LQ denotes revealed comparative advantage; $LQ > 1$ indicates regional overrepresentation.

[4] For example, engineers and technicians often collaborate on production tasks, but transitions from technician to engineer are relatively rare.

data, they demonstrate that the availability of job opportunities outside a worker's current firm significantly affects wages. Our study contributes to this literature by showing that, although workers in skill-related occupations may have more outside options, they are more likely to remain with their current employer by switching occupations internally.

3 Conceptual Background and Hypothesis

This section discusses the mechanisms that explain the relationship between occupational coherence and local labor market unemployment (section 3.1). It also examines the relative importance of occupational coherence compared to industrial coherence in influencing local unemployment rates (section 3.2).

3.1 Occupational Coherence and Employment Tenure

The prevailing consensus in the literature on the origins of unemployment disparities is that differences in separation rates—i.e., the rates at which individuals leave their jobs, whether voluntarily (e.g., quitting) or involuntarily (e.g., layoffs or retirement)—are the primary drivers of geographic variation in unemployment rates (Kuhn et al., 2021; Bilal, 2023). Separation rates essentially capture the frequency with which workers exit employment. Higher separation rates are associated with higher local unemployment. Put differently, regions with high unemployment are not necessarily characterized by a lack of job opportunities or by difficulty in finding a job. Rather, these regions often experience higher unemployment because workers repeatedly lose their jobs. Local labor market characteristics, and in particular, the local skill composition, may play a key role in shaping unemployment rates through their impact on job separations.

Theoretically, there are two main mechanisms that would explain why highly coherent CZs provide better insurance against unemployment. First, in more specialized regions, establishments often concentrate employment in a narrower set of skill-related occupations and adopt production processes closely aligned with the region's dominant skill base (Bilal, 2023). This specialization may enhance firms' ability to retain workers by facilitating internal reassignments to new occupations that require similar skills, thereby reducing job loss. Specialized firms may also be better able to absorb shocks in the long run by reorganizing, adapting, or transforming into new entities that continue to draw on the internal pool of workers (Dauth et al., 2021).

Second, workers in regions with strong occupational coherence and dense links between occupations are likely to experience shorter unemployment spells, as they are more likely to find new jobs either in the same occupation or in another related occupation more quickly.

Workers in labor markets specialized in skill-related occupations may face less competition due to expanded occupational mobility. The extent to which these mechanisms operate in practice, however, remains an empirical question.

3.2 Occupational Coherence and Industrial Coherence

This article also aims to compare the influence of occupational coherence and industrial coherence in shaping local unemployment rates. Both concepts reflect different dimensions of labor market structure: industrial coherence captures the relatedness of industries based on shared inputs, technologies, or supply chains, whereas occupational coherence reflects the relatedness of tasks and skills across occupations in a given locality. By analyzing their respective associations with unemployment outcomes, we seek to determine which form of coherence better explains variation in labor market performance. We conjecture that, since mobility between occupations is generally less costly than mobility between industries, occupational coherence may exert a stronger influence on local unemployment rates. Occupational mobility tends to be less costly because switching occupations can occur within firms or within industries often for promotion purposes or to facilitate the combination of complementary skills within the same plant. In contrast, mobility across industries typically requires moving between firms, which is more costly for workers (Kramarz et al., 2014; Baker et al., 1994; Eriksson, 2009; Neffke et al., 2012). As a result, movement across occupations is likely to occur more frequently than movement across industries over the course of a worker's career. We thus hypothesize that occupational coherence plays a more significant role than industrial coherence in shaping local unemployment dynamics.

4 Data and Cleaning Procedures

Our first source of information is the French database Déclarations annuelles des données sociales - Postes (DADS-Postes). This source provides information on the workforce composition of all establishments in France based on mandatory annual reports. All French employers, including national companies, public entities, and local governments, are required to provide information to state social security organizations and the national tax administration about each of their employees on an annual basis. For our analysis, as is customary in the literature, we consider full-time, full-year workers in their principal job employed in private companies. Each observation in the database corresponds to a particular job, that is an employee's position in an establishment. For each of these employer-employee records, the data contains information on the employee's occupation and the location of their establishment. We are then able to trace the workforce composition of each commuting zones

(CZ) from 2009 to 2015.[5] We intentionally choose this time span because starting in 2009 employers were required to report each occupation with a 4-digit classification. Before 2009 there are many missing values. We also limit the period of observations to year 2015 because DADS data underwent significant revisions starting in year 2016.[6]

Our second source of information is the administrative panel — the Déclaration Annuelle des Données Sociales (DADS-Panel). Like the first dataset, it is built from confidential yearly social security records, processed and provided by the French National Institute for Statistics and Economic Studies (INSEE). These administrative records are based on firms' mandatory reports to the tax authorities of workers subject to payroll taxes. This database covers all firms in the private and public sectors. From this administrative source, a panel of individuals born in October is constructed. Each observation consists of an employer–employee match and reports the individual's sex, age, place of residence, workplace region, yearly real earnings (in 2007 euros), and the number of hours and days worked each year. The dataset is large and noisy, which is why we apply various cleaning procedures. First, we focus on mainland France and exclude overseas territories. Second, we retain workers in the private sector (excluding traineeships and subsidized employment) within the working-age range (18–60). Third, to focus on meaningful work experience, we remove observations of jobs held for fewer than 30 days. Also, since workers in the DADS can be identified simultaneously in several positions, we keep only the worker–firm match with the longest job spell and highest salary, and remove occupations identified as ancillary. After these cleaning procedures, we end up with an unbalanced panel of workers observed yearly in 270 occupations.

In our 2009-2015 sample the workers held on average 2.7 occupations, and more than 30% of workers experienced at least one occupational transition, either within firms or between different firms.

[5] A CZ is a geographic area in which the working population both resides and works, and in which establishments can find the bulk of the workforce necessary to fill local job openings. We use the 2010 classification of locations into 304 commuting zones done by the French Statistical Institute.

[6] In 2016, all private establishments in all sectors of activity began to switch to the "Déclaration sociale nominative" which is a new way of collecting data and that definitively replaces DADS in private establishments in 2018. The declaration logic of DSN is very different from that of DADS. The INSEE had to develop a new computer application to accommodate data having a different format and making DSN and DADS coexist during the three years of transition (2016 to 2018). As a result, the INSEE files resulting from the DADS data for the 2016 then 2017 validity periods have undergone significant revisions, in level as in evolution.

5 Construction of Occupational Coherence, Variables Definition, and Descriptive Overview

To examine the relationship between local labor market performance and occupational coherence across 304 French CZs, we first measure bilateral occupational relatedness. We then apply this measure to local occupational composition to construct an index of CZ-level occupational coherence. Next, we describe the characteristics of French local labor markets based on this coherence index.

5.1 Occupational Relatedness

Human capital is not narrowly tied to specific occupations but is instead linked to a limited set of foundational skills that are transferable across occupations (Poletaev and Robinson, 2008, Kambourov and Manovskii, 2009). Occupational classifications, such as those used in our analysis, encompass a wide variety of roles some involving very different skill sets (e.g., carpenters and economists), and others that are functionally similar despite being classified separately (e.g., financial and banking executives, both falling under managerial occupations). To quantify the degree of skill proximity between occupations, we use data on worker flows across four-digit occupations from the DADS Panel. This approach is grounded in the idea that most occupational transitions do not involve a substantial change in workers' skill portfolios (Poletaev and Robinson, 2008), so the frequency of labor flows between occupations can serve as an empirical proxy for the degree of skill and human capital relatedness. Of course, labor mobility is influenced by a range of factors beyond skill portability, including occupational desirability, transition costs, and individual characteristics such as gender, education, and age. For example, younger, more educated men tend to switch occupations more frequently than older, less-educated individuals or women (Blumberg, 1980; Topel and Ward, 1992; Groes et al., 2015). Moreover, local labor market conditions also shape mobility patterns, with higher occupational mobility observed in urban areas where employment density is greater (Andersson and Thulin, 2013). To assess whether the observed labor flows between occupations reflect meaningful skill proximity, we must compare them against an appropriate baseline. Therefore, occupational relatedness between any pair of occupations i and j is measured as:

$$OR_{(i,j)} = \frac{F_{(i,j)}}{\hat{F}_{(i,j)}} \tag{1}$$

Where $F_{(i,j)}$ is the cumulative number of labor flows from origin occupation i to destination occupation j observed between 2009 and 2015.[7] We then follow the method proposed

[7] $F_{(i,j)}$ is a non-negative integer count derived from DADS-Panel data, capturing all observed occupational transitions over the 2009–2015 period. With 270 distinct occupations, there are 270 × 269 = 72,630 possible

by Neffke et al. (2013) to estimate $\hat{F}_{(i,j)}$.

Specifically, we estimate $\hat{F}_{(i,j)}$ by regressing the number of observed switches from occupation i to occupation j on a set of socio-demographic covariates describing both occupations. Given that the dependent variable includes a large proportion of zeros, the appropriate empirical specification is a Zero-Inflated Negative Binomial (ZINB) model. This model consists of two stages. In the first stage, a logit model estimates the probability of observing a positive flow between any pair of occupations. As explanatory variables, we include the total employment in occupations i and j, measured as the average over 2009–2015 and expressed in logarithmic form (denoted $lEmp_i$ and $lEmp_j$, respectively). The second stage of the ZINB model is a count-data regression that estimates the volume of flows from occupation i to occupation j conditional on observing a positive flow. We incorporate factors likely to affect both how desirable an occupation is and how easily workers can transition between occupations. We include three groups of explanatory variables, guided by the empirical literature on job switching, which identifies wage differentials, gender, and age as key determinants of occupational mobility (Kambourov and Manovskii, 2008; Lalé, 2012).

The first group of explanatory variables captures characteristics of the origin occupation, represented by the vector v_i. It includes the average age of workers, average hourly earnings (in log), the average share of male workers, the average number of workers employed (in log), and the annual employment growth rate (in percent)—each measured over the 2009–2015 period using DADS-Panel data. The second group of variables, denoted v_j, mirrors v_i and captures the same set of characteristics for the destination occupation j.

The third group, captured by the vector w_{ij}, includes variables that reflect comparative characteristics between occupations i and j. First, we include a dummy variable equal to one if average earnings in occupation j exceed those in occupation i, capturing upward wage mobility. Second, to control for spatial frictions in occupational mobility, we include a dummy equal to one if both occupations i and j exhibit a revealed comparative advantage in urban areas.[8] It is defined as the ratio of the share of an occupation's employment in urban areas to the share of total employment in urban areas. An occupation is classified as having an urban comparative advantage if this ratio exceeds one.

The estimated flows from occupations i to j are obtained using the following equation:

directed occupation pairs. Among these, 24,469 pairs exhibit a positive number of switches. The remaining flows are coded as zero. For confidentiality reasons and to exclude extremely marginal flows, all switches with a count below 10 are also set to zero.

[8] Urban CZs are identified using INSEE classification

$$E(F_{(i,j)}|v_i, v_j, w_{ij}, \epsilon_{(i,j)}) = [1 - \Pi_0(\gamma + \delta_i lEmp_i + \delta_j lEmp_j)]\, e^{((\alpha + v_i\beta_i + v_j\beta_j + w_{ij}\beta_i + \epsilon_{(i,j)}))}$$

With Π_0 denoting the probability that $F_{(i,j)} = 0$, estimated from the logit component of the Zero-Inflated Negative Binomial (ZINB) model. Accordingly, $1 - \Pi_0(.)$ represents the probability that a positive labor flow occurs between occupation i and occupation j. The expected count of flows is modeled as the mean of the negative binomial distribution, given by $e^{(\alpha + v_i\beta_i + v_j\beta_j + w_{ij}\beta_{ij} + \epsilon_{(i,j)})}$, where the predictor includes occupation-specific covariates v_i and v_j, comparative characteristics w_{ij}, and the associated parameter vectors β_i, β_j, and β_{ij}.

Table 1 reports the coefficients from the negative binomial component. Using the estimated model in Table 1, we compute the predicted labor flow for each pair (i, j) as $\hat{F}(i, j) = E\left(F(i, j) \mid v_i, v_j, w_{ij}, \epsilon_{(i,j)}\right)$. We then estimate occupational relatedness $OR_{(i,j)}$ as the ratio of observed to expected flows as detailed in equation (1).

When $OR_{(i,j)} \geq 1$, the observed number of labor flows between occupations i and j exceeds the baseline prediction $\hat{F}(i, j)$, indicating a higher-than-expected frequency of transitions and, by implication, a greater degree of skill proximity between the two occupations. Conversely, when $OR(i, j) < 1$, the observed flow is lower than expected, suggesting relative skill dissimilarity between occupation i and occupation j. The magnitude of $OR_{(i,j)}$ thus provides an index of bilateral occupational proximity: the higher the value, the more occupations i and j appear to share similar skill sets and task requirements, as evidenced by more frequent worker mobility between them.

5.2 The Occupation Space

Using occupational relatedness, $OR_{(i,j)}$, we construct a matrix of connections between 270 occupations and represent it as a network graph in Figure 1. Each node corresponds to an occupation (in the PCS 4-digit classification), with node size proportional to the occupation's share of total French employment in 2015. Links between nodes represent bilateral values of $OR_{(i,j)}$. For clarity, Figure 1 displays only those links for which $OR_{(i,j)} \geq 1$, i.e., where observed mobility from i to j exceeds the baseline prediction. We refer to this weighted and directed network of bilateral occupational relatedness as the Occupation Space. The intensity of relatedness between occupation i and j is represented by the transparency of the connecting lines. The layout algorithm used to construct the Occupation Space arranges occupations such that those with stronger relationships are positioned closer together in the graph.

The Occupation Space is a sparse network, with only 17% of occupation pairs connected consistent with limited skill portability across occupations. Moreover, the potential for redeployment is not only limited but also unevenly distributed. On average, each occupation is closely related (i.e., $OR_{(i,j)} \geq 1$) to 47 others (out of 270), but this number varies considerably. The most connected occupation, 479b (Technician-level experts), is related to 103 others, while the least connected, 546d (Flight attendants and stewards), is linked to only 6.[9]

5.3 CZ Occupational Coherence

Occupational coherence reflects the extent of local skill transferability, determined by the occupational composition of a region and the relative positions of these occupations within the occupation space. Before formally defining the measure of occupational coherence, Figure 2 provides an illustrative comparison of the occupation space in two distinct French cities. The left panel depicts the Arve Valley, while the right panel shows Saint Lô. These cities differ markedly in their occupational structures. In the Arve Valley, a larger share of workers is employed in occupations that are closely connected within the occupation space, as evidenced by the higher density and clustering of nodes. This visual pattern indicates that the Arve Valley has a greater concentration of employment in skill-related occupations, that is, occupations linked by high values of $OR_{(i,j)}$ compared to Saint Lô.

Our goal is to create a variable capturing this local skill transferability. Specifically, we create a local occupation coherence index OC_r as the weighted average of occupation relatedness within the CZ:

$$OC_{(r,t)} = \sum_{(i=1)}^{n} \sum_{(j=1)}^{(n-1)} \left(E_{(i,r,t)} E_{(j,r,t)} . OR_{(i,j)} \right) \tag{2}$$

where $E_{(i,r,t)}$ and $E_{(j,r,t)}$ denote the employment shares of occupations i and j in commuting zone (CZ) r in year t, for the 270 occupations included in the occupation space.[10]

[9] Close inspection of highly related occupation pairs confirms that the OR score is a meaningful proxy for skill proximity. The strongest relatedness is observed between 376b (Banking operations executives) and 376a (Financial market executives), with actual labor flows occurring 380 times more frequently than predicted by the baseline. The next closest pair is 353c (Artistic and technical-artistic executives for audiovisual production and shows) and 465b (Technical assistants in the production of live and audiovisual shows), with $OR_{(353c,656b)} = 261$. Moderately related pairs include 526a (Healthcare assistants) and 563b (Home help, domestic help), which yield $OR_{(526a,563b)} = 3.8$. Likewise, one of the least related occupation pairs is 372a (Human resources and recruitment managers) and 551a (Commercial self-service clerks and storekeepers), with an $OR_{(372a,551a)} = 0.06$, indicating that transitions between these roles occur 17 times less frequently than expected under the baseline, reflecting negligible skill overlap.

[10] These employment measures are derived from the French administrative labor market database Déclaration Annuelle des Données Sociales – Postes (DADS Postes), which provides detailed information on individual job positions. Each observation corresponds to an employee's position within an establishment, including both occupational classification (at the 4-digit level) and geographical location in a CZ.

Commuting zones with high values of OC_r are characterized by a concentration of employment in occupations that are proximate in the occupation space. As such, OC_r serves as a measure of local labor market thickness. A higher index reflects a dense concentration of employment in skill-related occupations, implying that the local workforce is organized around a coherent set of occupations.

5.4 Description of Occupational Coherence

The occupational composition of the 304 local labor markets in France displays heterogeneity. Across all CZs, the workforce is concentrated in a few occupations. 50% of the workforce is concentrated in only 50 occupations out of the 270 in our data. Moreover, the type of occupations local areas specialize in varies from one area to another. In Paris for example, 34% of the workforce is concentrated in managerial and engineering occupations. In some other regions, almost 60% of the workforce is concentrated in blue-collar industry jobs.

Although 30% of workers have changed occupations over the period, the local occupational coherence is stable over time as illustrated by a strong correlation coefficient between $OC_{(r,2009)}$ and $OC_{(r,2015)}$ of 0.9, showing that, within CZ, workers mainly move to occupations that are close in the occupation space.[11]

Figure 3 maps different CZ according to their occupational coherence. An interesting observation is that generally speaking, the eastern half of France displays more coherent regions than the western half of France. This could reflect the greater industrialization of eastern France because of its proximity to the European market, compared to a more agricultural western France. Although there is a clear distinction between eastern and western France, we find that the overall distribution of occupational coherence is log-normal with a fat right tail. This means that most CZs display an occupational coherence around the mean, and a there is large dispersion among highly coherent CZs.

5.5 Local Unemployment Rates

In this section, we display the evolution of unemployment rates between 2003 and 2015 in the sample of 'high coherence' CZs, (those above the median of the distribution of local occupational coherence in 2010, $OC_{r,2010}$) and 'low coherence' CZ (those below the median

[11] $OC_{(r,2009)}$ corresponds to occupational coherence measured from equation (2). $OC_{(r,2015)}$ superpose the occupation space on to the CZ occupational workforce composition in 2015: $OC_{(r,15)} = \sum_{(i=1)}^{n} \sum_{(j=1)}^{(n-1)} \left(E_{(i,r,15)} E_{(j,r,15)} .OR_{(i,j)} \right))$ with $E_{(i,r,15)}$ the employment share of occupation i in CZ r in 2015 and $E_{(j,r,15)}$ the employment share of occupation j in CZ r in 2015.

of the distribution).

Figure 4 shows that in 2009, during the peak of the unemployment shock, commuting zones (CZs) with high occupational coherence experienced a sharper rise in unemployment relative to other CZs. However, by 2010, these same CZs — initially more adversely affected by the Global Financial Crisis — had rapidly converged toward the unemployment levels of low-coherence CZs, and by 2011, they exhibited even lower unemployment rates. In other words, while high-coherence CZs faced the steepest average increase in unemployment between 2008 and 2009, they also demonstrated the fastest recovery.

This pattern highlights the trade-off inherent in local labor market structures: strong occupational coherence characterized by dense ties among a relatively narrow set of skill-related occupations can enhance labor market performance, but may also expose regions to sharper initial shocks due to higher specialization. This dynamic reflects the broader tension between Marshallian externalities, which enhance economic performance through thick, specialized labor markets (Neffke et al., 2018), and the benefits of occupational diversity, which can mitigate the impact of occupation-specific shocks (De la Roca et al., 2023). It also provides first evidence that, outside of recession periods, highly coherent CZs exhibit better employment performance, as indicated by lower unemployment rates compared to low-coherence CZs. We further investigate the relationship between occupational coherence and the performance of commuting zones (CZs) in the next section.

6 Occupational Coherence and Unemployment Rates

Do highly coherent regions display better employment outcomes than others? This is the question that we examine in more detail in this section. Section 6.1 presents our empirical design. Section 6.2 contains our preferred estimates. Section 6.3 compares occupational coherence to industrial coherence.

6.1 Methodology

The goal of this section is to describe the relationship between CZ occupational coherence and local unemployment rates between 2010 and 2015 using the following specification:

$$U_{rt} = \gamma OC_{(r,10)} + X'_{(r,10)}\beta + \epsilon_{(r,t)} \quad (3)$$

γ is our coefficient of interest associated with occupational coherence. To avoid contamination from the endogenous adjustment of the local labor force, we fix local occupational coherence and control variables to the year 2010, as described in equation (2). We choose

2010, rather than 2009 (the first year of observation in our study), as the baseline year to avoid capturing the spike of the Global Financial Crisis. However, the results presented here are not sensitive to the choice of baseline year. Using occupational coherence from 2009 does not alter the study's conclusions (section 6.6). U_{rt} is the CZ unemployment rate in percent between 2010 and 2015. $\epsilon_{(r,t)}$ is the error term, which we conservatively cluster by CZ.

The interpretation of occupational coherence is sensitive to potential confounding variables. The cross-sectional fact that highly coherent regions display better employment performance does not necessarily imply that it is due to local occupational composition in light of two selection threats. First, the endogenous sorting of employers in some regions can be synchronized with local occupational composition and local labor market performance (Manning and Petrongolo, 2017, Bilal, 2023). Spatial sorting decisions of firms arise from externalities in how employers value exogenous local conditions and endogenous recruiting conditions.[12] Second, even without selection on firms' characteristics, areas with low skill-relatedness may be disproportionately populated by occupations that would have suffered contractions because of a concentration of workers who are at risk to secular shocks.[13] Under either selection threat, local unemployment variation can be lower in some regions regardless of the skill proximity of occupations. To limit this endogeneity concern we include a set of confounding variables in X_r that account for geographical differentiation.

6.2 Control Variables

Spatial sorting of employers. We first control for the distribution of firms in space. We measure the local weighted average of firm productivity from firm-level information on the universe of French firms from the FARE database compiled by the French National Statistical Office. FARE provides information on firm accounting variables such as turnover, value added and the number of employees, drawn from firms' tax returns. We measure a firm's total factor productivity following Levinsohn and Petrin's (2003) approach. The approach allows one to control for endogeneity resulting from the correlation between unobservable productivity shocks and the input level. We use real intermediate consumption as the proxy variable for productivity shocks, value-added as the dependent variable, the number of employees as a proxy of the labor force, and total assets as a proxy of capital. Our variables are deflated using INSEE price indices and employment is measured in full-time equivalent. Because each firm identifier is associated with the headquarters' location, we measure a CZ

[12] Employers are looking for locations with high production complementarities (places with a diversified set of skills), and for locations with large local labor market pooling complementarities (places with a large pool of skill-related workers to fill vacancies).

[13] For example, Northern France is more intensive in offshorable tasks, whereas the South of France is more intensive in service occupations (Jennequin et al. 2017).

weighted average of firm productivity in 2010 as follows:

$$TFP_{(r,10)} = \sum_{(i=1)}^{n} (E_{(i,r,2010)}.TFP_i)$$

Where TFP_i is the total factor productivity of each firm i and $E_{(i,r,2010)}$ denotes the employment share of firm i in total employment in CZ r.

We also account for the local population of industries in ways that are useful to account for confounding mechanisms. In particular, regions with strong networks of inter-industry linkages are more likely to experience volatility when exposed to an idiosyncratic shock (Gabaix, 2011; Acemoglu et al. 2017, 2012; Baqaee and Fahri, 2019; Joya and Rougier, 2019). Therefore, we measure local industrial input-output linkages by using the value of inputs from 2-digit industry i over total value of output in industry j available from the French National Institute of Statistics, INSEE.[14] We label this variable IO_r. We measure IO_r for a baseline year 2010.

$$IO_{(r,10)} = \sum_{(i=1)}^{n} \sum_{(j=1)}^{(n-1)} (E_{(j,r,2010)}.E_{(j,r,2010)}.IO_{(i,j)})$$

$E_{(i,r,2010)}$ and $E_{(j,r,2010)}$ denote the CZ r employment share in 2-digit industry i and j at year 2010. $IO_{(r,t)}$ is then the regional average of industrial input-output linkages. The higher the index, the more the CZ employs workers in industries that have strong input-output linkages.

Finally, we add controls for the share of workers in four broad groups of manufacturing industries (low- and high-tech manufacturing and service industries). The categorization of industries is reported in Appendix A.

Spatial sorting of workers. We include a large set of control variables accounting for local workforce composition. First, based on Jacob's theorizing that diversity is a strong determinant of city-specific growth, we include a Herfindahl index of occupation concentration measured as the sum of the squared employment share of 4-digit occupations o employed in CZ r : $Herfindahl_r = \sum_j (E_{(j,r,2010)})^2 \times 100$, where $E_{(j,r,2010)}$ corresponds to the employment share of workers in occupation j in CZ r.[15]

[14] The table reports the value in million euros of intermediate consumption and the total values of production of each NAF 2-digit industry in France. We measure input-output linkages for year 2010.

[15] We checked for collinearity between concentration of occupational employment (Herfindahl) and occupational coherence (OC_r). We find a correlation coefficient of 0.537 between these two dimensions of local labor markets in 2015 and no collinearity between the two variables.

Next, because having a larger proportion of highly educated workers benefits all workers in the city (Moretti, 2004), we measure the share of skilled workers in the CZ. We define this variable as the CZ share of skilled blue-collar and white-collar workers (PCS-ESE code 3 and 4). Also, because larger cities offer more outside options than smaller ones (Papageorgiou, 2022), we also account for the average size of the CZ, defined as the total number of workers (in log).

Finally, because our estimations are made on years right after the financial crisis, we are concerned that our regressions capture CZs' faster recovery from the Global Financial crisis. We thus follow Yagan (2019) and define CZs' Great Recession shock as the percentage point change in the CZs' unemployment rate from the average local unemployment prior to 2007 to the local unemployment rate in 2009.

6.3 Measuring Industrial Coherence

We identify industrial coherence in a similar way to occupational coherence. However, instead of using the mobility of workers across occupations, we use Neffke and Henning's (2013) index of industrial relatedness that measures the skill-relatedness between industries, measured from worker flow between 4-digit NACE rev1 industries. Industrial relatedness is labeled $IR_{(i,j)}$, which corresponds to skill-relatedness between industry i and j. We then define Industrial Coherence (IC) as an employment-weighted average of industrial relatedness:

$$IC_{(r,10)} = \sum_{(i=1)}^{n} \sum_{(j=1)}^{(n-1)} (E_{(i,r,10)}.E_{(j,r,10)}.IR_{(i,j)})$$

Analogously to (2), $E_{(i,r,10)}$ and $E_{(j,r,10)}$ denote the CZ r employment share in 4-digit NACE rev1 industry i and j for year 2010, for the 380 industries identified in the industry space developed by Neffke and Henning (2013).[16] $IR_{(i,j)}$ is the relatedness of industry i with industry j.[17] A region with large industrial coherence employs a large share of workers in industries that are highly skill related.

Table 2 reports descriptive statistics for key commuting zone (CZ)-level variables used in the analysis. The average unemployment rate across the 304 French CZs is 9.54%, with a standard deviation of 2.31, ranging from 4.4% to 18.2%. The occupational coherence index has a mean of 3.64 (SD = 0.51), with values between 3.0 and 7.5, indicating substantial

[16] These measures come from administrative French labor market database from Déclaration Annuelles des Données Sociales- Postes (DADS Postes) to measure CZ workforce composition at the 4-digit industry level. DADS Postes reports information on industry of the establishment the worker is employed in (variable APET) corresponding to a 4-digit NAF classification that we match to the NACE rev1 classification.

[17] $IR_{(i,j)}$ is available on Neffke's website. To enhance comparability, we standardized $IC_{(r,t)}$ and $OC_{(r,t)}$.

variation in the degree to which local occupations are skill-related. Industrial coherence, by contrast, has a mean of 1.01 but a much larger standard deviation of 2.75, spanning from 0 to 37.0, suggesting that while most CZs have low industrial coherence, a few are highly concentrated industrially. The Great Financial Crisis shock variable averages 1.54 (SD = 0.56). Additional controls include the Herfindahl index of occupational concentration averages 1.25 (SD = 0.38), CZ population size (log mean: 10.07), the share of skilled workers (mean: 30.99%, SD: 6.41%), average firm productivity (mean: 1.11, SD: 0.39), and industrial input-output linkages (mean: 2.11, SD: 1.18). These figures demonstrate wide heterogeneity across French local labor markets, which is central to understanding the role of occupational structure in shaping regional unemployment outcomes.

6.4 Addressing Endogeneity

A final concern is that the set of control variables may not fully capture all relevant sources of confounding. For example, bias may arise from differences in local assortative matching if the quality of worker–firm matches varies across occupations in ways correlated with local occupational coherence. To address this, we provide a more causal specification by proposing an instrumental variable strategy. The necessary conditions for an instrument to be valid are that it is strongly correlated with occupational coherence and unlikely to be correlated with idiosyncratic local labor market conditions that affect unemployment rates.

Our instrument measures exposure to the China trade shock in eight other high-income markets: Denmark, Finland, Germany, Great Britain, Italy, Norway, Spain and Sweden. The variable construction is conventional in the literature (Autor et al. 2013) and is motivated by the fact that local labor markets differ in their industry composition. Because industries are exposed differently to imports of intermediate inputs from China, past local industry composition creates useful variation to predict current local occupational composition. Imports from China is measured from the French foreign inputs penetration by industry from the Inter Country Input Output (ICIO) data from the OECD. The input-output data identifies imported inputs in 45 two-digit ISIC rev4 codes in millions of US dollars by industry from the start-of-period year t to the end-of-period year T.[18] The variable $\Delta Globalization$ is our instrumental variable. It is defined as follows:

$$\Delta_{(2009-03)} Globalization_r = \sum_{(j=1)}^{J} \frac{l_{(j,r,2003)}}{l_{(r,2003)}} \cdot \frac{\left(\Delta_{(2009-03)} G_j\right)}{l_{(j,2003)}}$$

The term $\Delta_{(2009-03)} G_j$ measures the change in total imports of intermediate inputs (in

[18] We use a correspondence table to match ISIC Rev. 4 codes to the NAF classification, the French classification that allows us to measure the employment share in each industry using the DADS. The classification is described in Appendix A.

current thousand \$US) from China between 2003 and 2009 in industry j in eight other high-income countries. We purposefully choose this time span because we aim at measuring factors affecting occupational composition in 2010 in France. $\frac{l_{(j,r,2003)}}{l_{(r,2003)}}$ is the initial employment share in the industry-CZ cell in France and $l_{(j,2003)}$ is the initial employment in 2-digit industry j (in thousand workers). We use employment in 2003 for normalization to mitigate the simultaneity bias that would arise if the region anticipated exposure to imports. Finally, the sum of exposure weights, $\sum_r \gamma_{jr,2003}$ with $\gamma_{jr,2003} = l_{(j,r,2003)}/l_{(r,2003)}$, is included to account for the incomplete shares term in shift-share instrumental variables models (Borusyak, Hull, and Jaravel, 2022). The validity assumptions requires that out-of-CZ past exposure to imports from China is strongly correlated with local occupational composition, but is unlikely to be correlated with idiosyncratic local employment conditions.

6.5 Results

Table 3 presents 2SLS estimates of Equation (3), sequentially adding control variables one at a time. Before interpreting the sign and magnitiude of our coefficient of interest, we first provide a description of the quality of our estimations. First, it is worth noting that the R-squared values reported in each column are relatively high, even in column (1), which includes only occupational coherence as an explanatory variable. In particular, the coefficient on occupational coherence alone explains about 7% of the variation in regional unemployment rates. Second, regarding the quality of our instrumental variable, the Kleibergen-Paap F statistic indicates that the instruments are strongly correlated with the endogenous regressor.

When analyzing the coefficients associated with the independent variables in Equation (3), we find that the estimates for occupational coherence remain very stable with the sequential inclusion of additional controls — such as measures of occupational concentration, CZ size, the CZ share of skilled workers, local firm productivity, industrial input–output linkages, and industrial workforce composition — in columns (2) through (8).[19] The main exception arises with the introduction of the variable capturing the intensity of the Great Recession shock (i.e., the 2007–2009 increase in the CZ unemployment rate), which substantially increases the magnitude of the occupational coherence coefficient in the specification where it is added. This likely reflects the fact that highly coherent regions were more exposed to the initial impact of the global financial crisis, as illustrated in Figure 4.

In terms of magnitude, our preferred specification — which includes the full set of control variables (column (8) of Table 3) — implies that regions with a one-standard-

[19] Column (8) includes the share of employment in each of the four industry groups described in Table A.1.

deviation higher level of occupational coherence have, on average, a 0.6 percentage point lower working-age unemployment rate over the five-year period from 2010 to 2015. This effect represents almost 20% of the difference in unemployment rates between a CZ at the 25th percentile and one at the 75th percentile of the distribution. Quantitatively, comparing a local labor market at the 75th percentile of occupational coherence to one at the 25th percentile, the estimates imply that the more coherent market experiences a 0.44 percentage point ($[3.77–3.35] \times 1.044 = 0.44$) lower unemployment rate. For a CZ with an average workforce of about 49,307 workers (i.e., the average CZ size in our sample), this translates into roughly 217 fewer unemployed workers.

Regarding the estimates associated with our control variables, we find a positive coefficient on occupational concentration (Herfindahl index). Specifically, a 1 percentage point increase in occupational concentration is associated with a 0.47 percentage point higher unemployment rate (column 8). These results show that, unlike occupational coherence, which reduces unemployment by facilitating local skill redeployment, simple occupational concentration (i.e., having a more specialized or less diverse occupational structure) is associated with higher unemployment rates. This suggests that the benefits of coherence come from the quality of connections among skill-related occupations, not from narrow occupational specialization per se. It highlights that the organization of local skills matters more for reducing unemployment than the simple workforce composition or size, which is in line with the theory developed by Bilal (2023).

We also find a negative association between the intensity of input–output linkages in a locality and local unemployment rates. This suggests that regions with stronger industrial interconnections tend to display lower unemployment. One potential explanation is that dense local production networks facilitate reallocation across firms and sectors. This finding is consistent with prior evidence on the role of local input–output networks in sustaining employment and smoothing local labor market adjustments (e.g., Ellison, Glaeser, & Kerr, 2010; Duranton & Puga, 2005). The coefficients associated with CZ size, firm productivity, and the share of skilled workers are not significant once we control for local industrial employment composition.

Our last empirical exercise consists in including a variable capturing industrial coherence in column (9). We find a negative and significant coefficient associated with industrial coherence, but the effect is much smaller in magnitude. The comparison of a local labor market at the 75th percentile of industrial coherence to one at the 25th percentile shows that the more coherent market experiences only a 0.026 percentage point ($[0.94–0.29] \times 0.040 = 0.026$) lower unemployment rate. One potential explanation—explored further in Section

7—is that occupational coherence plays a more important role in shaping labor market performance, as it facilitates internal labor mobility. In regions with high occupational coherence, workers are more likely to transition into new roles within their original firms, which helps them retain employment and contributes to longer employment spells.[20]

6.6 Robustness Results

We perform a series of robustness tests to ensure that our findings are not sensitive to alternative measures of occupational coherence or to alternative model specifications.

Alternative Measures of Occupational Coherence. To ensure that our measure captures the intended concept and that our results are robust to alternative specifications, we construct two additional measures of occupational coherence. The construction of each measure is described in Appendix B.1 and B.2 respectively. These measures have been recently introduced in the literature: the first is an accounting-based measure of skill relatedness (Neffke et al., 2017; Hanne-Weijman et al., 2022), and the second models jobs as vectors of skills (Macaluso, 2025). We prefer our measure of occupational coherence because it is based on a directed occupation network estimated from a rich set of variables that explain observable mobility patterns. This means that our network is based on observed flows rather than declared occupational proximity and that it takes into account the infeasibility of certain reverse occupational transitions. For example, an engineer can work as a technician, but the reverse may not be true. The results displayed in Appendix C.1 are consistent with our baseline estimates and show a negative relationship between occupational coherence and the local unemployment rate.

Alternative Specifications. We then propose a series of robustness tests using alternative specifications, as described in Appendix C.2. The specifications includes, among other, estimations using a set of CZ fixed-effects. We also present an identification strategy based on a two-step estimation approach that retrieves CZ-specific unemployment growth between 2010 and 2015 and then estimates the contribution of occupational coherence to this growth, as described in Appendix C.3. Finally, we propose an alternative instrument in Appendix C.4 that uses past values of occupational coherence to instrument for $OC_{r,2010}$. Our main conclusions hold under alternative specifications, instruments, and measures of occupational coherence.

[20]The smaller effect of industrial coherence is also consistent with the findings of Neffke et al. (2018), who show that while industrial coherence may reduce out-migration from a region, it also increases the time it takes to find a job after a shock. A dense local concentration of skill-related industries may lengthen unemployment spells, as workers may choose to remain unemployed longer in order to find a job that matches their previous skill set, rather than switching to a less related occupation or sector.

7 Worker Level Estimates

This section shifts the focus from average CZ-level estimates to individual worker-level estimates. We examine individual employment outcomes based on each worker's occupation and the skill-relatedness of the local labor market surrounding them. The use of worker-level data allows us to identify long-term adjustment margins that help explain the higher employment performance observed in highly coherent CZs.

7.1 Methodology

In this section, we exploit the individual-level panel dataset Déclarations Annuelles des Données Sociales (DADS Panel) to identify the worker-level effect of being employed in a highly coherent CZ. We follow the standard practice in the literature and focus on workers with sufficiently high labor force attachment (e.g., Autor et al., 2014). This means that we restrict the sample to male workers who were i) between 22 and 44 years old, ii) had job tenure for at least two years in the base year 2010 (i.e., who were employed the entire year in 2009 and in the entire year of 2010).[21] We build on the estimation framework developed by Dauth et al. (2021), using the following specification:

$$E_{ir} = \beta.OC_{r,2010} + X_{r,2010}^{'}\gamma + Z_{i,2010}^{'}\eta + \epsilon_{ir} \tag{4}$$

E_{ir} represents the cumulative number of days spent in employment between 2010 and 2015 for the sample of workers observed throughout the entire period. The average worker is employed for around 2,031 days during the six-year observation window.[22] ϵ_{ir} is an individual-level error term, and standard errors are clustered at the CZ level. X_r includes the same variables as in Table 2, column 8. We also include control variables for workers' characteristics in 2010, captured in $Z_{i,2010}$. Specifically, we control for 2-digit occupation dummies, the 2-digit NAF industry code of the worker's principal employer, and continuous variables for age and the worker's hourly net earnings.

$OC_{r,2010}$ is constructed as before. The identifying assumption for estimating β in equation (4) is selection on observables: individuals are assumed to be as good as randomly assigned across CZs, conditional on observed characteristics. While we use rich longitudinal data to finely characterize workers along dimensions (e.g., age, earnings, occupation, and industry) that could be correlated with both local occupational coherence and unobserved determinants of endogenous location choices, we acknowledge that some unobserved factors (including the quality of the worker-firm match) may still bias our estimates. Therefore, we instrument $OC_{r,2010}$ using the same instruments described in Section 6.4.

[21] Results are very similar, however, when including also workers with lower attachment.
[22] The total possible duration over this period is 2,154 days.

Importantly, to better understand the role of location characteristics in shaping workers' adjustment processes, we decompose total employment duration into mutually exclusive channels based on changes across firms and across occupations. The decomposition is additive and, hence, easy to interpret. Specifically, we divide the total number of days spent in employment into time spent within the original 2-digit occupation (as held in 2010) versus in different occupations, and between time spent with the original employer (in 2010) versus with different employers. This allows us to distinguish whether workers adjust by switching occupations within the same firm or by moving to other firms, and in particular, to identify employment spells that involve occupational mobility.

Table 4 displays summary statistics on the total number of days spent in employment. We find that the number of days spent with a different employer during the six-year window represents approximately 9% of total employment over this period. When workers change employers, they also frequently change occupations. Within employment spell at a different employer around 56% of days are in an occupation different from the one held in 2009. Within employment spells at the original employer, approximately 30% of days are spent in a different occupation than the one held in 2009.

7.2 Results

Table 5 displays the 2SLS estimates of equation (4). Since the between-firm and within-firm channels are mutually exclusive, the coefficients in columns (2) and (5) sum to the total effect reported in column (1). Column (1) shows that workers employed in CZs with a one-standard-deviation higher level of occupational coherence spend roughly 3.52 more days in employment compared to those in low-coherence areas. Comparing a baseline worker who spends on average 2,053 days in employment (out of 2,154 days between 2010 and 2015) with someone who spends 3.52 more days implies that a worker employed in a highly coherent CZ is about 0.16 percentage points more likely to be employed on a given day.

Further decomposing within-firm employment by distinguishing between staying in the same occupation and switching reveals that the positive effect is largely driven by workers who remain with their original employer but change occupations. Specifically, workers in CZs with a one-standard-deviation higher level of occupational coherence spend around 31 more days employed at their original firm but in a different occupation compared to those in less coherent regions. The ability to transition into different roles within the same firm appears more common in skill-related CZs, which may help explain the lower unemployment rates observed in these areas. This result aligns with Bilal (2023), who shows that pooling externalities are crucial to rationalize the location choices of employers and the resulting differences in job loss rates. The idea is that occupational coherence creates effective labor pooling: workers with skill-related jobs are geographically concentrated, making it easier for firms to redeploy them internally, thereby increasing employment retention at the original employer.

Regarding the worker-level control variables, we find that older workers are less likely to change employers and more likely to stay in their current occupation compared to younger workers. We also find a positive correlation between hourly wages and the probability of being employed by the original employer but in a different occupation. This may reflect either a selection effect—whereby the most productive workers are more likely to be reassigned to new roles and tasks within the company—or it may illustrate that occupational mobility is rewarded with higher wages.

In the final step of our analysis described in Appendix D, we present a more granular approach by developing an individual-level measure of skill proximity. This measure reflects both a worker's position within the occupational network and the local concentration of jobs in that occupation. In other words, it captures the fact that local occupational coherence can benefit some workers more than others. For example, in Silicon Valley, a high local concentration of software engineers is likely to matter more for computer programmers than for lawyers. We estimate Equation (4) using this individual-level measure of skill proximity and find results that are similar in sign to our baseline estimates using OC_r. The marginal effect is substantial. In particular, workers with a one-standard-deviation higher level of skill proximity spend approximately 15 fewer days employed at a different firm. In contrast, they spend about 15 more days employed at their original employer, and this effect is entirely driven by time spent in a different occupation than the one held in 2010. This again suggests that workers whose skills more strongly align with the local skill mix are more likely to be employed in firms that can redeploy incumbent workers to other positions within the firm. Specifically, during the five-year period between 2010 and 2015, workers with a one-standard-deviation higher level of skill proximity spend more than 50 additional days at their original firm in a different occupation.

8 Conclusion

The question of why some regions perform better than others remains central, particularly amid growing global uncertainty and recurring economic shocks. This paper argues that regions where workers can more easily transition between related occupations face a lower risk of high unemployment. To test this hypothesis, we develop a novel network-based framework that maps inter-occupational connections using observed worker mobility. Using detailed administrative data that trace the career trajectories of a representative sample of French workers between 2009 and 2015, we construct an empirical network of occupational linkages and overlay regional occupational structures onto this "occupation space" to generate a measure of occupational coherence for 304 commuting zones in France. We then analyze the relationship between this coherence measure and local unemployment outcomes, providing new evidence on the role of occupational structure in shaping regional labor market performance.

Our findings demonstrate that the occupational coherence of local labor markets plays a significant role in shaping regional unemployment dynamics. Regions with more skill-related occupations experience lower unemployment rates, and this relationship is robust to endogeneity concerns and alternative specifications. The effect operates mainly through greater within-firm reallocation of workers into new roles, rather than through increased transitions to other employers. These results suggest that fostering a coherent occupational structure can strengthen labor market performance. Moreover, the fact that occupational coherence matters more than industrial coherence underscores the importance of focusing on the transferability of skills across occupations rather than industries alone. Taken together, our results highlight that policies promoting occupational mobility and supporting clusters of skill-related jobs can be effective tools for mitigating local unemployment risks.

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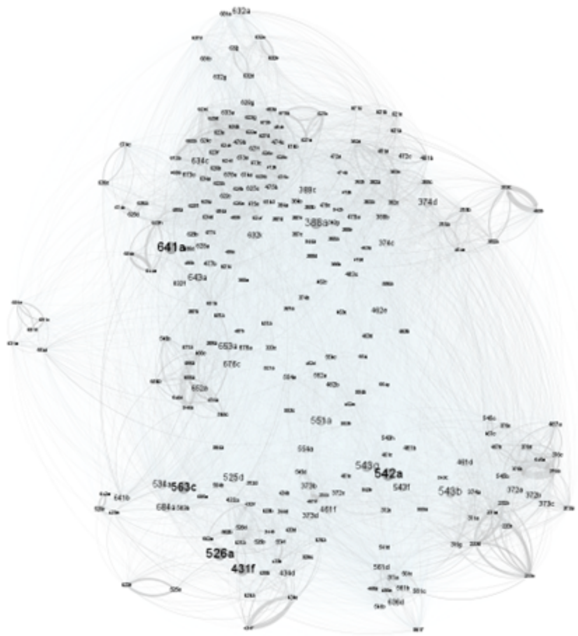
Figure 1: The Occupation Space

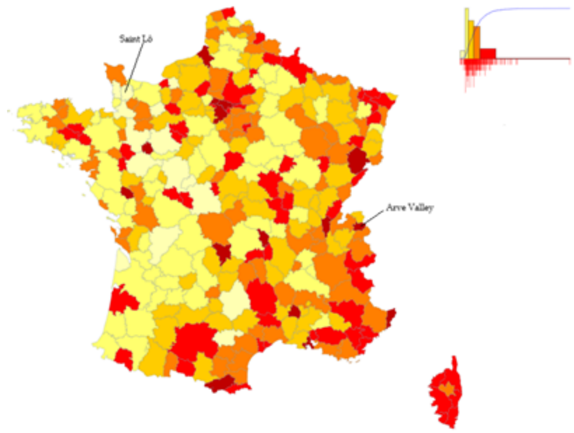


Note: Figure realized using Gephi software using OpenOrd visiualization algorithm that highlights communities. Each node corresponds to 4-digit occupation code. Their size is proportional to their employment share in France in 2015. Edge sizes are proportional to their weights. Only top 50% of edges are drawn for clarity purposes.

Figure 2: Local Occupation Spaces and coherence scores

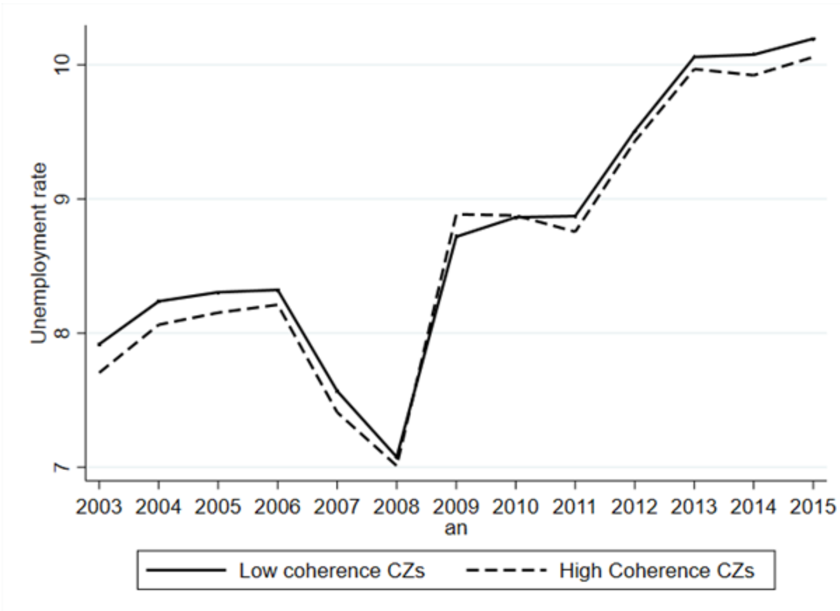
Notes: The graphs depict the occupation spaces. Node sizes correspond to the local share of employment in an occupation. The Arve Valley in the left panel is the CZ with the strongest OC_r. The occupation space shows a local concentration in closely related occupations. In Saint-Lô in the right panel is the CZ with the weakest OC_r. The occupation space shows that the main occupations are further away one to another.

Figure 3: Distribution of Occupational Coherence in France



Note: 5 classes distribution of Occupational Coherence. The warmer the color, the higher the OC. Arve Valley, a highly industrialized region neighboring Switzerland display the higher coherence, because of its concentration in closely related occupations (see figure 3 below). Indeed, the region is known for its specialization in steel industry, notably with many SMEs specialized in undercutting and turning activities. To the contrary, Saint-Lô in Normandy displays the lower coherence score, because of a sparser concentration of occupations, in unrelated activities.

Figure 4: Aggregate Change in Unemployment Rate



Notes: Data are from seasonally adjusted French BLS Office, INSEE, from 2003 to 2015. Data are annual and refer to the working-age population. CZ are divided into upper occupational coherence in plain line (above median of CZ occupational coherence in 2003), and lower occupational coherence in dashed line (below median of CZ occupational coherence in 2003).

Table 1: Zero Inflated Negative Binomial Model

	# switches from occ. i to j
Characteristics of origin occupation i (v_i)	
Number of employees in occ. i (log)	0.508***
	(54.85)
Average wage in occ. i (log)	0.153***
	(4.96)
Number of employees in occ. i (log)	0.507***
	(54.85)
Average age in occ. i	-0.004*
	(1.58)
Share of men in occ. i	-0.032
	(0.95)
Growth rate of employment share in occ. i	0.00
	(0.13)
Characteristics of Destination Occupation j (v_j)	
Average wage in occ. j (log)	0.178***
	(5.85)
Average age in occ. j	-0.001
	(10.43)
Share of men in occ. j	-0.047
	(1.38)
Growth rate of employment share in occ. j	-0.00
	(0.41)
Comparison of the origin and destination occupation w_{ij})	
Wage premium in occ j	0.064***
	(3.07)
Both urban occupations	0.442***
	(24.69)
Observations	72,630

Note: The dependent variable is the cumulative number of switches from the occupation of origin (occupation i) to the destination occupation (occupation j) from 2003 to 2015 that are derived from the DADS Panel database. The coefficients are estimated from a zero-inflated negative binomial estimation. We account for socioeconomic characteristics in occupation i and in occupation j (in v_i and v_j respectively) as well as dummy variables that compare the characteristics of the origin and the destination occupation (in w_{ij}). The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

Table 2: Means and Standard-Deviation of CZ-level Variables

	Mean	SD	Min	25th pct.	50th pct.	75th pct.	Max
Unemployment rate	9.54	2.31	4.4	7.9	9.2	10.9	18.2
Occ. Coherence	3.64	0.51	3.0	3.35	3.50	3.77	7.5
Ind. Coherence	1.01	2.75	0.0	0.29	0.51	0.94	37.0
GF crisis shock	1.54	0.56	0.05	1.25	1.5	1.8	5.1
Occ. Concentration	1.25	0.38	0.79	0.98	1.15	1.38	3.75
Size (in log)	10.07	1.06	7.64	9.31	9.89	10.78	14.61
Share of Skilled Workers	30.99	6.41	17.83	26.81	30.15	33.65	58.99
Avg. Firm Prod.	1.11	0.39	0.51	0.86	1.03	1.24	3.96
IO linkages	2.11	1.18	0.04	1.60	1.85	2.18	13.78

Notes: N=304 French CZs. Sources: DADS Postes, DADS Panel, INSEE input-output Tables, OECD input-output tables, Neffke et al. (2013) data on industrial skill-relatedness. Unemployment rate is the average between 2010-15 across 304 CZ. The other variables display the average for year 2010.

Table 3: CZ Unemployment rate and Occupational Coherence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Occ. Coherence	-0.336**	-1.184***	-1.298***	-1.415***	-1.330***	-1.178***	-1.037***	-1.174***	-1.044***
	(0.172)	(0.272)	(0.407)	(0.331)	(0.359)	(0.355)	(0.351)	(0.361)	(0.370)
Ind. Coherence									-0.040***
									(0.009)
GF crisis shock		1.074***	1.163***	1.253***	1.226***	1.233***	1.171***	1.985***	1.992***
		(0.166)	(0.210)	(0.192)	(0.210)	(0.206)	(0.199)	(0.173)	(0.172)
Occ. Concentration			0.640**	1.329***	1.276***	1.318***	1.261***	1.361***	1.247***
			(0.262)	(0.317)	(0.354)	(0.335)	(0.325)	(0.313)	(0.321)
Size (in log)				0.350***	0.325***	0.435***	0.354***	0.189	0.160
				(0.069)	(0.076)	(0.072)	(0.072)	(0.179)	(0.180)
Share of Skilled Workers					0.004	0.042***	0.040***	-0.022	-0.026
					(0.014)	(0.013)	(0.013)	(0.019)	(0.020)
Avg. Firm Prod.						-1.175***	-1.038***	-0.326*	-0.280
						(0.172)	(0.172)	(0.174)	(0.175)
IO linkages							-0.240***	-0.198***	-0.204***
							(0.040)	(0.043)	(0.043)
Ind. Emp. Comp.	No	No	No	No	No	No	No	Yes	Yes
R-squared	0.07	0.09	0.09	0.11	0.11	0.14	0.16	0.23	0.24
F-stat	18.9	18.9	20.8	20.5	23.7	19.6	19.8	21.6	18.9

N= 1,824. All columns report coefficient estimates of occupational coherence on CZ annual unemployment rate in percent for years between 2010 and 2015. Column 7 reports our preferred estimates (the article's main specification): a 1 percentage point higher occupational coherence is associated with a 1.04 percentage point lower local unemployment rate. Column 1 reports estimates of occupational coherence without control variables. Column 2 includes the intensity of the global financial crisis shock. Column 3 adds the Herfindahl index of occupation concentration. Column 4 includes the CZs size (in log). Column 5 adds the share of skill workers. Column 6 includes local firm average TFP. Column 7 adds industrial input-output linkages. Column 8 adds the employment share in each group of industries as described in Appendix A. Column 9 includes industrial coherence. All regressions include the sum of occupational exposure weights (Borusyak, Hull, and Jaravel, 2022) as well as year fixed effects. The last line reports the Kleibergen-Paap F-stat. Standard errors are clustered by 2010 CZ (reported in parenthesis). The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*)

Table 4: Summary Statistics, Worker level

	Mean	SD	Min	Max
Cumulative Number of Days Spent in Employment:				
Days Employed (total)	2053.41	236.31	359	2154
Days employed in the same company (total)	1875.27	548.96	0	2154
In the same occupation	1300.14	325.23	0	2154
In a different occupation	575.129	808.28	0	2154
Days employed in a different company	178.13	447.35	0	2154
In the same occupation	78.00	277.43	0	2154
In a different occupation	100.13	292.91	0	2154
Age	34.72	4.36	23	44
Hourly Wage	13.83	6.81	8.33	316.8

Notes: Summary statistics from DADS Panel for workers aged 18-60 years-old employed full-time full-year in 2010 and 2009 and that did not change location between 2010 and 2015. Own calculations.

Table 5: 2SLS Estimates — Worker-Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		youn			Same Employer		
	All	All	Same Occ.	Diff Occ.	All	Same Occ.	Diff Occ.
Occupational Coherence	3.52**	-0.81	0.17	-0.98	4.33	-57.25**	61.58**
	(1.74)	(10.55)	(5.73)	(6.78)	(11.00)	(28.80)	(31.68)
Age	-0.46***	-0.17	0.54**	-0.70**	-0.29	2.00**	-2.29**
	(0.08)	(0.40)	(0.24)	(0.34)	(0.39)	(0.96)	(0.91)
Hourly Wage	0.66***	-0.71	-0.49	-0.22	1.37**	-2.54	3.91**
	(0.08)	(0.64)	(0.33)	(0.36)	(0.59)	(1.55)	(1.64)
CZ control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.11	0.16	0.17	0.10	0.05	0.12

Notes: $N = 68{,}159$. The dependent variable is the cumulative number of days in employment over 2010–2015 in column (1). In column (2), employment days are cumulated only when they occur at the original employer (the one in 2009) in the original occupation (column (3)) or in a different occupation (column (4)). In column (5), employment days are cumulated when they occur at a different employer in the original occupation (column (6)) or in a different occupation (column (7)). The main regressor is OC_r. Controls include the worker's hourly net earnings and age, 2-digit NAF industry code dummies, and 2-digit occupation fixed effects. The sample is based on the DADS Panel for male workers aged 22–44 who were employed during the full years of 2009 and 2010. Standard errors are clustered at the 2010 CZ level (reported in parentheses). The first-stage F-statistic is equal to 606.41. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Appendix

(Not Intended For Publication)

Occupational Coherence and the Geography of Unemployment

Catherine Laffineur, Charlie Joyez, Raja Kali

A Classification of Industries

Table A.1: NAF classification of industries

NAF code	Definition	Group of Industries
CA	Food, Beverage and Tobacco Product Manufacturing	
CB	Textile Manufacturing	
CC	Wood product and paper Manufacturing	
CD	Petroleum and Coal Products Manufacturing	
CG	Plastic, Rubber and metal product manuf.	Low-Medium Tech Manuf.
CH	Primary metal manufacturing	
EZ	Water transportation and production	
FZ	Construction	
CE	Chemical Manufacturing	
CF	Pharmaceutical Industry	
CI	Computer and electronic product manufacturing	
CJ	Electrical Equipment, Appliance, and Component Manuf.	
CK	Equipment manufacturing	High-Medium Tech Manuf.
CL	Transportation manufacturing	
CM	Miscellaneous manufacturing	
DZ	Electricity and Gas Industry	
GZ	Wholesale Trade and repair of Automobile	
HZ	Transportation and wharehouse	
IZ	Food and Beverage Stores	
JA	Motion Picture and Sound Recording Industry	Low-medium Tech Services
JB	Telecommunications	
LZ	Real Estate and Rental	
LI	Leasing	
KZ	Finance and Insurance	
MA	Adminitrative and Support services	
MB	Professional and Scientific research and dev.	High-medium tech services
MC	Other technical and scientific services	
NZ	Management of companies and Enterprises	
OZ	Public administration	
PZ	Education	
QA	Activities for human health	
QB	Medical-social and social accommodation	Other Industries
RZ	Arts, shows and recreational activities	
SZ	Other service activities	

B Robustness Measures of Occupational Coherence

This section presents the construction of two alternative measures of occupational coherence.

B.1 Accounting Measure of Occupation Relatedness

The first robustness measure of OC_r follows the approach of Hane-Weijman et al. (2022) and Neffke et al., 2017. This alternative measure of $OP_{i,j}$ is based on the observed flow from occupation i to j (F_{ij}) over the entire study period, divided by the expected flow—calculated as the product of all inflows into occupation j and all outflows from occupation i, divided by total flows:

$$OP_{i,j} = \frac{F_{ij}}{\left(\sum_j F_j \times \sum_i F_i\right)/F}$$

For each commuting zone r, we construct a measure of occupational coherence as in equation (2):

$$A_r = \sum_i \sum_j E_{ir} \cdot E_{jr} \cdot OP_{ij} \tag{5}$$

where E_{ir} is the employment share of occupation i in region r, and OR_{ij} is the occupational relatedness as described above. Despite the methodological change, the two measures of occupational coherence, A_r and OC_r yield a similar ranking of French CZs with a correlation coefficient of 0.91.

We prefer our measure of occupational coherence, built on the strategy proposed by Neffke et al. (2013), as it uses a rich set of control variables to account for observable factors that may explain bilateral mobility patterns.

B.2 Occupations as Vectors of Skills

We also construct an alternative measure of $OR_{i,j}$ based on observed task similarity between occupations in the spirit of Macaluso (2025). This new measure leverages task-based information from the ONET database, after matching French occupations in the PCS-ESE classification to their counterparts in the SOC system used by ONET. Each occupation is represented by a normalized task-intensity vector spanning five skill dimensions: non-routine analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual tasks, as described in the following section.

B.2.1 Identification of the task-Content of Occupations

To build Q_r coherence measure, we define occupations according to their task intensity, following Macaluso (2025) and using data from the O*NET database. O*NET provides a detailed characterization of workers, occupations, and jobs, including information on occupational requirements that describe the typical activities performed across occupations. These data allow us to summarize the types of behaviors and tasks associated with each occupation.

The O*NET database is based on the American Standard Occupational Classification (SOC) system. We link SOC occupations to the French PCS-ESE classification using the mapping table developed by Laffineur and Mouhoud (2015).

O*NET task scores are derived from survey data collected from both workers and experts.[23] Respondents report the level of task intensity required to perform their current job, on a scale from 0 to 7, across 41 specific tasks.[24]

To classify the 41 tasks into broader categories, we follow the taxonomy introduced by Autor, Levy, and Murnane (2003). Tasks are grouped into five major categories: (i) Non-routine analytical tasks, typically performed by technical and managerial occupations, require cognitive skills such as problem solving, decision making, and creativity; (ii) Non-routine interactive tasks, common among service occupations (e.g., hairdressers, gardeners, truck drivers), require adaptability and interpersonal interaction; (iii) Cognitive routine tasks, often found in clerical and administrative jobs (e.g., secretaries, accounting officers), involve repetitive activities following established procedures; (iv) Manual routine tasks and (v) Non-routine manual tasks, characteristic of skilled and unskilled production occupations, include activities performed by handlers, machine operators, and similar roles.

Table B.1: Occupational Tasks

Non-routine Analytical	Organizing, Planning, and Prioritizing Work; Getting Information; Analyzing Data or Information; Making Decisions and Solving Problems; Developing Objectives; Judging the Qualities of Things, Services, or People; Updating and Using Relevant Knowledge; Interacting with Computers; Thinking Creatively; Estimating the Quantifiable Characteristics of Products, Events, or Information; Evaluating Information to Determine Compliance with Standards; Scheduling Work and Activities; Interpreting the Meaning of Information for Others; Processing Information and Strategies
Non-routine Interactive	Guiding, Directing, and Motivating Subordinates; Communicating with Supervisors, Peers, or Subordinates; Communicating with Persons Outside the Organization; Developing and Building Teams; Resolving Conflicts and Negotiating with Others; Performing for or Working Directly with the Public; Staffing Organizational Units Providing Consultation and Advice to Others; Coordinating the Work and Activities of Others; Selling or Influencing Others; Training and Teaching Others; Assisting and Caring for Others; Coaching and Developing Others; Establishing and Maintaining Interpersonal Relationships; Monitoring and Controlling Resources
Routine Cognitive	Performing Administrative Activities, Documenting/Recording Information
Routine Manual	Handling and Moving Objects; Performing General Physical Activities ; Repairing and Maintaining Mechanical Equipment; Repairing and Maintaining Electronic Equipment
Non-routine Manual	Operating Vehicles, Mechanized Devices, or Equipment; Inspecting Equipment, Structures, or Material; Monitoring Processes, Materials, or Surroundings; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment

Source: O*NET work activity file

[23]For occupations where worker sampling was infeasible, experts were recruited from professional and trade associations to complete the survey.

[24]For each task, respondents are provided with examples at levels 2, 4, and 6 to guide their responses. For example, for the task "getting information," a level of 2 corresponds to "follow a standard blueprint," level 4 to "review a budget," and level 6 to "study international tax laws." The task score reflects the average rating across all respondents within an occupation.

Table B.2 provides descriptive statistics, showing the mean intensity of each score for the seven major occupations.

Table B.2: Tasks' Intensity within Occupations

	Employees	Managers	Engineers	Technicians	Foremen	Skilled blue-collar	Non-skilled blue-collar
Non-routine analytical	0.40	0.72	0.79	0.67	0.61	0.42	0.34
Non-routine interactive	0.34	0.62	0.56	0.42	0.62	0.29	0.25
Routine manual	0.34	0.19	0.35	0.47	0.50	0.69	0.70
Non-routine manual	0.24	0.24	0.62	0.59	0.56	0.59	0.53
Routine cognitive	0.51	0.75	0.74	0.66	0.63	0.41	0.33

Source: O*NET work activity normalized measure, merged with French PCS-ESE classifications using EurOccupation correspondence tables. Authors' calculations.

It shows that skilled production workers (composed of skilled blue-collar workers, engineers, technicians and foremen) have an important index of non-routine manual, interactive and analytical tasks. Managers and engineers are the two occupations having the highest score of routine cognitive tasks, whereas skilled and unskilled blue-collar workers perform routine manual tasks more intensively.

B.2.2 Measuring Occupational Coherence

For each pair of occupations (i, j), we compute a cosine similarity score, s_{ij}, which reflects the angle between their respective task vectors and is defined as:

$$s_{ij} = \frac{v_i \cdot v_j}{||v_i|| \cdot ||v_j||}$$

where v_i and v_j denote the five-dimensional normalized task vectors for occupations i and j, respectively. The resulting similarity score ranges from 0 (indicating entirely dissimilar task profiles) to 1 (indicating identical ones), and captures the functional proximity between occupations based on the similarity of their underlying skill requirements.

For each commuting zone r, we replace the bilateral proximity measure in the Coherence score as follows:

$$Q_r = \sum_i \sum_j E_{ir} \cdot E_{jr} \cdot s_{ij} \tag{6}$$

where E_{ir} is the employment share of occupation i in region r, and s_{ij} is the cosine similarity between occupations i and j. A higher value of Q_r thus indicates a higher average similarity among occupations in the region, reflecting greater occupational coherence in terms of skill use. Consistent with previous results, our baseline measure and Qr_r yield highly similar rankings of French CZs, with a correlation coefficient of 0.90.

We prefer the network-based approach to occupational coherence because it allows for a pairwise description of the proximity between occupations. In particular, in our occupation space, the link from occupation i to occupation j is not necessarily the same as the link from j to i, which enables us to better capture the potential for occupational mobility within a locality than measures based on skill similarity. This will be particularly useful in the empirical analysis for incorporating different sets of fixed effects.

C CZ Robustness Results

To ensure the robustness of our conclusions to alternative specifications and measures of occupational coherence, we perform a series of robustness checks. We display the results with alternative measures of occupational coherence (Appendix C1); results from alternative specifications (Appendix C2); results from an estimation strategy based on a two-step estimation procedure (Appendix C3); and results with a different instrumental variable (Appendix C4).

C.1 Alternative Measure of Occupational Coherence

We first estimate equation (3) using different measures of occupational coherence, namely $OC_{r,2010}$, $A_{r,2010}$, and $Q_{r,2010}$, which fix the employment composition in occupations j and i to the year 2010. We present the results both using the instrumental variable described in Section 5.3 and using simple OLS estimates. The results are displayed in the following table.

Table C.1: Alternative Measure of Occupational Coherence

	Vectors of Skills	Accounting Measure
Occ. Coherence	-5.307***	-1.483***
	(0.862)	(0.300)
R-squared	0.20	0.19

Notes: N=1824. The Table displays robustness results of equation (3). All columns include the same control variables as in Table 3, column 8. Columns (1) and (2) use Q_r as described in Equation (6). Columns (3) and (4) use A_r as described in Equation (5). The average of A_r is 2.44 (sd=0.28) and the average of Q_r is 0.52 (sd=0.06). The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

The results always show a negative coefficient between occupational coherence and the unemployment rate. In terms of magnitude, a one-standard deviation increase in Q_r is associated with a 0.32 percentage point smaller unemployment rate, and a one-standard-deviation increase in A_r is associated with a 0.42 percentage point decrease in unemployment rate. This is smaller than our baseline estimates, but shows that the relationship remains economically meaningful and robust to alternative measures of occupational coherence. This suggests that regions with more coherent occupational structures tend to experience lower unemployment, even when accounting for different dimensions of coherence.

C.2 Alternative Specification

We begin by presenting results from alternative specifications. First, we estimate Equation (3) using the change in the unemployment rate between 2010 and 2015 as the dependent variable, denoted $\Delta\text{Unemployment}_{(2010\text{–}2015)}$, as follows:

$$\Delta\text{Unemployment}_{(2010\text{–}2015)} = OC_{r,2010} + X'_{(r,10)}\beta + \epsilon_{(r,t)}$$

Second, we estimate Equation (3) using occupational coherence measured in 2009 ($OC_{r,2009}$) instead of 2010. Third, we estimate Equation (3) after excluding the three largest commuting zones (CZs) in France — Paris, Lyon, and Marseille. We also estimate Equation (3) using the average unemployment rate over the decade 2010–2019.[25] Finally, we estimate the following specification:

$$U_{rt} = \gamma\, OC_{r,t-1} + \gamma_r + \epsilon_{rt}.$$

This specification includes CZ fixed effects and regresses contemporaneous unemployment rates on past values of occupational coherence to mitigate concerns about reverse causality. Table C.3 reports the results. Each column displays, in the same order, the results from the estimation strategies described above. We view these results as providing additional support for our main conclusion, which shows a negative relationship between CZ occupational coherence and local unemployment rates. In all columns, the coefficients are similar in sign and magnitude and are statistically significant.

[25] Although our measure of occupational coherence is only available through 2015 due to data limitations, unemployment data are available for the full 2003–2019 period.

Table C.2: Robustness Results

	(1)	(2)	(3)	(4)	(5)
Occ Coherence	-0.265**	-0.629*	-0.771***	-0.767***	-0.596***
	(0.116)	(0.351)	(0.242)	(0.236)	(0.155)
R-squared	0.11	0.23	0.25	0.24	0.01

The Table displays robustness results of equation (3). All columns include the same control variables as in Table 2, column 8. Column 1 uses ΔUnemployment$_{2015-2010}$ as the dependent variable. Column 2 replaces $OC_{r,2010}$ by $OC_{r,2009}$. Column 3 excludes Paris, Marseille and Lyon from the estimation. Column 4 estimates equation (3) over the period 2009-2019. Column 5 includes CZ fixed effects. The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

C.3 Two-Step Estimation Approach

We propose a last robustness test from a two-step procedure inspired by Yi et al. (2024). To build the two-step estimation approach, we retain only two years for each CZ: 2010 and 2015 and estimate the following specification:

$$u_{rt} = \gamma I_{2015} + \beta_r J_r \times I_{2015} + \epsilon_{rt}$$

where u_{rt} denotes the unemployment rate in CZ r in year t, and J_r is a fixed effect identifying each CZ in the sample. I_{2015} is an indicator variable equal to 1 in 2015 and 0 in 2010. The error term ϵ_{rt} is conservatively clustered at the CZ level. The coefficient β_r captures the change in the unemployment rate between 2010 and 2015 for CZ r.

From this specification, we obtain a set of 304 β_r estimates—one for each CZ. The average β_r is 1.26, indicating an average increase in unemployment of 1.26 percentage points over the period. The standard deviation is 2.34, with values ranging from -4.07 to 9.3.

In the second step, we regress β_r on CZ-level characteristics, including occupational coherence:

$$\beta_r = \gamma OC_r + X_{r,2010} + \epsilon_r$$

where OC_r denotes occupational coherence in CZ r, and $X_{r,2010}$ includes the same control variables as in column 9 of Table 2. The error term ϵ_r is robust to heteroscedasticity. The regression is weighted by the inverse of the variance of β_r.

The estimated coefficient on γ is -0.40 (p-value < 0.075), suggesting that a one-standard-deviation increase in occupational coherence is associated with a 0.20 percentage point smaller increase in unemployment between 2010 and 2015. This finding is consistent with our earlier baseline result and underscores the important role of occupational coherence in shaping local labor market employment performance.

C.4 Other Instruments and OLS

We reproduce the same specification as column (8) but uses OLS instead of 2SLS. The coefficient associated with OC_r is equal to -0.34 (p-value=0.004), which is substantially larger 2SLS estimates than the OLS estimates, which is consistent with attenuation bias in OLS, presumably due to endogenous sorting of workers across CZs. The strong first-stage F-statistic and the plausibility of the exclusion restriction provide confidence in the validity of the instrument. Although our estimation accounts for local occupational exposure through the sum of occupational weights (Borusyak, Hull, and Jaravel, 2022), the fact that the 2SLS estimate is almost five times larger than the OLS estimate may indicate that our instrument shifts occupational coherence only for a subset of local labor markets, especially regions strongly affected by the shift-share trade shock. Our 2SLS estimates may thus identify a local average treatment effect for this complier group, which could be larger than the population average. However, even when we interpret the OLS estimate as a lower bound, the effect is still substantial. Comparing a CZ at the 75th percentile of occupational coherence to one at the 25th percentile implies that the more coherent labor market experiences a 0.15 percentage point lower unemployment rate, which is already meaningful. This represents about 7% of the standard deviation of unemployment rates observed in the sample.

We also show the robustness of our result when using an additional instrument building on the work of Blundell and Bond (2000), who use lagged factor inputs as instruments for factor inputs to estimate production functions. We propose as an instrument for occupational coherence in 2010 the occupational coherence in 2009. This research design has the advantage of not requiring a stand on the determinants of local occupational demand, such as local skill supply, technological change, or organizational change. Rather, the occupational composition in 2009 summarizes the main forces driving the CZ occupational composition. The other advantage of this instrument Our approach requires that, after residualizing with respect to initial occupational composition, these determinants affect local areas only through their effect on occupational coherence and that our instrument does not affect the 2010-15 unemployment rates other than through 2010 occupational coherence, conditional on other CZ characteristics. The coefficient associated with occupational coherence is equal to -1.13 (p-value = 0.059), again providing support for the robustness of our result with instrumental variable in both sign and magnitude.

D Individual-Level Measure of Skill Relatedness

The individual-level variable capturing skill proximity is denoted as SP_{ir}. Unlike the measure of average local occupational coherence used in equation (2), which aggregates occupational relatedness weighted by employment shares across all occupations in CZ r, we construct SP_{ir} by weighting occupational relatedness with local employment shares only once. This approach yields a score that reflects the proximity between a worker's occupation i and all other occupations j in the locality r, rather than computing an average coherence score for all occupations in CZ r:

$$SP_{(i,r,2010)} = \sum_{(j \neq i)} E_{(j,r,2010)}.OR_{(i,j)}$$

For our baseline year 2010, we measure 82,080 different occupation proximity scores for each occupation i (270 4-digit occupations) located in French CZ r (304 French CZ). Thus, two workers in two different occupations employed in the same location can have different $SP_{(i,r,2010)}$ depending on the proximity of their occupation. Likewise, two workers in the same occupation employed in different locations have difference scores of $SP_{(i,r,2010)}$.

The skill proximity index ($SP_{(i,r,2010)}$) shows substantial variation across workers, with a mean of 0.97 and a standard deviation of 0.51; the 25th percentile is 0.66 and the 75th percentile is 1.16. Table D.2 displays the results of Equation (4) when including $SP_{i,r,2010}$ instead of $OC_{r,2010}$.

Table D.3: Individual-Level Occupational Skill Proximity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Diff. Employer			Same Employer		
	All	All	Same Occ.	Diff Occ.	All	Same Occ.	Diff Occ.
Individual Relatedness	0.57	-28.48***	-17.46***	-11.02***	29.05***	-74.81***	103.86***
	(0.51)	(4.86)	(2.86)	(2.94)	(4.71)	(12.52)	(12.82)
Age	-0.19**	-0.28	0.55**	-0.83*	0.09	5.40***	-5.30***
	(0.08)	(0.56)	(0.28)	(0.42)	(0.59)	(1.18)	(1.26)
Hourly Wage	0.26***	-0.85	-0.83	-0.22	1.11	-7.27**	8.38*
	(0.06)	(0.84)	(0.51)	(0.39)	(0.88)	-3.62	(4.36)
CZ control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.10	0.11	0.16	0.17	0.10	0.05	0.12

Notes: $N = 68{,}159$. The dependent variable is the cumulative number of days in employment over 2010–2015 in column (1). In column (2), employment days are cumulated only when they occur at the original employer (the one in 2009) in the original occupation (column (3)) or in a different occupation (column (4)). In column (5), employment days are cumulated when they occur at a different employer in the original occupation (column (6)) or in a different occupation (column (7)). The main regressor is OC_r. Controls include the worker's hourly net earnings and age, 2-digit NAF industry code dummies, and 2-digit occupation fixed effects. The sample is based on the DADS Panel for male workers aged 22–44 who were employed during the full years of 2009 and 2010. Standard errors are clustered at the 2010 CZ level (reported in parentheses). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.