Occupational Coherence and Local Labor Market Performance: Evidence from France.

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Abstract

Why do labor markets in some regions recover faster from an adverse economic shock than others? We conjecture that regions with occupations offering greater redeployment opportunities to other occupations are less at risk of long-term unemployment. We examine this by creating a network of inter-occupation relatedness from worker mobility data that provides occupational transitions for a representative sample of French workers. Superimposing local occupational composition on to this "occupation space" yields a measure of occupational coherence for 304 commuting zones in France. We find that regions with stronger occupational coherence are more sensitive to a shock but recover faster.

Keywords: occupational mobility, regional occupational composition, occupational coherence, economic shocks, unemployment dynamics

JEL Classification: E24, E32, J21, J24

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This work has been supported by the French government, through the UCAJEDI Investments in the Future project managed by the National Research Agency (ANR) with the reference number ANR-15-IDEX-01 and the French Bureau of Labor (Pôle Emploi) from the project « Territoires et chômage, quels sont les emplois vulnérables et les facteurs de disparités territoriales ». Access to the data is provided by the CASD dedicated to researchers authorized by the French *Comité du secret statistique*.

1. INTRODUCTION

Different regions within the same country display considerable variation in how they recover from adverse economic shocks. For example, following the global financial crisis, between 2009 and 2015, the average unemployment growth rate in France was 14%. Some regions in France experienced unemployment growth of as much as 53% while other regions reduced the unemployment rate by nearly 8%. What accounts for the ability of some regions to cushion the impact of a shock better than others?

The literature on regional unemployment hysteresis and resilience to shocks has largely focused on firm-side factors that facilitate adjustment to macroeconomic volatility. Among such factors are the pattern of industrial specialization (Martin and Sunley, 2015, Martin et al., 2016), diversification of production and inter-industry linkages (Gabaix, 2011, Acemoglu et al. 2012, 2017, Baqaee and Farhi, 2019, Joya and Rougier, 2019, Fadinger et al., 2021), labor market institutions, access to finance, and government institutions supporting labor market flexibility (Martin and Sunley, 2015). Less attention has been given to the question of job opportunities available to workers after a shock. A fuller explanation should consider adjustments not only from firms but also from workers. Could the ability to recover from an adverse shock be dependent upon the occupational composition of a region? This question is the focus of this paper.

One way to approach this question is to ask if it is better to have a diversified occupational base or a related set of occupations in a city. There is a fine balance between having strong ties among a smaller set of occupations that increases occupational coherence, and a larger number of weak ties between diverse occupations that reduces occupational coherence. The intensity of a shock can be very large if the shock is occupation-specific and directed towards the occupations in which the city is specialized. However, in the long run, it should be easier to recover from an occupation-specific shock due to the strong occupational coherence of the city -- in terms of skills, tasks, or functions, which increase the likelihood of finding new jobs in related occupations. The trade-off between the two is thus clear. Inter-occupation linkages increase economic coherence, efficiency, and performance, which increases the capacity of workers to find another job in their city, while a diversified set of occupations reduces sensitivity to economic shocks (Owen-Smith and Powell, 2004, Rychen and Zimmermann, 2008, Crespo et al. 2014, Diodato and Wetterings, 2015).

Our empirical approach starts by mapping a network of occupational relatedness derived from occupational mobility in a unique French database that provides career paths for a representative sample of French workers over 13 years (2003-2015). To this end, our first step is to construct a measure of the relatedness between occupations based on the frequency of job transitions between them. The idea here is that mobility between two occupations reveals that they are likely to share similar tasks, skills, and know-how that are easily transferable. Mapping the proximity between all the occupations in our data gives us a network of relatedness between occupations that we refer to as occupation space. Central occupations in the occupation space benefit from greater redeployment capabilities, while peripheral occupations perform very specific tasks that are less fungible across jobs.

Our second step is to superimpose local occupational composition on to this occupation space to obtain a measure of coherence between occupations for 304 commuting zones (CZ hereinafter) in France. A CZ is a geographic area in which the working population reside and work, and in which establishments can find the bulk of the workforce necessary to fill the jobs offered[1]. The more a CZ possesses occupations that are closer in the occupation space, the stronger will be occupational coherence.

We are then in a position to examine local labor market performance in the face of an economic shock. We consider three different types of shocks: an economy-wide shock such as the Global Financial Crisis of 2009, sector-level shocks such as robotization and exposure to globalization, and occupation-level shocks that consider whether occupations that are intensive in routine (and thus codifiable) tasks are more at risk of unemployment.

Our key results are the following. First, regions with strong occupational coherence are more sensitive to an adverse event at the time of the shock but recover faster than regions with weak occupational coherence. Second, industrial coherence is more important than occupational coherence to reduce the intensity of a sector-specific shock, but occupational coherence is more important to reduce the sensitivity to occupation-specific shocks. Third, occupational coherence improves labor market performance through within-firm labor reallocation and a reduction of unemployment length, whereas industrial coherence works through a reduction of the spatial scope of job search. We summarize our analysis below.

First, we examine if regions with strong occupational coherence are more sensitive to adverse events at the time of the shock but recover faster than regions with weak occupational coherence. We see this most clearly for the economy-wide shock of the Global Financial Crisis. Using an event-study design for the Global Financial Crisis, we find that at the time of the shock, in 2009, a 1 percentage point higher occupational coherence is associated with a 0.33 percentage point higher local unemployment compared to 2008. We also find that as soon as in 2014, highly coherent CZs display better unemployment performance. This finding is robust to alternative formulations. In other words, at the time of the event, CZs with strong occupational coherence are more vulnerable to the economic shock but recover faster than CZs with weaker occupational coherence.

Second, we compare the influence of occupational and industrial coherence on local labor market performance. These measures capture the local redeployment capability of workers across

[1] A Commuting Zone is akin to a Metropolitan Statistical Area (MSA) in the US.

occupations and industries respectively. Our results show that occupational coherence is more important than industrial coherence to limit growth in the unemployment rate. We find an important influence of occupational coherence on local labor market performance but no significant correlation with industrial coherence. We find that a one standard deviation increase in the CZ's occupational coherence reduces the average French unemployment rate by 0.4 percentage points in the five years between 2010 and 2015. This corresponds to around 36% of the post-recession decline of the national unemployment rate. On the contrary, we do not find any significant effect of industrial coherence on the 2010-2015 unemployment rate change.

Third, we find that occupational coherence is more important than industrial coherence in shaping regional unemployment dynamics following an occupation-specific shock, but industrial coherence is more important to limit the depth of a sector-specific shock. We find that CZs with strong industrial coherence manage to limit the depth of the effect of increasing exposure to globalization on unemployment. However, CZs with strong occupational coherence are less at risk of high unemployment following an increased exposure to occupation-specific shocks. In addition, we find that workers in routine-task-intensive occupations living in high coherence CZs are 21% less likely to be unemployed than those living in low coherence CZs.

Finally, we examine two potential mechanisms that could be behind the role of occupational coherence: within-firm labor reallocation that facilitates firm reorganization and restructuring in the aftermath of a shock, and labor market thickness that reduces unemployment duration. As we explain later, both mechanisms are facilitated in regions with strong occupational coherence. We find evidence for both mechanisms, with more occupational change and lower unemployment duration in regions with higher occupational coherence. We also find that the positive effect of industrial coherence on CZ employment works through a reduction in the spatial scope of job search.

The rest of the paper is organized as follows. Section 2 provides conceptual background and motivates our hypothesis in terms of the related literature. Section 3 describes the data and cleaning procedures. Section 4 explains our methodology. We describe the construction of occupation space, occupational coherence, and additional variables used in the empirical analysis. Section 5 contains the analysis and results. Sections 6 considers the magnitude of the effects and explanatory mechanisms. Section 7 concludes.

2. CONCEPTUAL BACKGROUND AND HYPOTHESIS

2.1 Occupational composition and Regional Resilience

A key factor for regional heterogeneity in growth and employment dynamics is the capacity of firms located in a region to absorb shocks better than elsewhere, either by adjusting their mix of inputs or by adapting their products to match demand shifts (Martin et al. 2016, Martin 2012, Combes, Magnac and Robin, 2004). Such adjustments depend on the characteristics of the region that can facilitate firm transitions towards new suppliers or products. In particular, the resilience of a region is enhanced when there are a variety of skill-related and technology-related industries with little local input-output relationships with one another 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).

The technology-relatedness between industries 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, as in 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. In essence, measuring the co-occurrence of industries, activities, products, or research areas within an entity captures economies of scope. If two industries are often found in one and the same entity, this is likely because the production processes from that entity generate economies of scope, such as similar technologies that can be used in both industries (Hidalgo et al. 2018). Along these lines, 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.

Along similar lines, skill-relatedness between industries has been measured using actual job transitions between industries (Neffke and Henning, 2013, Neffke, Otto and Weyh, 2017). The core assumption underpinning the use of job transitions between industries is that if individuals can easily move from one industry to another, then it is because the production processes in the two industries likely draw upon similar skills. In other words, labor flows that cannot be explained by the characteristics of the two industries indicate skill-relatedness between those industries.

We build on this assumption to measure skill relatedness by considering job transitions between occupations rather than worker movement between industries. This approach relies on the fact that human capital is skill specific but not necessarily occupation specific. Consequently, human capital is more portable across occupations than previously thought (Poletaev and Robinson, 2008, Kambourov and Manovskii, 2009). Thus, worker flows are not random, and workers move from one occupation to another because they share similar skills and task requirements (Gathmann and Schonberg, 2010). The larger the share of common human capital, the easier is the flow between two occupations, entailing more frequent jobs-switching patterns.

The core motivation for using occupation mobility is that local performance, resistance to shocks, and resilience crucially depends on the ability of workers to be reabsorbed into the local labor market. The literature has already pointed out the importance of Marshallian externalities that manifest themselves in a thick labor market to facilitate worker re-employment after an economic shock (Neffke et al. 2018). We build on this idea to show that the ability of workers to reintegrate into the workforce following an adverse shock relies also on local occupational coherence.

We also conjecture that occupational coherence could be more important than industrial coherence in supporting regional resilience. There are at least three arguments that can be made supporting this conjecture.

First, there is increasing evidence that regions are moving from industrial specialization to occupational specialization. (Duranton and Puga, 2005, Defever, 2005), particularly in service-intensive regions (Diodato, Neffke and O'Clery, 2018). 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. Along these lines, a recent paper by 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.

Second, mobility between occupations is less costly than worker mobility between industries since occupation switching can occur within-firm or within-industry for promotion reasons or to bring together competences in the same plant to benefit from economies of scale or to save on communication costs. Labor movement within firms reduces asymmetric information because worker skills are likely to be known and information on the conditions of the new job are also likely to be easily available. On the contrary, labor mobility between industries mostly implies between-firm moves which are more costly for the worker (Kramarz et al., 2014, Baker et al., 1994, Eriksson, 2009, Neffke et al. 2012). Consequently, movement across occupations within a region should be more frequent in a worker's career life than movement across industries.

In addition, internal labor movement is essential to support business adaptability and flexibility to economic shocks and is crucial for regional employment performance and recovery (Martin and Sunley, 2015). For example, Dauth et al. (2021) show that most workers are retained by their firms in the wake of automation and are reassigned to new occupations. Worker mobility between industries does not consider such within-firm mobility, unless it implies mobility between establishments within a firm that are in different industries.

Third, economic shocks are more often occupation-level rather than industry-level. For example, even shocks that are sector specific, such as information technology and offshoring have an heterogenous effect across occupations (Autor et al. 2003, Acemoglu and Autor, 2011). Such shocks have mainly impacted employment in routine and codifiable occupations such as handlers, cashiers, and administrative employees (Becker and Muendler, 2015, Arntz et al. 2017, Frey and Osborne, 2017). More recently, the Covid-19 global pandemic has adversely affected occupations that could not work remotely because of the need to be close to the final consumer. Therefore, extending the analysis from industries to occupations arguably facilitates an improved perspective on local labor market performance.

2.2 Hypothesis and Mechanisms

We can synthesize the preceding review of the literature to suggest two conjectures for our study.

First, there is a tradeoff between having a small number of occupations that maximizes economic coherence and performance, and a large number of occupations that reduces volatility to economic shocks and thus maximizes resilience (Crespo et al., 2014). Since CZs with strong occupational coherence employ a large share of workers in a related group of occupations, it should reduce local unemployment duration by reabsorbing laid-off workers from one occupation into other occupations. From this perspective, highly coherent regions, which are more susceptible to being adversely affected by occupation-level shocks, may experience quick recovery by offering outside options to workers, particularly in comparison to regions with low occupational coherence.

Second, occupational coherence may be more important than industrial coherence to reduce local unemployment and increase the speed of recovery. This could be because occupational coherence supports firm reorganization in the aftermath of a shock more than industrial relatedness. Occupational coherence could alleviate firm reorganization by facilitating intra-firm worker reassignments to tasks and jobs. Industrial coherence does not allow for such within-firm reorganization. In addition, occupational coherence facilitates worker reintegration into the labor market due to a thicker labor market and a higher potential for labor reallocation. Finally, from the worker perspective, it might be easier to switch occupations than to change industries since human capital is easily transferable between occupations (Kambourov and Manovskii, 2009).

To summarize, we conjecture that at the time of an adverse economic shock, regions with strong occupational coherence may be more sensitive to the shock. However, after the adverse shock, regions with occupational coherence should be able to better absorb the economic shock by offering redeployment options towards other occupations. We also expect that the speed of recovery should be faster in regions with strong occupational coherence compared to those with strong industrial coherence, especially when the shock is occupation specific (Grossman and Rossi-Hansberg, 2008, Autor et al. 2003).

3 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. Each observation in the database corresponds to a particular job—an employee's position in an establishment. For each of these employer-employee records, the data contain information on the employee's age, occupation, hours worked, annual wage, and information on the employer's tax identification number, location of activity, and sector. Using the 2010 clustering of locations into 304 commuting zones done by the French Statistical Institute, we are able to trace the workforce composition of each CZ over time. For our analysis, as is customary in the literature, we consider full-time, full-year workers in private companies. The final database tracks changes in workforce composition at the CZ, industry, and occupation level from 2003 to 2015.

Our second source of information is the administrative panel - *Déclaration Annuelles des Données Sociales (DADS-Panel)*. The data is built from confidential yearly social-security records, treated and transmitted by the French National Institute for Statistics (INSEE). Administrative records are based on firms' mandatory report of workers subject to payroll taxes to fiscal authorities. The database covers all firms in the private and public industries. From this administrative record, a panel of individuals born in October is built. Each observation consists of an employer-employee match, and reports the sex, age, residence, workplace region, yearly real earnings (in 2007 euros), and the number of hours and days worked each year by the individual. Since wages and careers are likely to be affected by personal events such as birth or marriage, we use data enhanced by information from the Permanent Demographic Sample (*échantillon démographique permanent, EDP*). The EDP Sample is augmented with variables from annual census surveys. This data source provides details on education, marital status, and the number of children.

This dataset is large and noisy, which is why we apply various cleaning procedures. First, we focus on mainland France and remove overseas territories. Second, we keep workers in private industry besides traineeship and subsidized employment, within working age range (15-65). Third, to focus on meaningful working experiences, we remove observations of occupations held for less than 30 days. Also, since workers in the DADS can be identified simultaneously in several positions, we only keep the worker-firm match for which the job spell and salary is the highest, and remove occupations identified as ancillary ones. After our cleaning procedures, we end up with a non-balanced-yearly-worker panel that includes 1,081,665 workers representative of the French workforce employed in 270 occupations, with an average of 7.3 years of observations per workers.

Occupational mobility increased in France since the 1980s, and jobs switches are more frequent than commonly thought. In our 2003-2015 sample the workers held on average 2.7 occupations, and more than 61% of workers experienced at least one occupational transition, either within or between firms. Our mobility figures are also in line with the existing research that shows higher mobility of young, educated men in urban areas (Kambourov, G., & Manovskii, I, 2008, 2009).

4 VARIABLE DEFINITION AND DESCRIPTIVE OVERVIEW

To examine the relationship between local labor market performance and local occupational coherence for 304 French CZ over the calendar years 2003 to 2015, we first measure bilateral occupational relatedness (section 4.1). We then superimpose this on to local occupational composition to obtain a picture of CZ occupational coherence (section 4.2) and industrial coherence (section 4.3). We also build control variables for the local unemployment rate (section 4.4 and 4.5).

4.1 Occupational Relatedness

The frequency of occupation switching patterns should partly reflect the skill-proximity between any two pairs of occupations because the larger the share of common human capital, the easier the flow between two occupations. Therefore, we measure occupational relatedness by worker flows between two occupations from the *DADS Panel* between 2003 and 2015.

Cross-occupation flows obviously depend on factors other than just the skill-proximity between two occupations. Job mobility is also determined by socio-economic characteristics of jobs and workers, including earnings, gender, and education. For instance, educated young men change jobs much more frequently than older workers, women, and non-educated employees (Blumberg, 1980; Groes, et al., 2014). Occupational transitions are also determined (or limited) by local occupational demand, with a positive influence of the spatial employment density of urban (versus rural) areas on the probability of job transition (Andersson and Thulin, 2013). Job transition opportunities also depend on current and future earnings (Topel and Ward, 1992). Thus, worker flows between occupations are not sufficient to capture the skill-proximity between occupations.

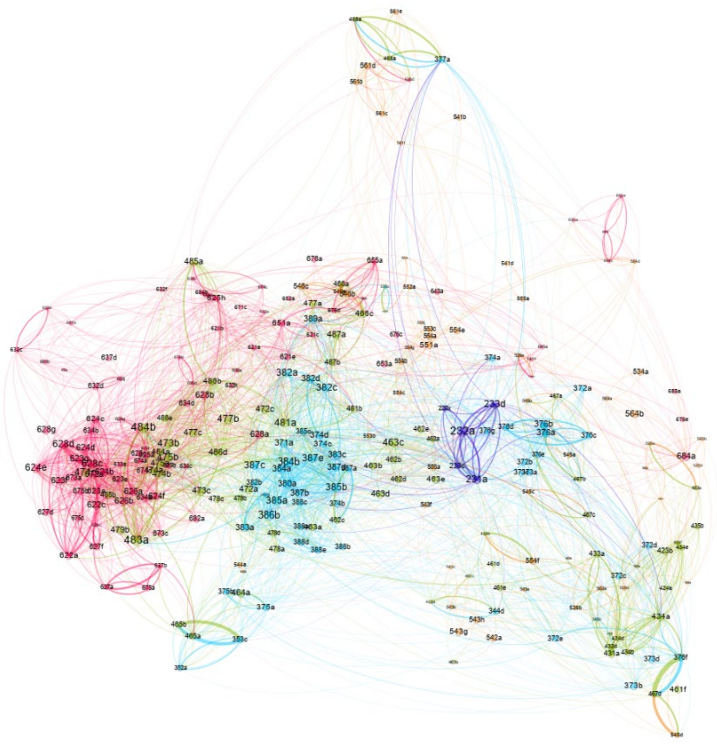
We therefore need to determine whether the flow is *exceptionally* large compared with a baseline. Neffke and Henning (2013) and Neffke et al. (2018) suggest such an approach to the estimation of skill-relatedness between industries. We apply this approach to cross-occupation labor flows. Following their methodology, the baseline reflects the expectation of the magnitude of bilateral worker flows based upon general characteristics of the two occupations. The occupation relatedness score $OR_{i,j}$ is then defined as the following ratio:

$$OR_{i,j} = \frac{F_{i,j}}{\widehat{F_{i,j}}}$$

Where $F_{i,j}$ is the number of workers who switch directly from occupation i to occupation j and $\widehat{F_{i,j}}$ is the baseline expectation of labor flows determined by socio-economic characteristics of the occupations. The predicted labor flows ($\widehat{F_{i,j}}$) come from a regression analysis of $F_{i,j}$ (i.e., total employment from the occupation of origin i to the occupation of destination j) that accounts for various socio-economic factors.[2]

Using occupation relatedness, we depict a matrix that covers 270 occupations as a network graph that connects related occupations in Figure 1. Each node in the graph represents an occupation (in PCS4-digits classification), and the lines connecting them represent occupation relatedness. The arrangement of occupations in this graph is such that more related occupations are located closer together. We refer to this network of bilateral relatedness between occupations as the occupation space.

Figure 1- The Occupation Space



Notes: Figure realized using Gephi software using OpenOrd visiualization algorithm. Each node corresponds to 4-digits occupation code. Their size is proportional to their outward centrality, and their color corresponds to the PCS 1-digit. Edge sizes are proportional to their weights. Only top 50% of edges are drawn for clarity purposes.

[2] See Appendix A for further details on measuring $\widehat{F_{i,j}}$, and the resulting Occupation Relatedness score $OR_{i,j}$

4.2 CZ Occupational Coherence

Having quantified how occupations are related from $OR_{i,j}$, we now use the local workforce composition to construct our measure of occupation coherence (OC). Specifically, we create a local occupation coherence index $OC_{r,t}$ as the weighted average of occupation relatedness within the CZ:

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

Where $E_{i,r,t}$ and $E_{j,r,t}$ denote the employment share in occupation i and j in CZ *r,* at time *t,* for the 270 occupations identified in the occupation space.[3] $OR_{i,j}$ is the relatedness of occupation i with occupation j described above in section 4.1.[4]

This index is a good measure of local labor market thickness. A high index indicates a dense concentration of employment in related occupations. The higher the index, the more the CZ offers a coherent set of occupations, that is, a large fraction of occupations that are strongly skill related. Because $OR_{i,j}$ reflects the dyadic proximity between any pair of occupations, $OC_{r,t}$ captures the ease with which workers could redeploy locally if they had to switch from their current jobs.

4.3 CZ Industrial Coherence

The role of industrial coherence on local labor market resilience has been well-documented in a large and growing literature that focuses on how skills, capabilities, and technologies can be re-allocated rapidly among industries, thus improving regional capacity to respond to external shocks (Cainelli et al. 2019). We build on Neffke and Henning's (2013) measure of *industrial relatedness* to identify industrial coherence in a similar way to occupational coherence in 4.1. However, instead of using the mobility of workers across occupations, they measure the skill-relatedness of industries with 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,

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

[3]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 occupation level. Every row in the declaration corresponds to a particular employee's position in an establishment, and reports information on its occupation and its location in a CZ.

[4] Note that we have a directed network of occupation so $OR_{i,j}$, the relatedness of occupation i with occupation j is different than $OR_{j,i}$ the relatedness of occupation j with occupation i.

By analogy, $E_{i,r,t}$ and $E_{j,r,t}$ denote the CZ *r* employment share in 4-digit NACE rev1 industry *i* and *j* at time *t,* for the 380 industries identified in the industry space developed by Neffke and Henning (2013).[5] $IR_{i,j}$ is the relatedness of industry *i* with industry *j*. [6]

4.4 Regional input-output linkages

An influential literature shows that firm-level or sector-level shocks can have an important effect even in diversified economies due to inter-sectoral linkages in production networks (Gabaix, 2011, Acemoglu et al. 2017). To account for the CZ industrial composition and particularly the input-output linkages of the local industries, we construct a variable analogous to the occupational coherence measure that we use. Specifically, we use the value of inputs from 2-digit industry *i* required to produce one unit of output in industry *j* available from the French National Institute of Statistics, INSEE. We label this variable $IO_{i,j}$. We use information for a baseline year that is the year before our period of observation in 2002.

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

By analogy, $E_{i,r,t}$ and $E_{j,r,t}$ denote the CZ *r* employment share in 2-digit industry *i* and *j* at time *t.* $IO_{r,t}$ 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.

4.5 Other Covariates

Our estimates of local resilience would be biased if there was a secular skill-biased change and if skills differed across CZs in a way correlated with the shocks (Martin and Gardiner, 2019, Duschl, 2014, Glaeser et al. 2014). To address this possibility, we control for 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: managers and engineers). Because larger cities offer more outside options than smaller ones (Papageorgiou, 2021), we also account for the average size of the CZ, defined as the total number of workers (in log). Additionally, because we know from prior theories of comparative advantage that regional specialization influences a region's competitiveness, 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* : $Herfindahl_r = \sum_o (h_{or})^2 * 100$. The employment shares are all aggregated up from the universe of individual social security records from the DADS Postes. Some regressions also include age-industry-earnings fixed effects that are interactions between age, measured in one-year

[5]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.
[6] This is available on Neffke's website.

increments, 2-digit NAF industry code on the worker's principal employer and 15 bins of the worker's net earnings. We explain more precisely when each covariate is used. Table 1 reports summary statistics for our variable.

Table 1- Means and Standard-Deviation of CZ-level Variables

	Mean	Std. dev.	Min	Max
CZ characteristics:				
Average Occupational Coherence (2003-2009)	4.42	0.79	3.37	8.72
Average Industrial Coherence (2003-2009)	19.53	19.30	1.38	224.22
Occupational Coherence in 2009	3.96	0.69	3.05	10.09
Industrial Coherence in 2009	20.57	20.36	1.30	179.30
Occupational Coherence in 2003	4.82	1.25	2.97	11.11
Industrial Coherence in 2003	17.17	20.75	1.05	252.54
CZ control Variables in 2009:				
Input-Output linkages	2.11	1.19	0.04	13.78
Size (in log)	9.97	1.19	5.77	14.38
Concentration of occupations	1.43	1.71	0.80	29.37
Share of skilled workers	30.04	7.28	9.33	64.76

Notes: N=304 French CZs.

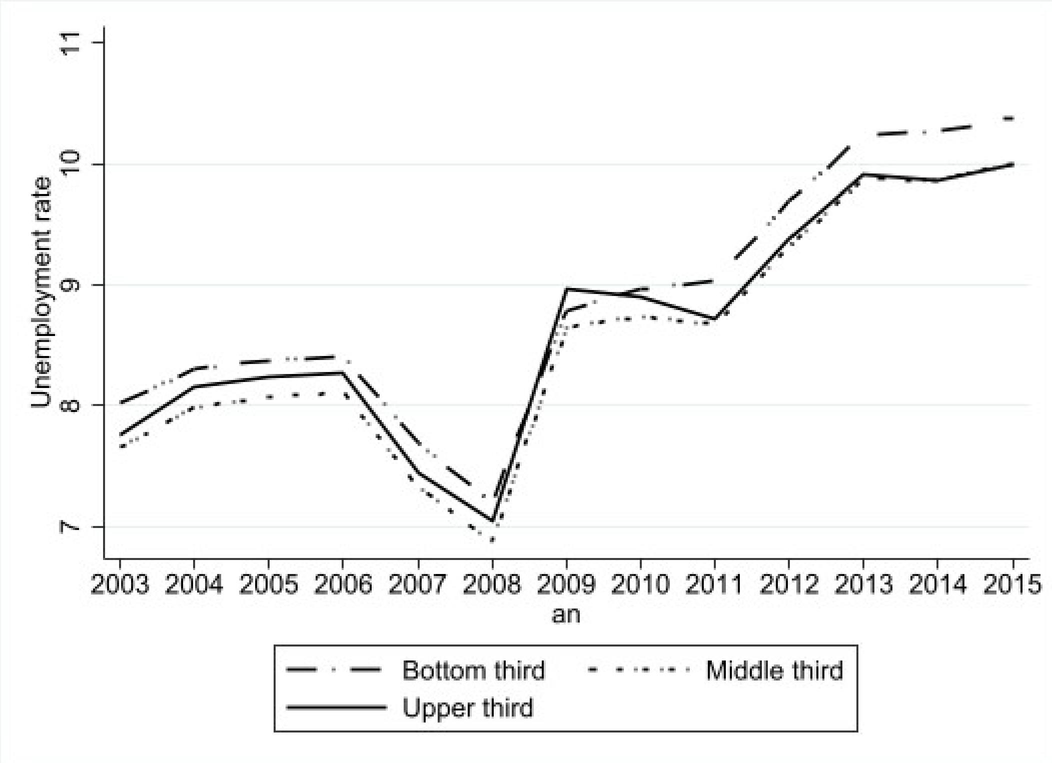
5. REGIONAL RESILIENCE TO SHOCKS

This section estimates the influence of occupational coherence on the local unemployment rate after an adverse shock. Section 5.1 considers an economy-wide shock such as the Global Financial Crisis. Section 5.2 studies local unemployment in the aftermath of sector-specific shocks such as technological progress and globalization. As described earlier, sector-specific shocks can have heterogeneous effects on occupations. Some occupations, especially routine-task-intensive occupations, are more likely to be adversely affected by globalization and technological progress. In order to examine this, section 5.3 analyses the influence of occupation-specific shocks according to worker CZ occupational coherence.

5.1 The Global Financial Crisis

The question we ask in this article is whether occupational coherence led to both a higher vulnerability to economic shocks as well as a faster recovery. We provide a first answer to this question by depicting the evolution of the unemployment rate for CZs in the bottom, middle and upper third of the distribution of occupational coherence. Figure 2 displays the evolution of unemployment rate between 2003 and 2015 in the sample of 'high coherence' CZs, those above the upper third tercile of the distribution of the 2003 occupational coherence and other 'low coherence' CZ (those in the bottom and middle tercile of the distribution).

Figure 2- 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 (highest-tercile of CZ occupational coherence in 2003), middle occupational coherence in dotted line (middle-tercile of CZ occupational coherence in 2003), and lower occupational coherence in dashed line (lower-tercile of CZ occupational coherence in 2003).

The first interesting feature from this figure is that the spike in unemployment as a consequence of the financial crisis happened in 2009 in France. Therefore, in the rest of this article, we will consider year 2009 as the year of the Global Financial Crisis. The second interesting observation from figure 2 is that before the Global Financial Crisis the unemployment growth in the two groups of CZs was very similar, but there is considerable heterogeneity among French CZs in their recovery from the Global Financial Crisis. In 2009, at the time of the spike in unemployment, high coherence CZs displayed a higher unemployment rate growth compared with other CZs. But as soon as in 2011, the same CZs, that were more adversely affected by the Global Financial Crisis, converged rapidly towards middle coherence CZs' unemployment rate. In other words, high coherence CZs experienced the highest average increase in unemployment between 2008-09 but recovered faster from the shock. On the contrary, low coherence regions display the highest unemployment rate, both before and after the shock, but also experience the lowest unemployment spike at the time of the shock. The next section investigates whether occupational coherence drives both higher vulnerability to the Global Financial Crisis as well as faster labor market recovery.

5.1.1 Empirical Strategy

The goal of this section is to analyze the relationship between CZ occupational coherence and CZ unemployment rate over the course of the recession that followed the Global Financial Crisis. We adopt an empirical design that closely follows earlier work using longitudinal CZ-level data to estimate long-term impacts of labor market shocks (e.g. Acemoglu, D., & Restrepo, P., 2020; Autor et al., 2013)

The causal interpretation of occupational coherence is sensitive to potential confounding pre-recession trends. It is typically difficult to evaluate the causal impact of occupational coherence due to sorting on human capital. Some areas have a pre-existing concentration of workers who are at risk to secular shocks. For example, regions with a strong concentration of low- to middle-skilled workers could experience a more dramatic unemployment shift after a nationwide secular shock. This would disproportionately affect the local unemployment rate as well as the local occupational composition. One way to limit this endogeneity concern is to include a set of confounding variables in X_r' that account for geographical differentiation. Additionally, to avoid contamination by the endogenous adjustment of the local labor force after the shock, we fix the local occupation coherence to year 2009. We intentionally choose year 2009 to measure occupational coherence because starting in 2009 employers were required to report each occupation with a 4-digit classification. Before 2009 there are some missing values. We label this variable $OC_{r,09}$ in equation 2. $OC_{r,09} = \sum_{i=1}^{n}\sum_{j=1}^{n-1}(E_{i,r,2009}.E_{j,r,2009}.OR_{i,j})$

$$\Delta U_r = \delta\ OC_{r,09} + \gamma\ IC_{r,09} + X_{r,09}'\beta + \epsilon_{r,t} \quad (2)$$

where ΔU_r is the percentage point change of unemployment rate between 2010 and 2015 in CZ r. $X_{r,09}'$ is a vector of CZ-level controls in 2009. Specifically, we control for local industrial composition by adding the CZ input-output linkages, the share of qualified workers, the concentration of occupations (Herfindahl index of 2-digit occupations), and the CZ size (log total employment) for year 2009. δ is our coefficient of interest. Even after controlling for CZ characteristics in $X_{r,09}'$, it is typically difficult to interpret δ as the causal effect of occupational coherence on local unemployment rate growth for the simple reason that other secular forces may affect both occupational composition and unemployment over long horizons (Ramey, 2012). For example, firms' location choices influence local occupational demand as well as local labor markets performance (Keller et al. 2020). We attempt to overcome this challenge by proposing a strategy in the spirit of Blundell and Bond (2000), who use lagged factor inputs as instruments for factor inputs to estimate production functions. In this setting, we propose an instrument for occupational coherence in 2009 as the occupational coherence that would be obtained in CZ *c* if it had the same occupational composition as in 2003: $OC_{r,03} = \sum_{i=1}^{n}\sum_{j=1}^{n-1}(E_{i,r,2003}.E_{j,r,2003}.OR_{i,j})$. This research design has the advantage of not requiring taking a stand on the determinants of local occupational demand, such as local skill supply, technological change, or organizational change. Rather, the occupational composition in 2003 summarizes the main forces driving the CZ occupational composition. 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 rate change other than through 2009 occupational coherence, conditional on other CZ characteristics.

Another coefficient of interest in equation 2 is γ, the coefficient associated with industrial coherence. Similar to δ, γ can suffer from endogeneity bias if industry-level determinants of labor demand, such as changes in technology, consumer tastes, or trade policy, affect both CZ unemployment rate and CZ industry employment. We adopt the same strategy as before by instrumenting $IC_{r,09}$ with $IC_{r,03}$, the CZ industrial coherence in 2003. When comparing industrial and occupational coherence, we are not only interested in statistical significance, but also in the size of the effect in order to disentangle the most relevant factors influencing the regional unemployment rate. Meaningful metrics in this context are standardized regression coefficients (MacKinnon et al., 2012). Therefore, we provide the results with standardized coefficients for occupational and industrial coherence to facilitate comparison between coefficients within each of our models.

5.1.2 First-Stage Estimates

Table 2 presents the first stage estimates of occupational coherence (columns 1 and 2) and industrial coherence (columns 3 and 4). As we expected, Table 2 reports a positive relationship between start-of-the-period occupational coherence in 2003 and occupational coherence at the time of the crisis, and between industrial coherence in 2003 and in 2009. As discussed in section 5.1.1, the data on 4-digit occupations has some missing values before 2009. To see whether missing values are creating noise in the estimation of predicted industrial coherence, we follow the same strategy as Laffineur and Mouhoud (2015) by focusing on CZ where at least 70% of the 4-digit occupational composition is available. Columns 1 and 3 report the results on the entire CZ sample. Columns 2 and 4 report estimates when at least 70% of the CZ occupational composition is available. Restricting the estimation to a subset of CZs does not significantly modify the estimates. It reduces slightly the F-statistics, but it still remains above the Staiger and Stock (1997) rule of thumb of 10. This result gives us confidence on the validity of our instrument (start-of-the-period occupational coherence) since it is not sensitive to missing values and to the modification of the sample of CZ. Therefore, in the rest of the study we consider the entire sample of CZ.

Table 2- First Stage Regressions

	(1)	(2)	(3)	(4)
	Occupational Coherence		Industrial Coherence	
Right-hand-side variables :				
Start-of-the-period Occupational Coherence	0.243***	0.244***	-0.012	-0.017
	[0.043]	[0.043]	[0.040]	[0.042]
Start-of-the-period Industrial Coherence	-0.001	-0.000	0.028***	0.028***
	[0.003]	[0.003]	[0.002]	[0.002]
Control Variables	Yes	Yes	Yes	Yes
F-stat	13.81	10.94	25.32	24.58
R2	0.22	0.19	0.34	0.35
N	304	276	304	276

Notes: Standard errors are given in parentheses and clustered by CZ. *** denotes significant at the 1% level

5.1.3 Baseline Results

We start by reporting IV-OLS estimates from equation 2. Our preferred specification with full controls and instrumental variable in column 5 of Table 3 implies that, a one unit standard deviation increase in the region's occupational coherence reduces the average working-age-French unemployment rate by 0.4 percentage points in the five years between 2010 and 2015. The coefficient is highly significant as given by a t-statistic of 2.6. A simple extrapolation exercise suggests that CZ occupational coherence caused a post-recession decline of the national unemployment rate of around 36%.

It is important to stress that this exercise is speculative but highlights the economic importance of occupational coherence. This estimate comes from our preferred coefficients associated with occupational coherence in column 5. We then adopt a strong 'naïve' assumption that the predicted change in unemployment ΔU_c (the percentage point change of the unemployment rate between 2015 and 2010 in France) is identical to a weighted average of the Great Recession local shock: $\Delta \widehat{U}_c = \sum_r (w_r \hat{\delta}\, \Delta OC_r)$ where r indicates the 304 French CZs, $\hat{\delta}$ is the estimate in Table 3 column 5 ($\hat{\delta} = -0.401/0.69 = -0.6$), w_r is the relative size of the CZ and ΔOC_r is the CZ change in occupational coherence between 2015 and 2010. The predicted change in 2015 unemployment is $\Delta \widehat{U}_c$ =0.45, as compared to an overall increase in the unemployment rate (measured as the CZs average of ΔU_c) of 1.26. Occupation coherence thus accounts for about one third (0.45/1.26=36%) of the 2015 unemployment change.

Another interesting feature from Table 3 is that while better occupational coherence improves local employment performance, occupational concentration increases unemployment rate between 2010 and 2015. Precisely, we find that a 1 percentage point higher Herfindahl index of occupational concentration increases 2010-15 unemployment rate by 0.05 percentage points. This result suggests that while specialized local areas perform worse in the aftermath of the Global Financial Crisis, those with a coherent set of occupations display better employment performance.

Table 3- CZ Unemployment rate and Occupational Coherence

N=304 CZ	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				IV			OLS
Occupational Coherence	-0.324***	-0.322***	-0.293**	-0.443***	-0.443***	-0.401**	-0.087**
	(0.114)	(0.116)	(0.130)	(0.167)	(0.168)	(0.159)	(0.037)
Industrial Coherence		0.020	0.018	-0.027	-0.027	-0.019	-0.095***
		(0.070)	(0.069)	(0.074)	(0.074)	(0.073)	(0.034)
Input-output linkages			-0.038	-0.041	-0.041	-0.052	-0.087**
			(0.038)	(0.038)	(0.038)	(0.036)	(0.035)
Size (in log)				-0.190***	-0.186**	-0.156**	-0.053
				(0.060)	(0.077)	(0.073)	(0.044)
Share of skilled workers					-0.001	0.000	-0.007
					(0.009)	(0.008)	(0.006)
Occupation concentration						0.050***	0.036***
						(0.015)	(0.010)
R-squared	0.07	0.02	0.05	0.06	0.06	0.08	0.08
Standard Deviation of $IC_{r,09}$	20.36	20.36	20.36	20.36	20.36	20.36	20.36
Standard Deviation of $OC_{r,09}$	0.69	0.69	0.69	0.69	0.69	0.69	0.69

All columns report coefficient estimates of occupational coherence on percentage points unemployment rate change between 2015 and 2010 in the balanced sample of CZ. Column 6 reports our preferred estimates (the article's main specification): a 1 percentage point higher occupational coherence before the Great Financial crisis caused CZ to have a 0.4 percentage point lower unemployment rate difference between 2015 and 2010. Column 1 reports estimates of occupational coherence without control variables. Column 2 includes industrial cohrence. Column 3 adds CZ input-output linkages and column 4 includes the CZ size (in log). Column 5 includes the CZ share of skilled workers and column 6 includes the Herfindahl index of occupation concentration. Column 7 reports the results without instrumenting for occupational and industrial coherence. 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% (*)

A final interesting result from Table 3 is that CZ industrial coherence did not reduce the 2010-15 unemployment rate. This result contradicts studies which find better local employment resilience when there are a variety of local skill-related technologies 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). However, the bulk of these studies do not account for potential bias stemming from the endogenous sorting of workers and firms across areas. When we do not instrument for industrial coherence (column 6 in Table 3), we also find a significant relationship between occupational coherence and the 2010-15 unemployment rate. OLS estimates show that the magnitude of the effect of industrial coherence is as large as the one of occupational coherence. A one unit standard deviation increase in the region's industrial coherence reduces the average working-age-French unemployment rate by 0.09 percentage points between 2010 and 2015.

Table 4- CZ Unemployment rate and Alternative Definition of Occupational Coherence

N=304 CZ	(1) IV	(2) OLS	(3) IV	(4) OLS
Occupational Coherence	-0.178***	-0.153***	-0.191***	-0.168***
	(0.072)	(0.045)	(0.072)	(0.045)
Industrial Coherence	0.003	-0.057*	0.003	-0.058*
	(0.053)	(0.032)	(0.051)	(0.032)
Input-output linkages	-0.049	-0.057*	-0.058*	-0.065*
	(0.034)	(0.033)	(0.035)	(0.034)
Size (in log)	-0.075	-0.068	-0.098	-0.093*
	(0.047)	(0.043)	(0.060)	(0.056)
Share of skilled workers	-0.008	-0.009	0.000	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Occupation concentration	0.033***	0.032***	0.070**	0.065*
	(0.012)	(0.011)	(0.028)	(0.034)
R-squared	0.09	0.10	0.09	0.10

All columns report coefficient estimates of percentage points unemployment rate change between 2015 and 2010 in the balanced sample of CZ. Columns 1 and 3 report IV-OLS estimates and columns 2 and 4 OLS estimates. Column 1-4 measures OC and IC as the average value over the period 2003-2009. Columns 1-2 include control variables defined as their values at the beginning of the period in 2009 and columns 3-4 include control variables defined as their average values in 2003-2009. 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% (*)

Our results are robust to a series of robustness specifications on the way occupational coherence and our control variables are specified, either by taking the average over the period 2003-2009 or only year 2009. Table 4 shows estimates when occupational coherence and industrial coherence are defined as the CZ average value over the period 2003-2009. Columns 1-2 include control variables in 2009 and columns 3-4 include control variables averaged over the period 2003-2009. We find very similar results, both statistically and economically, to those obtained in Table 3, though the magnitude is around two times smaller in IV specifications and two times larger in OLS specifications.

How do OLS and 2SLS estimates compare for our preferred specification in column 6 of Table 3? Estimates are subject to both measurement error in CZ occupational coherence due to missing values of CZ occupation composition before 2009 and simultaneity associated with CZ occupational composition and the unemployment rate. It is possible to partially separate the importance of these two sources of bias. If we measure the change in unemployment rate using 2003-2009 occupational composition, the OLS coefficient increases in magnitude from -0.087 (column 7 in Table 3) to -0.153 (column 2 in Table 4). Therefore, accounting for measurement error in CZ occupational coherence halves the size of the effect. Addressing measurement concerns regarding occupational composition may account for half of the difference between OLS and IV-OLS estimates, with the remaining difference (between column 6 and 7 in Table 3) associated with the correction for endogeneity.

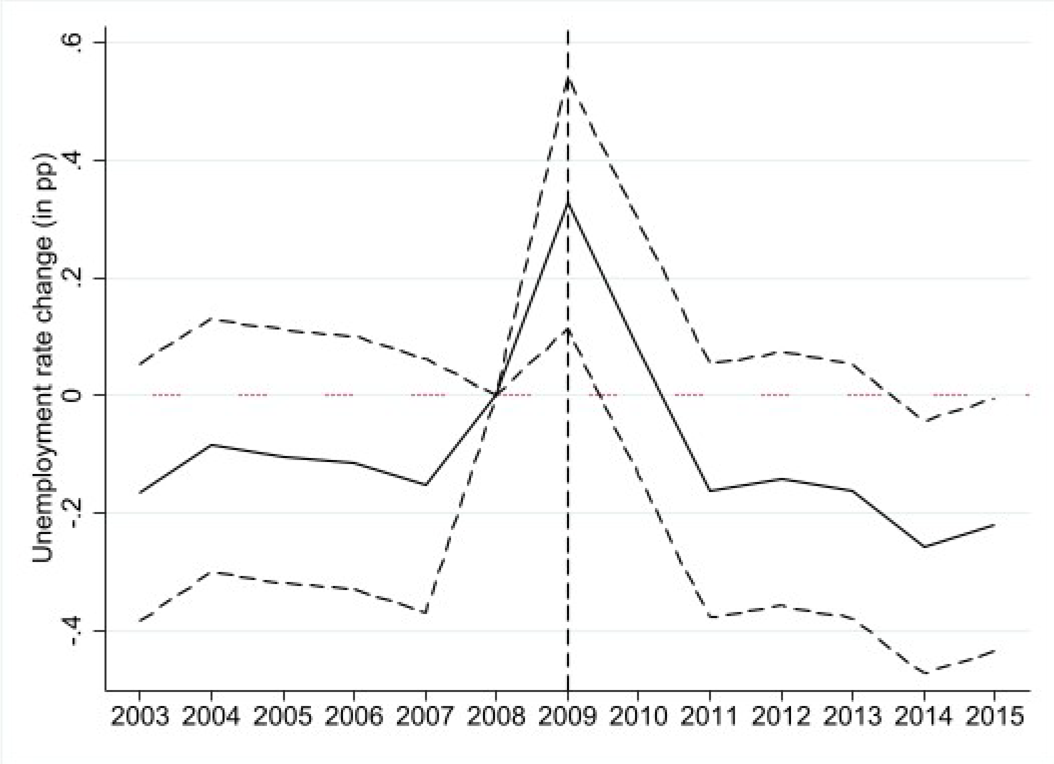
5.1.4 Timing of the effect

The unemployment effect of a shock is sensitive to time. In section 2, we conjectured that at the time of the shock, regions with strong occupational coherence are more at risk from high unemployment, especially when the shock is directed towards the CZs' occupational specialization. After the shock, regions with strong occupational coherence should recover faster by allowing inter-occupation labor mobility after layoffs. We investigate the timing of the effect using the full unemployment histories of the French CZs between 2003-15. Specifically, we estimate the following equation:

$$Unemployment_{r,t} = \sum_{k=-6}^{6} \delta_k I(t = t^* + k)\widehat{OC_{r,09}} + \alpha_r + \theta_t + W'_{rt}\beta + u_{r,t} \qquad (3)$$

Unemployment denotes the unemployment rate at time *t* in CZ *r* over the calendar years 2003 to 2015, expressed as a percentage of the French working-age population. $\widehat{OC_{r,09}}$ is defined as in section 5.1.1. It is the predicted occupational coherence in 2009 from a first stage estimation that includes the beginning-of-the-period occupational coherence ($OC_{r,03}$) and $X'_{r,09}$, a vector of CZ-level controls in 2009 similar to those included in equation 2. α_r denotes fixed effects for CZ *r* and θ_t are time fixed effects for year 2003-15. W'_{rt} is a vector of time-varying CZ-level controls including CZ input-output linkages, CZ industrial coherence, the average share of qualified workers, the concentration of occupations (Herfindahl index of 2-digit occupations), and CZ size (log total employment). $u_{r,t}$ is a disturbance term. We cluster the standard-errors at the level of the CZ. Our coefficient of interest is δ_k, the coefficient associated with local occupational coherence. In this setting, we consider occupational coherence as a continuous treatment at different periods of time. δ_k can be interpreted as the weighted average causal incremental effect of occupational coherence on unemployment rate over the course of the Global Financial Crisis. Identification requires strong parallel trend assumptions – that the causal response to more occupational coherence is the same across CZs conditional on having the same occupational coherence and being in the same time period. . As discussed in Figure 2, we find similar unemployment rate trends before the crisis along the distribution of occupational coherence, which provides some support for the parallel trend assumption. Note that it is also unlikely that CZs intentionally choose their level of occupational coherence as it is most likely determined by broader economic factors influencing labor supply and demand, which rules out CZ selection into a particular dose of occupational coherence (Callaway et al. 2021)

Figure 3- Regression Estimates of Unemployment rate change before and after the Global Financial crisis



Notes: The figure shows regression estimates of equation 2. It measures the effect of occupational coherence in 2009 six years before and after the Global Financial crisis (as defined in equation 3). The bands are 95% confidence interval. The omitted category is year t=-1. We control for region's size (in log), the region's share of highly skilled workers, the region's industrial input-output linkages and occupation concentration in 2009. Estimates come from clustered and the CZ level standard errors CZ fixed effect IV-OLS estimation on unemployment rate.

Figure 3 reports the coefficients δ_k with 2008, the year before the Global Financial crisis, as a baseline year. The 95 percent confidence interval are plotted in horizontal dashed lines, based on standard errors clustered by CZ. We find that at the time of the shock, in 2009, a 1 percentage point higher occupational coherence is associated with a 0.33 percentage point higher local unemployment compared with 2008. We also find that unemployment reduction is significant (at the 10% level) 5 to 6 years after the shock: the coefficient becomes negative and significant in 2014. We find that a 1 percentage point higher occupational coherence is associated with a 0.26 and 0.22 percentage point lower local unemployment rate in 2014 and 2015 respectively, compared with 2008. These results are in line with our conjectures. At the time of the event CZs with strong occupational coherence are more vulnerable to the economic shock but recover faster than CZs with weaker occupational coherence. This result is in line with many others, including the canonical analysis of Blanchard and Katz (1992) who show that after an adverse employment shock, states' employment returns to parity after 5-6 years. Our conclusions are qualitatively similar when running an OLS estimation.

5.1.3 Worker-Level Estimates

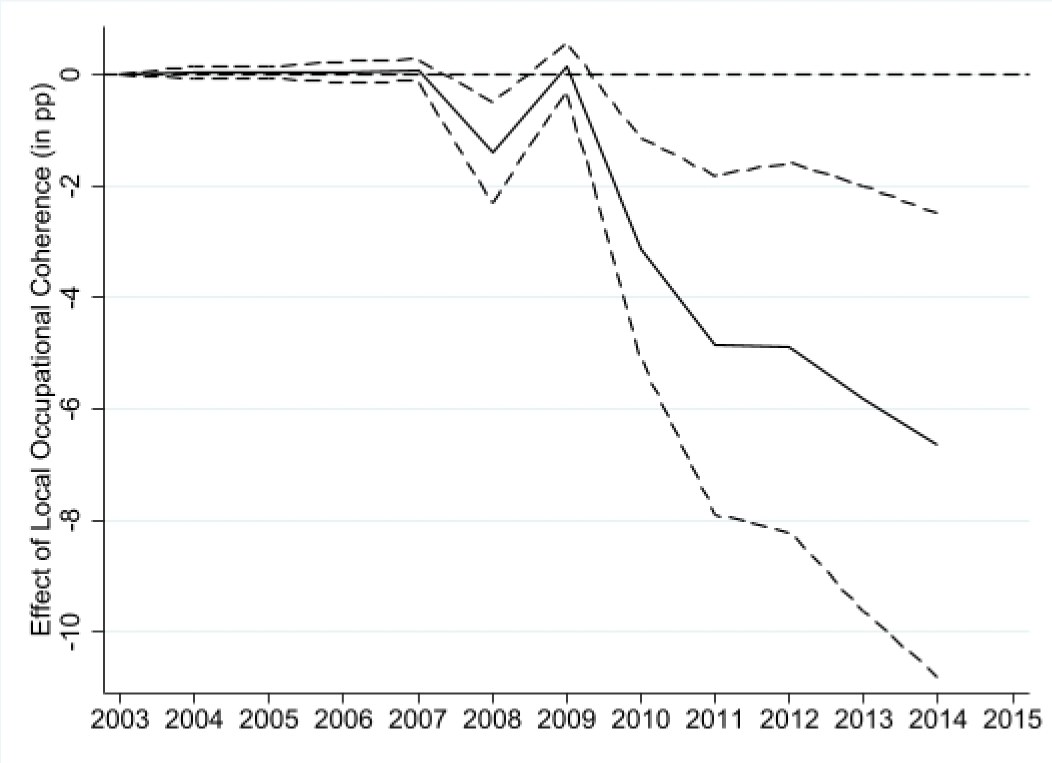
We now shift the focus from local labor market adjustments to individual workers. This complements the previous model, because it directly studies the effect of characteristics of the worker's place of residence (including local occupational coherence) on post-recession unemployment outcomes. We analyze individual worker's unemployment history according to cross-CZ characteristics from the cleaned sample of *Déclaration Annuelles des Données Sociales (DADS Panel)* as described in section 3 and we use the same empirical design as in Yagan (2019):

$$u_{i,t} = \delta\widehat{OC_{r}}_{,09}+X'_{r,09}\beta+Z'_{i,09}\gamma + \epsilon_{i,t} \qquad (4)$$

The dependent variable is computed from individual relative unemployment change. $u_{i,t} \equiv Unemployment_{i,t} - (\frac{1}{7})\sum_{s=2003}^{s=2009} Unemployment_{i,s}$ is worker i's change in unemployment rate from pre-recession years to year $t \in [2003;2015]$. $X'_{r,09}$ is a vector of CZ-level controls in 2009 as in equation 2. $Z'_{i,09}$ is a vector of worker-level controls. We include dummies for gender and age-earnings-industry fixed effects as described in 4.5. Including control variables before the crisis allows us to account for selection concerns that would occur if workers who are secularly out of the labor force would have disproportionately stayed in areas with high occupational coherence. $\widehat{OC_{r}}_{,09}$ is defined as in equation 3. We also restrict the sample to workers who stayed in the same area during the entire timespan to avoid capturing worker movement from low-occupational coherence areas to high-occupational coherence CZs with conceivably higher employment opportunities. In other words, we measure the capacity of workers to find a job in their locality without relocating. Focusing on non-migrant workers also provides full support to the identifying assumption of $OC_{r,03}$ being a good instrument for $OC_{r,09}$, because it relies on the assumption that workers are as good as randomly assigned across CZs.

Our variable of interest is δ and is reported in Figure 5 for years 2003 up to 2015. The 95 percent confidence intervals are plotted in horizontal dashed lines from CZs clustered standard errors. The main result of Figure 5 is the following: a one percentage point higher local occupational coherence in 2009 caused the average working-age French from that area to be an estimated 7.01 percentage points less likely to be unemployed in 2015. Importantly, we find that OLS estimates display similar results but twice as small as the 2SLS estimates, suggesting strong simultaneity bias. This result is also robust to different specifications. Table 5 displays 2015-point estimates from equation 4 under various specification. Columns 1-4 replicate the analysis with smaller and coarser confounding variables. The table yields similar results. The coefficients are similar in magnitude to our baseline.

Figure 5- Unemployment Impact of Occupational Coherence before and after the crisis



Notes: The figure shows regression estimates of CZ fixed effect OLS estimation on unemployment of equation 4. It measures the effect of occupational coherence six years before and after the Global Financial crisis on relative unemployment (as reported in Table 4). Each year t outcome represents relative unemployment: the worker's year t unemployment indicator minus the individual's mean unemployment status between 2003 and 2009. The bands are 95% confidence interval. The omitted category is year t=-1. We control for region's size (in log), the region's share of highly skilled workers, the region's industrial input-output linkages and occupation concentration. We include industry-earning-age fixed effects and gender fixed effects. Estimates come from clustered standard errors at the CZ level standard errors.

Table 5- 2015 unemployment impact of occupational coherence relative to pre-Great Financial crisis mean

	2015 Unemployment rate			
	(1)	(2)	(3)	(4)
Occupational Coherence (IV-OLS)	-13.62***	-15.21***	-9.26***	-7.02***
	(2.96)	(3.78)	(2.36)	(2.22)
Occupational Coherence (OLS)	-4,794***	-4,758***	-2,839***	-3,031***
	[1,208]	[1,298]	[0,809]	[0,872]
Input-output Linkages		X	X	X
Gender FE			X	X
Industry-Age-Earnings FE			X	X
Size (in log)				X
Share of skilled workers				X
Occupation concentration				X
Observations	280,373	280,373	241,175	241,175
R-squared	0.01	0.01	0.01	0.01
Standard Deviation of OC	0.69	0.69	0.69	0.69

All columns report coefficient estimates of occupational coherence on postrecession 2015 unemployment status in the balanced sample of full-time working age French population who stayed in the same CZ. The outcome is the individual's unemployment status minus the individual's mean 2003-2009 unemployment status. Column 4 reports estimate from Figure 5 (the article's main specification): a 1 percentage point higher occupational coherence before the Great Financial crisis caused individuals to be 7 percentage points less likely to be unemployed in 2015. Column 1 reports estimates without control variables. Column 2 includes CZ input-output linkages and column 3 adds worker control variables: industry-earning-age fixed effects and age fixed effects. Earning FEs are indicators for 15 bins of the worker's earning in 2009. Industry FE is the worker's 2-digit principal industry in 2009. Age FE are birth year indicators. 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% (*)

5.2. SECTOR-LEVEL SHOCKS

This section aims to analyze local labor markets resilience when regions are hit by sector-level shocks. We identify two different sector-level shocks: exposure to globalization and robots. There is an important distinction from estimating the unemployment impact of the Global Financial Crisis shock (as in the previous section), and sector-level shocks (as in this section) because globalization and technological progress are ongoing processes, that built momentum in the 1990s and continued to accelerate over a period of time. Consequently, this does not constitute an 'event study' as for the Global Financial Crisis. Here, we consider globalization and technological progress as a single long change over the period 2010 through 2015 as it is customary in the literature.

5.2.1 Variable Description

Our variable construction is conventional in the literature (Dauth et al. 2021, Acemoglu and Restrepo, 2020, 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 globalization and technological progress, local industry composition creates interesting variation to measure local exposure to technological progress and globalization. We thus create measures of predicted local exposure to technological change and globalization from the region's share of national industry employment. We use a shift-share design to create the variable $\Delta\widehat{Shock_r}$ in equation 7, i.e., the local exposure to occupation-level shocks. We define two types of occupation-level shocks: exposure to robots and globalization.

Exposure to robots. Exposure to robots is based on the counts of the French stock of robots per 1000 workers by industry from the start-of-period year *t* to the end-of-period year *T.* This information comes from the International Federation of Robotics (IFR). The IFR is a yearly survey on a sample of 50 countries in 25 industries on robot suppliers. A robot in this data is defined as an "automatically controlled, re-programmable, and multipurpose machine".[7] Specifically, exposure to robots is defined as follows:

$$\Delta\widehat{Robots_r} = \sum_{j=1}^{J} \frac{l_{j,r,2010}}{l_{r,2010}} . \frac{\Delta_{2015-2010}Shock_j}{l_{j,2010}} \quad (5)$$

The term $\Delta_{2015-2010}Shock_j$ measures the total number of robots in industry j between 2010 and 2015. $\frac{l_{j,r,2010}}{l_{r,2010}}$ is the initial employment share in industry-CZ cell and $l_{j,2010}$ is the initial employment in 2-digit industry j (in thousand workers). $\Delta\widehat{Robots_r}$ is then the variation in robot usage per thousand workers.

Exposure to Globalization. Exposure to globalization is based on the French foreign inputs penetration by industry from the start-of-period year 2010 to the end-of-period year 2015. This information comes from the World input-output data from the OECD. The input-output data identifies the share of imported inputs over total output in 45 two-digit ISIC rev4 codes in millions of US dollars.[8] We then measure exposure to globalization as follows:

$$\Delta\widehat{Globalization_r} = \sum_{j=1}^{J} \frac{l_{j,r,2010}}{l_{r,2010}} . \frac{\Delta_{2015-2010}Shock_j}{l_{j,2010}} \quad (6)$$

[7] The limitation of the data is that it does not provide detailed set of industries outside manufacturing (roughly at the two-digit level: agriculture, forestry and fishing, mining, utilities, construction, education, research and development, other non-manufacturing industries). Table C1 in the Appendix report the list of industries in IFR and the corresponding French classification of industries (NAF).

[8] We merge the 45 two-digit ISIC rev4 codes to the French classification of industries and drop agriculture (NAF code AZ)

The term $\Delta_{2015-2010}Shock_j$ measures the total imports of intermediate inputs (in current thousand $US) between 2010 and 2015. $\frac{l_{j,r,2010}}{l_{r,2010}}$ is the initial employment share in industry-CZ cell and $l_{j,2010}$ is the initial employment in 2-digit industry j (in thousand workers). $\Delta\widehat{Globalization}_r$ is then the variation in $1 thousand of exposure to imports per worker. Table 6 reports summary statistics for our shock variables.

Table 6- 2010-15 Exposure to Trade and Robots in France and Other Selected High-Income Countries

Exposure to Robots in France	-1.13	1.51	-12.81	0.94
Exposure to Globalization in France	0.04	4.24	-48.85	10.21
Exposure to Robots in 7 high-income countries	0.60	0.55	-1.14	2.96
Exposure to Globalization in 7 high-income countries	-0.66	1.84	-21.91	1.53

Notes: 304 French CZs

5.2.2 Methodology

The purpose of this section is to analyze whether occupational coherence limits the depth and intensity of sector-level shocks on local unemployment. To this end, we include an interaction variable to the estimation. We estimate the following equation at the CZ level.

$$\Delta U_r = \delta_1 \Delta\widehat{Shock}_r + \delta_2 \widehat{Coherence}_{r,09} + \delta_3 \widehat{Coherence}_{r,09} \times \Delta\widehat{Shock}_r + \beta X_{r,09} + u_r \quad (7)$$

Where ΔU_r is the percentage point change of unemployment rate between 2010 and 2015 in CZ r. $\Delta\widehat{Shock}_r$ measures alternatively $\Delta\widehat{Robots}_r$ as defined in equation 5 and $\Delta\widehat{Globalization}_r$ as defined in equation 6. $X_{r,09}$ includes the same demographic characteristics of the local workforce as in equation 2. Since the variation of the variable comes from two sources, we also account for the start-of-period industry shares within a CZ so as to focus on variation in exposure to occupation-specific shocks than on CZ differential concentration of industrial employment. $\widehat{Coherence}_{r,09}$ measures alternatively $\widehat{OC}_{r,09}$, as described in equation 3, and $\widehat{IC}_{r,09}$, which is the predicted industrial coherence in 2009 from a first stage estimation that includes the beginning-of-the-period industrial coherence $IC_{r,03}$, and $X'_{r,09}$ a vector of CZ-level controls in 2009, similar to the ones included in equation 2.

Finally, as is already well described in the literature, the estimation of the variable $\widehat{Shock}$ might suffer from endogeneity due to simultaneity between the variable $Shock, U_r$, and other industry-specific demand shocks. To address this concern, we apply the Bartik instrumental variable strategy proposed by Autor et al. (2013) and Acemoglu and Restrepo (2020). In this approach, we measure exposure to globalization and technological progress analogously to equation 5 and 6 in seven other high-income markets: Denmark, Finland, Germany, Italy, Norway, Spain and Sweden. Specifically, we measure the exposure to robots and globalization as the average exposure in the seven high-income markets and we weight this average exposure by using lagged employment counts. Specifically, we use employment in 2003 for normalization. This normalization allows mitigation of the simultaneity bias that would arise if the region anticipated exposure to globalization and robotization.

5.2.3 Regression Estimates

Table 7 reports 2SLS estimation of equation 7. Panel A estimates the influence of exposure to globalization on the percentage point change of unemployment rate between 2010 and 2015 and Panel B estimates the influence of exposure to robots. The Kleibergen and Paap (2006) statistic indicates there is no problem of weak instruments, and the Hansen test values when the equation is overidentified do not reject the null hypothesis of valid instruments. We also report shift-share standard errors with 304 2010 CZ clusters as suggested by Adão et al. (2019) to account for cross-section correlation between regions with similar industry structures.[9] The correlation of the error term is then represented by a matrix of regional industry shares rather than by discrete clusters.

The first column in each panel displays the results without the interaction variable. The positive impact on unemployment is highly significant and large in magnitude.

Panel A reports the results of exposure to globalization. The coefficient of 0.02 in column 1 indicates that a $1000 exogenous 5 year rise in a CZ's intermediate inputs import exposure per worker is predicted to increase the unemployment rate by 0.02 percentage points. Table 6 shows a standard-deviation of $4,230 exposure to globalization across CZs. Applying this value to Table 7 estimates imply that one-standard deviation exposure to imports of intermediate inputs increases the unemployment rate by 0.08 percentage points.

Panel B reports the results of exposure to robots. An additional robots-per-1000 workers implies an increase in the unemployment rate between 2010 and 2015 of 0.09 percentage points. This estimate is significant and economically important. A quick calculation implies that an additional robot caused roughly one additional unemployed worker in the affected commuting zone.[10] The magnitude is similar

[9] We run a just-identified IV-OLS estimation to estimate shift-share standard errors. Specifically, we use as an instrument the variable $\Delta\widehat{Shock_r}$ to that is defined as the average value across all seven other high-income countries.

[10] This extrapolation is made from the following simplification exercise. If the unemployment rate is $U_t = \frac{u_t}{E_t}$, with E_t the total active population and u_t the total unemployed head counts in t, then the percentage point change in unemployment between 2015 and 2010 is $\Delta U_{15-10} = (\frac{u_{2015}}{E_{2015}} - \frac{u_{2010}}{E_{2010}}) * 100$. Our estimates in equation 7, without the interaction variable, is then:

$$\Delta U_{15-10} = \delta_1 \left(\frac{R_{15} - R_{10}}{E_{10}}\right) * 1000$$

With R the number of installed robots. If we assume constant active population, we get $u_{2015} - u_{2010} = \delta_1(R_{15} - R_{10}) * 10$. Notice that our simplification exercise relies on a stricter assumption than in Dauth et al. (2021), Acemoglu and Restrepo (2020) and Aghion et al. (2019a) who assumed constant population (rather than constant active population).

to the one obtained on the employment-to-population ratio measured by Acemoglu and Restrepo (2020) on US data and Aghion et al. (2019a) on French data.

We next evaluate if CZ occupational coherence mitigates the positive effect of occupation-level shocks on unemployment rate by adding an interaction variable between exposure to shocks and occupational coherence.

The interaction variable is negative and only significant in Panel A. The positive effect of exposure to globalization on change in the unemployment rate is smaller in CZs with strong industrial coherence. This result is in line with what we expected and discussed in section 2. Industrial coherence is more important than occupational coherence to mitigate sector-specific shocks. A simple extrapolation exercise tells us that an additional thousand-exposure to intermediate inputs per workers between 2010 and 2015 caused an average increase in the unemployment rate of 0.05 percentage points (0.07 - (0.68 x 0.02)) in regions with the smallest industrial coherence, those with $\widehat{IC_{r,09}}$ =0.68 (p-value=0.031). Whereas an additional thousand-dollar exposure to intermediate inputs per workers between 2010 and 2015 caused an average reduction in unemployment rate of 0.43 percentage points (0.07 - (23.68 x 0.02)) in regions with the highest industrial coherence, those with $\widehat{IC_{r,09}}$ =23.68. The coefficient is significant at the 10% level (p-value=0.096). On the contrary, we do not find any significant coefficient associated with the interaction variable between CZ occupational coherence, CZ industrial coherence and CZ exposure to globalization and robots.

Table 7- The Mitigating Effect of Occupational Coherence on the Unemployment Effect of Robotization and Globalization

N= 304 CZ	Panel A Globalization			Panel B Robots		
$\Delta\ \widehat{\text{Shock}}$	0.02***	-0.11	0.07**	0.09***	0.10	0.11
	(0.00)	(0.11)	(0.03)	(0.03)	(0.38)	(0.07)
Occupational Coherence ($\widehat{OC_{r,09}}$)	-0.49**	-0.50**	-0.51**	-0.37*	-0.37	-0.37*
	(0.20)	(0.20)	(0.21)	(0.20)	(0.25)	(0.20)
	[0.06]			[0.04]		
Industrial Coherence ($\widehat{IC_{r,09}}$)	-0.00	-0.00	0.00	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\widehat{OC_{r,09}} \times \Delta\ \widehat{\text{Shock}}$	-	0.03	-	-	-0.00	-
	-	(0.03)	-	-	(0.09)	-
$\widehat{IC_{r,09}} \times \Delta\ \widehat{\text{Shock}}$	-	-	-0.02*	-	-	-0.01
	-	-	(0.01)	-	-	(0.01)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.09	0.09	0.09	0.12	0.12	0.12

Notes: The table shows 2SLS regression estimates of the effect of Occupational Coherence and Industrial Coherence in 2009 on the percentage points change of the unemployment rate between 2015 and 2010 with 7 instruments, that are the average exposure to the shock in 7 other high-income countries. Estimation includes local characteristics (IO linkages, CZ size, CZ concentration of occupations and CZ share of skilled workers in 2009). Panel A runs the estimation with globalization and Panel B with exposure to robots. Columns 1 and 3 reports the results without the interaction variable, columns 2 and 4 with interaction with Occupational Coherence and Columns 3 and 6 with interaction with Industrial Coherence. The p-value of the Hansen-J statistics in Panel A column 1 is 0.66 and in Panel B column 3 is 0.24. The Kleibergen and Paap F-stat is 47.42 in Panel 1 column 1 and 19.06 in Panel B column 3. Standard errors are clustered by 2010 CZ (reported in parenthesis) and shift-share standard errors are in brackets. The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

In the next section, we evaluate whether occupational coherence helps mitigate occupation-specific shocks, more than industrial coherence.

5.3 OCCUPATION-LEVEL SHOCKS

Industrial exposure to robots and globalization has heterogeneous effects across occupations: even within industries, some occupations are more adversely affected than others in the event of a shock. For example, routine-task-intensive occupations are more at risk from technological progress and firms' offshoring strategy than non-routine occupations (Grossman and Rossi-Hansberg, 2008). This section investigates whether being employed in a highly coherent CZ mitigates the negative employment effect of working in a routine-task-intensive occupation.

5.3.1 Methodology

We build on Autor et al. (2003) to identify routine manual-intensive occupations which are more at risk to globalization and technological progress than other non-routine occupations. We account for the occupation's potential for replacement by machines or foreign workers by identifying the importance of the task "Handling and Moving objects" to perform the occupation. This information comes from the ONET Work Activity Database. ONET provides a Work Activity files that identifies the importance of 41 tasks in more than 900 occupations. The ONET provides a score on the level of "Handling and Moving objects" needed to perform an occupation on a scale from 0 to 7.[11]

Our empirical strategy builds on equation 4 at the worker level to identify the effect of living in a high occupational coherence CZ on unemployment depending on the routine-intensive nature of the worker's occupation. Specifically, we include an interaction variable between the CZ occupational coherence of the worker's place of residence $\widehat{OC_{r,09}}$, and the routine-manual task intensity of the worker i's occupation o ($TC_{i,09}$).

$$u_{i,t} = \delta_1 \widehat{Coherence}_{r,09} + \delta_2 TC_{i,09} + \delta_3 TC_{i,09} \times \widehat{Coherence}_{r,09} + X'_{r,09}\beta + Z'_{i,09}\gamma + \epsilon_{i,t} \quad (8)$$

The dependent variable is measured from individual relative unemployment change $u_{i,t}$, where $u_{i,t} \equiv Unemployment_{i,2015} - (\frac{1}{7}) \sum_{s=2003}^{s=2009} Unemployment_{i,s}$ is the worker i's change in unemployment rate from pre-recession years to year 2015. $\widehat{Coherence}_{r,09}$ measures alternatively $\widehat{OC_{r,09}}$ and $\widehat{IC_{r,09}}$ as in equation 7. $TC_{i,09}$, is the worker i's occupation o's score in routine-manual tasks in 2009 that is interacted with the worker's place of residence occupational coherence $\widehat{Coherence}_{r,09}$. The other variables are identical to the ones included in equation 4.

5.3.2 Regression Estimates

Column 1 in Table 8 reports result without the interaction variable and columns 2-3 report estimates with the interaction variable. Unsurprisingly, we find that routine intensive occupations are more at risk to unemployment in 2015. We find that being employed in a one-unit higher routine manual intensive occupation is associated with a 0.57 percentage point higher likelihood of being unemployed in 2015. As with estimates from equation 4, we find that a one percentage point higher occupational coherence reduces the likelihood of being unemployed in 2015 by around 8 percentage points. From column 2, we find that living in a high coherence CZ reduces the negative effect of being employed in a routine-intensive occupation on unemployment. We find that the positive effect of a one-unit rise of $TC_{i,09}$ on 2015 unemployment rate is 21% (= 0.72/3.34) smaller for workers living in a CZ with a one-unit higher occupational coherence. On the contrary, we do not observe any direct or indirect effect of industrial coherence on 2015 unemployment. The coefficient associated with industrial coherence and the interaction of industrial coherence and $TC_{i,09}$ is not significant.

[11] We mapped ONET occupation classification with the French PCS-ESE classification from the corresponding Table built in Laffineur and Mouhoud (2015). The ONET score is derived from a questionnaire completed by workers and experts on the level of task needed to perform the current job. Three examples on the level of tasks are given at rank 2, 4 and 6 to help respondent answering to the question on the level of tasks.

Table 8- Occupation-specific shock: comparing industrial coherence and occupational coherence

	Unemployment Rate Difference in 2015		
		N=168,287	
Occupational Coherence ($\widehat{OC_{r,09}}$)	-8.36***	-5.47**	-8.36***
	(2.65)	(2.44)	(2.59)
Industrial Coherence ($\widehat{IC_{r,09}}$)	0.43	0.43	0.27
	(0.50)	(0.50)	(0.33)
Routine Manual Intensity ($TC_{i,09}$)	0.57***	3.34**	0.57***
	(0.14)	(1.31)	(0.14)
$\widehat{OC_{r,09}} \times TC_{i,09}$		-0.72**	
		(0.32)	
$\widehat{IC_{r,09}} \times TC_{i,09}$			0.04
			(0.08)
Control Variables:			
Input-output Linkages	X	X	X
Size (in log)	X	X	X
Share of skilled workers	X	X	X
Occupational concentration	X	X	X
Worker Control Variables	X	X	X
R2	0.02	0.02	0.02

Notes: All columns report coefficient estimates of occupational coherence and industrial coherence on 2015 unemployment status in the balanced sample of full-time working age French population who stayed in the same CZ. The outcome is the individual's 2015 unemployment status minus the individual's mean 2003-2009 unemployment status. Column 2 adds interaction of routine-intensive tasks with occupational coherence. Column 3 adds interaction of routine-intensive tasks with industrial coherence. 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% (*)

Summing up, thus far our results are in line with conjectures described in section 2. We find that CZs with strong occupational coherence are more at risk to an adverse event at the time of the shock but display better labor market performance after the shock. We also find that occupational coherence works better at mitigating an occupation-specific shock than industrial coherence whereas industrial coherence is more important to limit the depth of a sector-specific shock such as exposure to globalization than occupational coherence.

6. UNDERLYING MECHANISMS

In this section, we make use of detailed administrative data to better understand the channels through which local occupational coherence improves regional performance. We consider two potential mechanisms at work, reallocation within firms and labor market thickness. First, if firms in the region are hit by an economic shock, such as globalization or technological progress, then it is possible for surviving firms or even new firms formed in the aftermath of the shock to reconstitute, reorganize, and morph into entities and applications that utilize the existing deep pool of labor in related occupations by reallocating workers to other jobs *inside* the company. Second, if the shock implies layoffs and movements out of the labor force, regions with stronger occupational coherence and an associated higher density of links between occupations provide thicker labor markets. As a result, higher unemployment is likely to persist for longer in regions with low labor market thickness than regions with high labor market thickness. We investigate the importance of these two channels below.

6.1 Reallocation Within Firms

We leverage the availability of detailed administrative data to better understand the role of occupational coherence on organizational change and within-firm movement. Specifically, we make use of information on the worker's past occupation to count the total number of workers in a CZ who changed occupations between 2010 and 2015. We then opt for the most straightforward cut of the data to account for within-firm and between-firm changes in occupations. Specifically, we count the number of workers who changed occupations *within* the same firm and those who changed occupations by changing employer in a given CZ.

We regress these count variables on the predicted CZ occupational coherence and industrial coherence, $\widehat{OC_{r,09}}$ and $\widehat{IC_{r,09}}$ as described in equation 7. To ease interpretation and comparison between coefficients, we include standardized variables. We include the same control variables as in equation 2. Results are reported in Table 9. Column 1-3 include the different channels of the reallocation effect: between-occupations (column 1), within-firms (column 2) and between-firms (column 3). The only significant coefficient is the one associated with occupational coherence, industrial coherence is not significant in any column. We thus focus our attention on the estimates associated with occupational coherence. Unsurprisingly, we find that regional occupational coherence increases the change in employment in different occupations. Specifically, a one standard deviation increase in occupational coherence leads to an average increase of 579 workers who change occupations in a given CZ. This increase is mainly the result of changes occurring within the firm, rather than movements between firms. A one standard-deviation increase in CZ occupational coherence is associated with 766 more workers who changed occupations within the same firm between 2010 and 2015.

Table 9- Theoretical Mechanism I: Reallocation Within Firms

N=304 CZ	Different Occupation		
	Average	Same Employer	Different Employer
	(1)	(2)	(3)
Standardized Coefficients:			
Occupational Coherence	579.12**	766.45*	-155.94
	(289.15)	(428.89)	(240.82)
Industrial Coherence	43.21	134.29	-75.38
	(87.32)	(87.88)	(57.29)
Control Variables:			
Input-output linkages	X	X	X
Size (in log)	X	X	X
Share of skilled workers	X	X	X
Occupational concentration	X	X	X
N	304	304	304
R2	0.13	0.05	0.35

Notes: This Table reports Results of an estimation of the change in employment between 2010 and 2015 on predicted occupational coherence in 2009, industrial coherence in 2009 (with standardized coefficients), and a set of control variables: CZ input-output linkages, CZ size in log, CZ share of skilled workers and occupational concentratio. Standard errors are clusetered by 2010 CZ (reported in parenthesis). The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

6.2 Labor Market Thickness

We account for labor market thickness by measuring unemployment length. We leverage the availability of detailed administrative panel data to measure a worker's time spent in unemployment from 2003 and 2015. We use the balanced sample of DADS Panel so we only keep workers observed during the entire time span.[12] We then build a variable that varies between 0 and 100. A value of 100 indicates that the worker has spent 100% of the time-period being unemployed. Measuring unemployment time relative to each worker's career-history allows for a baseline unemployment rate difference as in the previous sections. We then regress worker's unemployment length on several regional characteristics and workers characteristics as in Equation 4. This estimation analyzes whether the characteristics of the place of residence influence the time spent in unemployment. The first column in Table 10 focuses on the entire balanced sample and column 2 restricts the balanced sample to workers who stayed in the same commuting zone. Results from column 1 shows that a one standard-deviation increase in occupational coherence reduces unemployment length by 0.32 percentage points. We also find that the sign associated with industrial coherence is negative but smaller in magnitude. A one standard-deviation increase in industrial coherence reduces unemployment length by 0.14 percentage

[12] Here unemployment is identified by workers who received unemployment benefits from the French Administration 'Pôle Emploi'.

points. When restricting the sample to workers who stayed in the same CZ, we find that occupational coherence reduces unemployment length by 0.11 percentage points. Interestingly, when restricting the sample to workers who stay in the same CZ during the entire period of observation we find that industrial coherence increases unemployment length. Workers living in areas with a high concentration of related industries spend longer time in unemployment. This result is in line with Neffke et al. (2018) who find that local concentration of skill-related industries increases the time it takes to find a new job for displaced workers because workers living in areas with a dense concentration of related industries might opt to stay longer in unemployment to find a job in an industry requiring similar skills than the industry in which they were previously employed.

This cross-over therefore suggests that regional characteristics also influence the spatial scope of job search. Indeed, Neffke et al. (2018) find that industrial relatedness reduces the rate at which workers leave the regions and reduces the spatial scope of job search to other CZs. To provide further support to this, we measure the distance between the place of residence and place of work for unemployed workers who re-enter employment, i.e. workers who were in unemployment and start a new job.[13] We include the same control variables as before and estimate the distance between the place of work and place of residence. Column 3 in Table 10 shows that a one standard deviation increase in industrial coherence reduces the distance between the place of residence and the place of work. We do not find any significant coefficient associated with occupational coherence. This result supports our prior of a reduction in the spatial scope of job search in regions with strong industrial coherence, but the magnitude is extremely small. The distance between the place of residence and the place of work is only reduced by an average of 0.31 miles with a one standard-deviation higher CZ industrial coherence. This corresponds to a reduction of around 4% (=0.31/8.01) of the average distance between place of work and place of residence (8.01 miles over the period 2010-2015).

Summing up, our results show that occupational coherence influence CZ resilience through a combination of labor reallocation within firms and thick labor markets. Strong occupational coherence thus makes it more likely for some regions to reinvent themselves and recover, in comparison to regions with weak occupational coherence. Industrial coherence is associated with a longer unemployment period, very likely because of an increase in the spatial scope of job search. Although this analysis is descriptive in nature, we find this preliminary evidence of interest for future research on the spatial scope of job search and CZ characteristics.

[13] The distance is calculated as the smaller distance between the city where the worker lives and the city where the worker works. Geographical distance is measured by the length of the shortest path between the city center along the surface of a mathematical model of the earth.

Table 10- Theoretical Mechanism II: Unemployment Length

N=304 CZ	Unemployment length Balanced Sample	Same CZ	Distance Re-employed workers
	(1)	(2)	(3)
Standardized Coefficients:			
Occupational Coherence	-0.32***	-0.11***	-0.01
	(0.02)	(0.01)	(0.14)
Industrial Coherence	-0.14***	0.03***	-0.31*
	(0.03)	(0.01)	(0.19)
Control Variables:			
Input-output linkages	X	X	X
Size (in log)	X	X	X
Share of skilled workers	X	X	X
Occupational concentration	X	X	X
Gender FE	X	X	X
Industry-Age-Earnings FE	X	X	X
N	339,723	202,102	166,081
R2	0.10	0.10	0.01

Notes: This Table reports Results of an estimation of the percentage points change in unemployment length between 2015 and 2010 and the distance between the place of work and the place of residence on occupational coherence, industrial coherence (with standardized coefficients), and a set of control variables. The average unemployment length is 0.11 and the standard-deviation is 0.23. The average distance between work-living place is 8.1 miles with a standard deviation of 4.1. Standard errors are clusetered by 2010 CZ (reported in parenthesis). The asterisks indicate the significance of the coefficient at the threshold of 1% (***), 5% (**) and 10% (*).

7. CONCLUSION

The question of why some regions are more resilient than others in the face of economic shocks is of enduring importance, never more so than in the context of increased global uncertainty and recessionary risks. A myriad of external events such as economic downturns, major policy changes, technological breakthroughs, increased competition from foreign countries, extreme natural events, and pandemics can undermine a region's performance at short notice. An understanding of the key ingredients of local labor market performance in the face of such shocks is imperative for both academic research and policy discussions. We conjecture here that regions with occupations offering greater redeployment possibilities to other occupations are less at risk of long-term unemployment. We examine this by developing a novel network-based approach to identify how occupations within a region are connected to each other via the mobility of workers between them.

We take an agnostic approach to which skills or tasks are at risk to economic shocks since many workers, including the most qualified ones, are vulnerable to economic shocks in some way or another. We develop a network of inter-occupation linkages from occupational mobility observed in a database that provides career paths for a representative sample of French workers over 13 years (2003-2015). We superimpose regional occupational composition on to this “occupation space” to provide a picture of local occupational coherence for 304 commuting zones in France. We then examine the relationship between occupational coherence, measured from the average linkages of a commuting zone in this occupation space, and local unemployment after an adverse shock.

Our key results are the following. regions with strong occupational coherence are more at risk to an adverse event at the time of the shock but recover faster than regions with weak occupational coherence. We also find that occupational coherence works better at mitigating an occupation-specific shock than industrial coherence whereas industrial coherence is more important to limit the depth of a sector-specific shock. Occupational coherence improves labor market performance through within-firm labor reallocation and a reduction of unemployment length, whereas industrial coherence works through a reduction of the spatial scope of job search.

Our paper provides an additional perspective to the literature on the roots of geographic resilience and suggests a new path to future research on the implications of occupational mobility. It highlights the importance of the regional workforce composition, and it could be helpful to policymakers in identifying regions that are vulnerable to economic shocks.

There are several promising research directions that could stem from the occupation space approach developed in the paper. Our approach might be of interest to researchers going beyond the traditional view of considering routine tasks or unskilled jobs at risk from external shocks. For example, Brynjolfsson and McAfee (2011) suggest that autonomation is no longer limited to routine tasks. In fact, 9 to 47% of employment could be at risk of automation (Arntz et al. 2017, Frey and Osborne, 2017). The occupation space approach takes an agnostic view about which occupations are at risk to shocks. Instead, it identifies those from which it is easier to switch to other occupations in case of an occupation specific shock. Additionally, the occupation space could be of interest for researchers looking at the origin of workers’ wage premia by investigating the bargaining power of workers employed in central occupations since they have several outside options to their current occupation (Caseilli et al. 2021, Amiti and Davis, 2012). Finally, the question of how occupation space evolves over time and its implications for economic development and growth offers a promising research agenda (Hidalgo et. al. 2007, Kali et. al. 2013).

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APPENDIX A- MEASURING OCCUPATION PROXIMITY

We measure skill-proximity between occupations by comparing excess occupation flows with expected flows that would be only driven by observable characteristics of occupations, such as occupation's demographic size and trend, average wage, or social composition.

The expected flows come from a regression of the number of switches observed for each of the 72,632 possible movements from occupations i to occupation j on a set of occupation characteristics.[14] Therefore, our estimation of labor flows is based on a count variable that is always positive and of integer value. Specifically, there are 24,469 positive switches from occupation i to j. The rest of the switches are set to 0. We also set to 0 all switches for which the count was less than 10, for confidential restrictions, but also to avoid analyzing very marginal linkages. With such a dependent variable, the most appropriate regression model is a Zero-Inflated Negative Binomial regression (ZINB) which consists in two steps. The first step runs a logit regression determining the probability of observing a flow between any two pairs of occupations. The second step is a count data model estimating the number of flows from one occupation to another.

We control for observable occupations' characteristics, including the size of both occupations in log ($lEmp_i$ and $lEmp_j$), and the growth rate of employment in each occupation over 2003-2015 (*lDeltaEmp*) to capture expanding or declining trends in occupations' demography that would explain labor flows. We add the average annual wage in each occupation in log euros (*lWage*) as well as a binary variable *WagePremia* capturing a wage increase from occupation i to j that motivates labor flows. Also, we capture the socio-composition of each occupation in two dimensions: the average age and the share of men in each origin and destination occupations, as it is reported that both gender and age influence worker's mobility (Topel and Ward, 1992). Finally, we included two variables controlling whether both occupations are mainly in rural or urban commuting zones, to account for a geographic restriction of occupational mobility. An occupation is said to be urban if it is over-represented in urban area according to the INSEE classification, and rural otherwise.

The estimated model is the following:

$$E(F_{i,j}|v_i, v_j, w_{ij}, \varepsilon_{i,j}) = [1 - \pi_0(\gamma + \delta_i\ lEmp_i\ \delta_j\ lEmp_j)]\ e^{\propto + \beta_i v_i + \beta_j v_j + \beta_i w_{ij} + \varepsilon_{i,j}}$$

Where the vectors v_i and v_j correspond to the occupation-level variable *lEmp lDeltaEmp* and *lWage*. w_{ij} is the occupation-pair level variables $WagePremia_{ij}$. π_0 is the probability of $F_{ij} = 0$.
Results are reported in Table A1.

[14] We use the 269 occupations identified from DADS-panel data over the period 2003-2015

Table A.1- Zero Inflated Negative Binomial Model

	Occupation movement from occupation i to j
Number of employees in occ. i (log)	0.508
	(54.85)***
Number of employees in occ. j (log)	0.507
	(54.85)***
Wage premium in occ j.	0.064
	(3.07)***
Average wage in occ. i (log)	0.153
	(4.96)***
Average wage in occ. j (log)	0.178
	(5.85)***
Average age in occ. i	-0.004
	(1.58)*
Average age in occ. j	-0.001
	(10.43)
Share of men in occ. i	-0.032
	(0.95)
Share of men in occ. j	-0.047
	(1.38)
Growth rate of employment share in occ. i	0.00
	(0.13)
Growth rate of employment share in occ. j	-0.00
	(0.41)
Both urban occupations	0.442
	(24.69)***
Both rural occupations	0.584
	(30.35)*
constant	22.872
	(119.68)***
Observations	72,632

Note: Labor flow is the cumulative flow of labor 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 cleaned as explained above. All other variables are constructed from the same the DADS Panel.

The model confirms that the volume of employment in each occupation largely explains both incoming and outcoming flows. In addition, wage premium increases the actual labor flows between occupations, while average age reduces the occupations' mobility. Finally, the employment growth of the occupation does not influence the job switches.

By dividing actual labor flows $F_{i,j}$ by the prediction of the ZINB model $\widehat{F_{i,j}}$, we obtain our index of bilateral occupation proximity: $OR_{i,j} = \frac{F_{i,j}}{\widehat{F_{i,j}}}$

Table A2 reports statistics for five occupations with the strongest and lowest relatedness score $OR_{i,j}$. The five occupations that are closely related correspond to occupations for which labor movement are more frequent than the prediction. On the contrary, the bottom five labor flows are less frequent than the baseline prediction, precisely because they require a complete different set of skills.

Table A.2- Top and Bottom 5 Occupational Relatedness

Centrality rank	Occupation code	Occupation	Out degree	Out strength	Relatedness
1	232a	Managers of medium-sized companies with 50 to 499 employees	60	668.9	200.3
2	483a	Supervisors in mechanical engineering, metalworking	46	823.1	194.6
3	484b	Manufacturing supervisors: metallurgy, heavy materials and other processing industries	51	702.7	189.3
4	384b	Engineers and manufacturing executives in mechanics and metalworking)	56	613.0	185.3
5	386b	Engineers and managers of study, research and development of energy and water distribution	60	547.9	181.3
…					
266	431f	Nurses in general care, salaried	16	138.4	47.1
267	526c	Auxiliary nurses	14	130.2	42.7
268	451a	Intermediate professions in the postal service	12	149.4	42.3
269	642a	Taxi drivers	8	152.8	35.0
270	546d	Air hostesses and stewards	6	52.2	17.7

Note: The bottom occupations are those for which OR>0

APPENDIX B- Additional Analysis

Table B1- Impact of Occupational Coherence Before and After the Great Recession

N=282 CZ R2=0.83	Difference of Unemployment Rate with Year 2011 (pp)					
Year	2003	2004	2005	2006	2007	2008
Occupational Relatedness	-0.01	-0.00	-0.00	-0.00	-0.00	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year	2009	2010	2012	2013	2014	2015
Occupational Relatedness	0.04***	0.02***	0.00	-0.00	-0.02***	-0.02**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)

Notes: The table shows regression estimates of the effect of Occupational Coherence on Unemployment rate six years before and after the Global Financial crisis (baseline year 2011). Estimates come from a CZ fixed effect OLS estimates on CZ unemployment rate as described in equation 4. It is a robustness estimates to Table 2 by excluding year 2009 from the measuring of occupational coherence. Standard errors are clusetered by 2010 CZ (reported in parenthesis). Estimation includes year fixed effects and local characteristics (CZ size, CZ concentration of occupations and CZ share of skilled workers). For reference, year 2015 indicates the paper's main specification: a 1 percentage point higher local occupational coherence before 2009 caused the unemployment rate difference between 2011 to be 0.02 percentage point lower. The asterisk indicates the significance of the coefficient at the threshold of 5%

APPENDIX C- INDUSTRY CLASSIFICATION

Table B1- Corresponding Table between IFR NAF classification of industries

IFR classification	NAF classification
A-B-Agriculture, forestry, fishing	AZ
C-Mining and quarrying	BZ
D-Manufacturing	CD
10-12-Food and beverages	CA
13-15-Textiles	CB
16-Wood and furniture	CC
17-18-Paper	CM
19-22-Plastic and chemical products	CG
19-Pharmaceuticals, cosmetics	CF
20-21-other chemical products n.e.c.	CE
22-Rubber and plastic products (non-automotive)	CG
229-Chemical products, unspecified	CH
23-Glass, ceramics, stone, mineral products (non-auto	CH
24-28-Metal	CK
24-Basic metals	CJ
25-Metal products (non-automotive)	CJ
28-Industrial machinery	CK
289-Metal, unspecified	CH
26-27-Electrical/electronics	CI
275-Household/domestic appliances	CK
271-Electrical machinery n.e.c. (non-automotive)	CK
260-Electronic components/devices	CI
261-Semiconductors, LCD, LED	CL
262-Computers and peripheral equipment	CI
263-Info communication equipment, domestic and prof. (	CI
265-Medical, precision, optical instruments	CK
279-Electrical/electronics unspecified	CK
29-Automotive	CL
91-All other manufacturing branches	CM
E-Electricity, gas, water supply	DZ, EZ
F-Construction	FZ
P-Education/research/development	MB, MC, PZ
90-All other non-manufacturing branches	GZ, HZ, IZ, JA, JB, JC, KZ, LZ, LI, NZ, OZ, QA, QB, RZ, SZ, TZ, UZ