Sectoral Diversity and Local Employment Growth in France

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Abstract – This article investigates the links between sectoral diversity and local employment growth in France over the period 2004-2015. Starting from the seminal contribution of Frenken *et al*. (2007), we take into account both the within and between sectoral diversities at the local level and at the neighbourhood one. Our empirical investigations confirm that within sector diversity (so called related variety) is positively associated with employment growth. Moreover, this association seems to be driven by the local related variety in growth phase and by the related variety in the neighbourhood in crisis period. We also find that the negative relationship between unrelated variety and employment growth goes only through the neighbourhood canal.

JEL: R11, O18, D62
Keywords: related variety, unrelated variety, employment growth, spatial interactions, France

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In a context of market globalisation, increasing competition, and recurrent crises, which type of economic composition matters in regional development remains strategically important information for policymakers and scholars.

The literature on innovation has long highlighted the importance of the geographical dimension in knowledge exchange among companies. A large bunch of papers shows that specialised or diversified clusters of firms can create conducive environments for the development of innovations, as knowledge flows between firms. In research on economic geography, urban economics, and regional science this discussion refers to the long-running debate between Marshall-Arrow-Romer's (MAR) approach conceptualised by Marshall (1920) and later by Arrow (1962) and Romer (1986) on the one hand and Jacobs' approach (Jacobs, 1969) on the other hand.

However, these externalities do not capture all the dimensions involved in proximity. Recent theoretical advances have highlighted the importance of considering relational proximities – cognitive, organisational, institutional, political, cultural, etc. – in modulating the benefits linked to geographical proximity (Boschma, 2005). The benefits attached to industrial diversity (Jacobs externalities) have since been broken down into related variety (between closely related industries) and unrelated variety (Frenken *et al.*, 2007). The related variety measures variety within sectors defined at an aggregated level, i.e. between industries relatively close to each other, belonging to the same aggregated industry, while the unrelated variety measures variety between industries defined at an aggregated level, i.e. between industries (broadly classified) different from one another (Mameli *et al.*, 2012). While the potential impact of related and unrelated varieties on regional growth has been widely empirically examined,[1] some open questions about the empirical application of this concept can still be identified.

This article tackles this question considering to what extent intra-industry externalities foster employment growth. It appears that most empirical analyses aiming to assess the contribution of related and unrelated variety to territorial dynamism rest upon modelling and economic techniques considering the phenomenon within each spatial unit considered. Some other, mainly case studies, interested in disentangling related and unrelated varieties focus either upon one or on a small number of territories (Brenet *et al.*, 2019; Elouaer-Mrizak & Picard, 2016) or on some specific activities (Tanner, 2014 among many others). To our knowledge, the spatial dimension of this family of externalities has not yet been explored. Indeed, the relevance of extra-regional knowledge to regional growth is largely neglected by the Glaeser-Henderson related literature, which mostly focuses on the structure of the regional industry mix (Boschma, 2005).

This article seeks thus to determine if, and to what extent, variety (related and unrelated) affects local employment growth, focusing on the local industrial structure of labour market areas (*zones d'emploi*) in France and, mostly, considering spillover effects to take into account the possible interactions and complementarity between the economic activities operating within a given labour market area and those operating in other labour market areas. It proposes to empirically distinguish between the local variety (so called direct dimension) and the variety in the neighbourhood (so called indirect dimension). Further refinement is presented, by relating local and neighbourhood varieties to the technological intensity of industries, on the one hand, and, on the other hand, by running separate analysis for the rural and the urban areas. In that respect, some investigations have stressed the relevance of sectoral specificities in examining the impact of variety on employment growth (Bishop & Gripaios, 2010; Boschma & Iammarino, 2009). Hartog *et al.* (2012), for example, introduce differences in innovation processes in high-tech and low-medium-tech sectors to explain the variation in the influence of related variety on employment. There are additional arguments supporting the idea that the mechanisms linking diversity and employment variations differ depending on geographical contexts, such as the ones between cities or between rural and urban areas (Frenken *et al.*, 2007; Duranton & Puga, 2005). According to Grabner & Modica (2022), related variety was an important driver of industrial resilience in US counties during the 2008 economic shock, and this effect was driven by intermediate and rural counties. Our approach is based on a unique dataset representative of 304 French labour market areas over the period 2004-2015. The econometric specification is inspired by those introduced by Glaeser *et al.* (1992), Henderson *et al.* (1995) and Combes (2000), but innovates by dealing with the spatial dependence serious issue. The model framework used in this study

1. Frenken et al. *(2007) for Netherlands; Boschma & Iammarino (2009) and Mameli* et al. *(2012) for Italy; Bishop & Gripaios (2010) for the UK; Hartog* et al. *(2012) for Finland; Boschma* et al. *(2012) for Spain.*

includes related and unrelated varieties as key variables and controls for density, skills and the rural or urban character of the area.

Our empirical investigations confirm that related variety is positively correlated with employment growth. Moreover, this correlation seems to be driven by the local (direct) dimension of related variety in economic growth times and by its indirect dimension in times of crisis. We also find that the negative relationship between unrelated variety and employment growth goes only through the indirect canal. Our empirical evidence also shows, that the relation between related variety and local employment is conditioned by rural-urban differences and, in some way, by the technological intensity of the local industries.

The central contribution of this article is investigating which type of variety influences employment growth and what is the origin of this influence (inside or outside the spatial unit). To the best of our knowledge, no prior studies have directly examined the link between spatial unit's dynamics and the structure of the productive fabric. Moreover, we introduce a distinction between the role played by the features of a spatial unit and the ones of the neighbouring areas. We also test the possibility of a change of regime corresponding to the financial and global crisis in 2008-2009, running estimations before, during and after the shock. Moreover, we produce new insights when considering our two forms of variety concerning the R&D intensity of sectors and territory type.

The article is organised as follows. Section 1 discusses the literature and presents the theoretical considerations for the variables of interest. The dataset and the variables are presented in Section 2. Section 3 includes results and robustness checks, then we conclude.

1. Literature Review and Theoretical Background

In the last three decades, there has been a continuous discussion on the contribution of different types of agglomeration economies to local economic development. This growing literature is not unconnected to the development of the modern economic growth theory (Romer, 1986; Lucas, 1988) that stresses the critical role of knowledge externalities in economic growth. Glaeser *et al.* (1992) initiated the research trend dedicated to the impact of the types of agglomeration economies on local economic growth. In short, the controversy centred on whether the regional specialisation of economic activities (Marshall-Arrow-Romer externalities) or regional diversity (Jacobs's externalities) is more conducive to regional solid economic performance. Yet, to date, the empirical evidence around this debate has failed to reach a consensus. Studies find as much evidence in favour of the "MAR" approach as Jacobs' hypothesis (for a recent review, see De Groot *et al.*, 2016). This ambiguity in empirical testing may be due to the theoretical concepts of specialisation and diversity[2] which are still unclear (Content & Frenken, 2016), to the level of spatial aggregation (metropolitan, local, or regional), to the type of sectors analysed (manufacturing and services) and the sector classification level (2-digit or more), to the nature of regional economic performance measure (employment, total factor productivity or labour productivity, wages, or gross domestic product), and finally to sectoral lifecycles and institutional context (O'Huallachain & Lee, 2011). Recently, a new trend of studies stemming from a conceptual renewal in institutional and evolutionary economic geography has started advocating for a more differentiated perspective on how diversification and specialisation affect regional economic growth (van Oort *et al.*, 2015; Boschma, 2005). Relying heavily on the studies that have focused on the degree of relatedness between technologies used in industries and the diffusion of knowledge and innovation (Rosenberg & Frischtak, 1983; Cohen & Levinthal, 1990; Nooteboom, 2000), scholars have integrated these concepts in the literature on agglomeration externalities and regional growth. Frenken *et al.* (2007) have stated that Jacobs' externalities cover two different forms of variety – related and unrelated varieties – that should be disentangled because they generate different economic impacts. These authors argue in line with Nooteboom (2000) that some parts of knowledge are easier to recombine and spill over across sectors when their cognitive proximity and distance are neither too small nor too big. This complementarity between sectors is captured by what Frenken *et al.* (2007) call "related variety" defined as diversity between industries that share some

2. A largest number of studies published before Frenken et al. *(2007) modelled regional diversity in terms of the inverse Hirschman-Herfindahl index (Combes* et al.*, 2004; Henderson* et al.*, 1995; Combes, 2000) without admitting diversity in related industries into the analysis. Beaudry & Schiffauerova (2009) emphasize that this can cause an underestimation of Jacobs's externalities and an overstatement of MAR externalities owing to diversity, which would be measured as simply unrelated variety. Moreover, the entropy (or the Shannon index) approach in measuring related and unrelated variety seems preferable to the Simpson/Herfindahl-Hirschman index (for a technical discussion, see Nagendra, 2002).*

complementarities in terms of knowledge bases, technologies, inputs/outputs or competences, i.e., within-industry diversity.

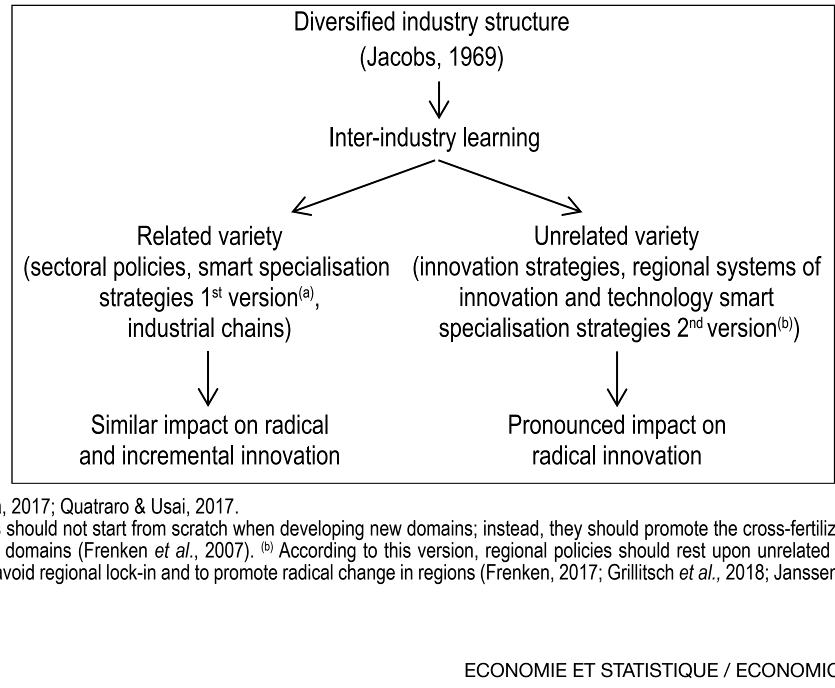
Regarding unrelated variety, between industries with no apparent or only limited linkages or complementarities (i.e., between-industry diversity), Frenken *et al.* (2007) claim that it captures a portfolio-effect. Thus, the higher the presence of unrelated sectors in a region, the higher the ability to limit sector-specific shocks (Essletzbichler, 2007) through better risk spreading. That is, the local vulnerability stabilizer function increases regional resilience and mitigates unemployment growth (Content *et al.*, 2019; Boschma & Iammarino, 2009).

Several empirical studies have been conducted over the past twenty years to investigate how the related and unrelated varieties explain regional economic development in terms of employment growth, unemployment and productivity growth, value-added growth and innovation performance or capacity (for a review and synthesis, see Content & Frenken, 2016). These investigations have found strong support for the importance of related variety for regional economic growth in the Netherlands (Frenken *et al.*, 2007), Spain (Boschma *et al.*, 2012), Great Britain (Bishop & Gripaios, 2010), Italy (Mameli *et al.*, 2012; Boschma & Iammarino, 2009) and the United States (Castaldi *et al.*, 2015).

However, this is less true of the influence of unrelated variety. While Frenken *et al.* (2007) found that Dutch Nuts 3 regions with a high level of unrelated variety between 1996-2002 dampen unemployment growth (portfolio effect), other studies show no robust correlation (Fitjar & Timmermans, 2016; van Oort *et al.*, 2015; Boschma & Iammarino, 2009).

Figure I presents the conceptual origin, the sources and ways of knowledge transfers corresponding to related and unrelated variety and how they impact local growth. Each type of variety can be linked to a particular type of territorialised public policy. Related variety, for example, inspires measures designed to boost a region's performance through greater specialisation in one or more sectors likely to share common resources, particularly technical and technological. A region could first be specialised in the automotive industry and abandon it to develop the aircraft industry and then develop train engineering. A related diversification strategy, utilising quantitative and qualitative methods, targets new activities in regions closely linked to existing local activities. The integration of relatedness metrics and qualitative analyses, inspired by entrepreneurial self-discovery, aids in identifying diversification opportunities. Advocates contend that aligning new activities with local capabilities enhances their survival rates, supported by evidence. While empirical evaluations are lacking, studies such as Balland *et al.* (2019) suggest that related diversification can effectively enhance the complexity of activities in a region, particularly in complex technologies. Rigby *et al.* (2022) further highlight the economic benefits, revealing that European regions diversifying into related and complex activities experienced higher growth from 1981 to 2015.

Figure I – **Related and unrelated variety: filiation and mechanisms**



Source: Boschma, 2017; Quatraro & Usai, 2017.
Notes: [(a)] Regions should not start from scratch when developing new domains; instead, they should promote the cross-fertilization of knowledge and ideas across domains (Frenken *et al.*, 2007). [(b)] According to this version, regional policies should rest upon unrelated rather than related diversification to avoid regional lock-in and to promote radical change in regions (Frenken, 2017; Grillitsch *et al.*, 2018; Janssen & Frenken, 2019).

The unrelated variety inspires public policies that encourage structural change in an area by developing new activities unrelated to existing industries. This would be the case when a textile region would diversify into aircraft making or pharmaceuticals. Some scholars advocate for public policies promoting unrelated diversification, departing from local capabilities but aiming to create new growth paths. This approach, proposed by Grillitsch *et al.* (2018) and Janssen & Frenken (2019), combines unrelated local capabilities to foster innovation. The focus on unrelated diversification is driven by the need to prevent regional lock-in, with proponents arguing that overcoming economic development challenges requires radical change and the development of entirely new trajectories. Additionally, the rarity and difficulty of unrelated diversification justify government support, as it involves building new capabilities and bridging cognitive distances, requiring collective action and policy intervention.

Finally, using European data from the Global Entrepreneurship Monitor on NUTS-2 and NUTS-1 regions, Content *et al.* (2019) find an empirical support for positive relationships between related and unrelated variety and regional employment growth. An important caveat resulting from this research points out that new business formation moderates the relationship between unrelated variety (but not related variety) and employment growth. This finding suggests that technological aspects are not the only elements guiding the relationship between variety and regional dynamics.

Therefore, exploring direct and neighbourhood aspects of the relatedness perspective presents opportunities for new insights into the nature of externalities of the two types of variety. Scholars' recent discussions on the function of knowledge production have suggested the importance of geographical proximity for knowledge creation and diffusion (Boschma, 2005; Buzard *et al.*, 2020; Balland & Boschma, 2021). For example, in a study on five US manufacturing sectors and 853 metropolitan counties, Kekezi *et al.* (2022) point out the role of interregional knowledge spillovers and highlight that both intra- and inter-sectoral spillovers within a county are important determinants of knowledge production. The underlying assumption is that access to extra-regional knowledge is a way of avoiding regional lock-in. Thus, complementarity or cognitive proximity between the local knowledge base and external sources of knowledge also contributes to regional innovation and economic growth.

2. Data, Variables, and Descriptive Analysis

2.1. Data and Definition of Variables

We use an original dataset depicting French "labour market areas" (*zones d'emploi* in French), the *Connaissance locale de l'appareil productif* (Local knowledge of the productive system – CLAP), provided by the French National Institute of Statistics and Economic Studies (INSEE), for the period 2004-2015. The CLAP database is an information system fed from various administrative sources (SIRENE, DADS, URSSAF and SIASP). Since 2003, it has provided localised data on paid employment and earnings at fine geographic levels (municipality). It covers the whole country and activities in both the market and non-market sectors. We use data aggregated at the labour market area level (using the 2010 division, see Aliaga (2015) for additional details) and different sectoral levels. Our study covers labour market areas from metropolitan France (labour market areas located in overseas departments are excluded from our analysis[3]), and thus include both urban and rural spaces. A labour market area is a geographical unit within which most of the labour force lives and works. Mainland France is composed of 304 labour market areas. This division is used because it is functional (see, for example, Broekel & Binder, 2007), and labour market areas are much more homogeneous than political or administrative units and make spatial analysis possible insofar as it covers the entire territory.

2.1.1. Dependent Variable

Our dependent variable is employment growth (*Growth*). It is defined as the change in the total number of employees working in area i (with i=1, …, I) over the period covered:

$$Growth_{i,t'} = \log(E_{i,t'}) - \log\left(E_{i,t}\right)$$

where E is employment, t is the beginning of the period and t' the end.

2.1.2. Independent Variables

Following Frenken *et al.* (2007) and related works later, we use two indicators of regional diversity: related variety and unrelated variety. To this end, employment data are identified at five-digit sector of the French classification of activities (NAF rev.2, 2008). Barring a few exceptions, this classification corresponds to the

3. These areas are not considered because of their geographical distance from metropolitan France (too far from the mainland and, in a few instances, geographically isolated).

NACE rev.2 (statistical classification of economic activities in the European Community), which is, in turn, derived from the International Standard Industrial Classification (ISIC) of economic activities. The indicators of related and unrelated varieties will constitute our main independent variables. They have been constructed using an entropy measure based on Shannon's function. Entropy captures economic variety of an area by measuring the uncertainty or disorder against a uniform distribution of employment across sectors. The entropy of related variety estimates variety within sectors, while the entropy of unrelated variety estimates variety between sectors.

The related variety indicator ($RelVar$) captures the diversity of related sectors. In our case related sectors are the detailed five-digit sectors belonging to the same two-digit aggregate sector. The indicator is the weighted sum of five-digit entropy within each two-digit class of French classification of activities such as:

$$RelVar_i = \sum_{g=1}^{G} P_{g,i} H_{g,i}$$

where $H_{g,i}$ is the degree of entropy (or variety) within the two-digit sector g of the labour market area i. $H_{g,i}$ is calculated as:

$$H_{g,i} = \sum_{j \in S_g \text{ with } P_{j,i}>0} \frac{P_{j,i}}{P_{g,i}} \log_2 \left(\frac{1}{\frac{P_{j,i}}{P_{g,i}}} \right)$$

where $P_{g,i}$ is the share of employees working in two-digit sector g (NAF A88) relative to the total employment in labour market area i, and $P_{j,i}$ the ratio of the number of employees working in five-digit sector j (with j=1,…,J) within two-digit sector S_g, relative to the total employment of area i. Thus, we have:

$$P_{g,i} = \sum_{j \in S_g} P_{j,i}.$$

The related variety indicator varies between a lower bound of 0 (when employment in each two-digit sector is concentrated in only one of its five-digit sectors) to $\log_2(J) - \log_2(G)$ (if all five-digit sectors within a two-digit sector have the same employment share, for more details on calculation – see Theil, 1972) Since our study is conducted on 732 five-digit sectors (J) within 88 two-digit sectors (G), our indicator takes as the theoretical upper bound a value of 3.06.

The unrelated variety indicator ($UnrelVar$) captures diversity across two-digit sectors or inter-sector diversification. It's calculated as the entropy of the two-digit level (NAF A88):

$$UnrelVar_i = \sum_{\substack{g=1 \\ with\ P_{g,i}>0}}^{G} P_{g,i} \log_2 \left(\frac{1}{P_{g,i}} \right).$$

It ranges from 0 (concentration of employment in just one two-digit sector) to $\log_2(G)$ (all sectors employ an equal number of employees). As our analysis distinguishes 88 two-digit sectors, the upper bound of the unrelated variety indicator is 6.46.

Subsequently, we decompose our two indicators according to the R&D intensity of the sectors (see Figure A1 in Appendix). We use the OECD taxonomy of economic activities based on R&D intensity (Galindo-Rueda & Verger, 2016) for both manufacturing and nonmanufacturing sectors.[4] We therefore distinguish, on the one hand, related variety in high-tech sectors and related variety in low- and medium-tech sectors, and on the other hand, unrelated variety in high-tech sectors and unrelated variety in low- and medium-tech sectors. It allows us to examine whether the relationship between related and unrelated varieties and employment growth varies with the technological intensity of local industries (Hartog *et al.*, 2012).

Machinery and equipment (NAF: 28) is the industry that contributes the most to related variety and unrelated variety in high-tech sectors. It's followed by industries like motor vehicles, trailers and semi-trailers (NAF: 29), chemicals and chemical products (NAF: 20), and information technology (NAF: 62) but not in the same order and same proportion. For related variety in low- and medium-tech sectors, it's industries like wholesale and retail trade (NAF: 46-47), specialised construction activities (NAF: 43) that topped the podium. For unrelated variety in low- and medium-tech sectors, it's nonmanufacturing industries like public administration and defence; compulsory social security; education; human health; residential care and social work activities (NAF: 84-88) that contribute largely.

2.2. Main Descriptive Features

The descriptive statistics of the variables used in the analysis are reported in Table 1. Our dependent variable is the employment growth rate between 2004 and 2015, a period marked by the 2008 global financial crisis. The relation

4. Based on the NAF 2 or 3-digit level, high-tech sectors comprise the following sectors in the manufacturing industry: air and spacecraft and related machinery (30.3), pharmaceuticals (21), computer, electronic and optical products (26), weapons and ammunition (25.4), motor vehicles, trailers and semi-trailers (29), chemicals and chemical products (20), electrical equipment (27), machinery and equipment (28), railroad, military vehicles and transport (30.2, 30.4 & 30.9), medical and dental instruments (32.5); and in the nonmanufacturing industry the following: scientific research and development (72), software publishing (58.2), IT and other information services (62 & 63). Remaining sectors are included in the low- and medium-tech sectors (without excluding sectors like public administration, education and human health).

between variety and employment growth may differ depending on whether one is in a period of growth or one of recession. For Bishop & Gripaios (2010), the industrial structure is more conducive to rapid change during economic slumps that may disrupt the relationship between variety and employment growth. We thus split the overall period into three sub-periods: the first one (2004-2008) precedes the 2008 global crisis, the second (2008-2012) covers the crisis phase, and the third (2011-2015) covers the post-crisis period and run the analysis separately for each sub-period.[5]

The top part of Figure II shows the employment growth in each labour market area over the three periods. Globally, for the three sub-periods, the "winning" territories are located more in the west and the south, while the territories in decline are rather in the north-east, south-west axis. The 2004-2008 period is characterized by a broader distribution of growth rates (from −0.13 to +0.48) than the 2008-2012 (from −0.13 to +0.16) and the 2011-2015 (from −0.13 to +0.11). This shrinking of the interval corresponds to the general economic slowdown in the country.

5. CLAP data is not available beyond 2015. To ensure that the three periods have the same duration (of 4 years), we have overlapped the second (2008-2012) and the third (2011-2015).

Table 1 – **Summary statistics**

Variable	Mean	Std. Dev.	Min	Max
Local employment growth 2004-2008	0.01	0.05	−0.13	0.48
Local employment growth 2008-2012	−0.02	0.04	−0.13	0.16
Local employment growth 2011-2015	−0.01	0.03	−0.13	0.11
Characteristics of the area in 2004:				
Related variety	1.87	0.27	1.09	2.37
High-tech related variety	0.06	0.05	0.00	0.26
Low- and medium-tech related variety	1.80	0.25	1.07	2.28
Unrelated variety	4.84	0.23	3.63	5.31
High-tech unrelated variety	0.36	0.20	0.00	1.06
Low- and medium-tech unrelated variety	4.46	0.21	3.44	4.84
Density	3.31	1.01	0.88	8.55
Share of highly-skilled white-collars	0.13	0.03	0.09	0.32
Characteristics of the area in 2008:				
Related variety	1.95	0.24	1.18	2.40
High-tech related variety	0.06	0.05	0.00	0.27
Low- and medium-tech related variety	1.88	0.22	1.15	2.34
Unrelated variety	4.87	0.21	3.98	5.34
High-tech unrelated variety	0.36	0.20	0.02	0.99
Low- and medium-tech unrelated variety	4.51	0.19	3.63	4.89
Density	3.32	1.01	1.03	8.58
Share of highly-skilled white-collars	0.13	0.03	0.08	0.32
Characteristics of the area in 2011:				
Related variety	1.96	0.24	1.13	2.42
High-tech related variety	0.05	0.05	0.00	0.25
Low- and medium-tech related variety	1.91	0.22	1.11	2.38
Unrelated variety	4.85	0.20	4.04	5.31
High-tech unrelated variety	0.34	0.19	0.01	0.97
Low- and medium-tech unrelated variety	4.51	0.18	3.73	4.90
Density	3.31	1.01	0.96	8.59
Share of highly-skilled white-collars	0.11	0.03	0.06	0.31
Observations	304	304	304	304

Source: INSEE, CLAP 2004-2015. Authors' calculation.

The middle and bottom of Figure II show the distribution of related and unrelated varieties across labour market areas in 2008 and 2011 respectively. As the maps show, the two measures of variety presented as a share of total entropy[6] have different regional patterns. Related variety is higher in urban areas, whereas unrelated variety seems more equally distributed in both 2008 and 2011.[7] Many areas with a high level of total entropy show a strong resemblance with those on the map of related variety, which also have high levels; that is the case, for instance, for Lyon, Nantes, Tours and Bordeaux. When we look at the maps of unrelated variety and entropy, some differences emerge: territories with strong performances in terms of unrelated variety show an average contribution to total entropy. Some areas with relatively low levels of unrelated variety are rural (La Lozère, Pontivy and Villeneuve-sur-Lot). However, some of them are high-density zones such as Avignon, Créteil, Quimper, Lorient and Orly. An interesting fact to note is the high enough correlation (0.58) between the two types of variety. This value remains close to levels found by Aarstad *et al.* (2016) on Norwegian data and Content *et al.* (2019) on 204 European regions.

Table S1 in the Online Appendix (link to the Online Appendix at the end of the article) reports the correlation matrix of control variables used in our three-period analysis. Overall, the results of the correlation matrix revealed no serious evidence of multi-collinearity.

3. Estimation Strategy and Main Findings

3.1. Estimation Procedure

To estimate the relation of variety with regional employment growth, it is essential to consider various types of spatial interaction. Generally, three different types of interaction may explain why an observation relating to a specific location may be dependent on observations relating to neighbouring areas:

- An endogenous interaction, when the value of the dependent variable for one geographical area is jointly determined with that of its neighbours;
- An exogenous interaction, where the value of the dependent variable for one geographical area depends on the observable characteristics of its neighbours;
- An interaction effect among the error terms due to omitted variables from the model that are spatially autocorrelated.

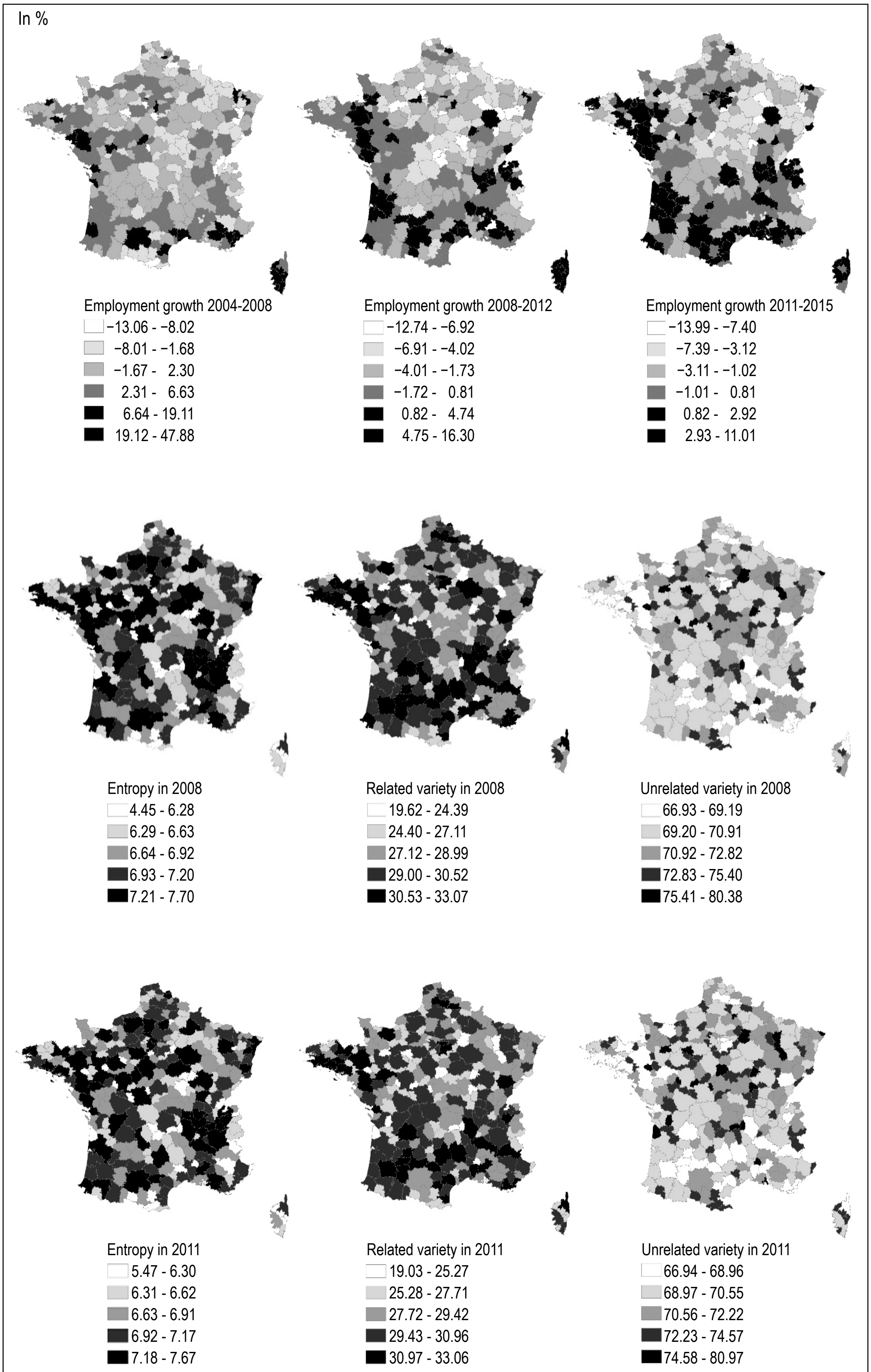
These three types of interaction are derived from a General nesting spatial model called the Manski model (1993). The Manski model is less used in empirical works because, on the one hand, its weak identifiability leads to higher uncertainty in parameter estimates (Elhorst, 2014). On the other hand, this model is often overparameterized (Burridge *et al.*, 2016). The preferred solution in the empirical literature is to remove one of the three forms of spatial correlation, which is the solution we adopt.We apply a spatial Durbin error model (SDEM), in which the dependent variable is influenced by the independent variables, the spatial lags of the independent variables, and the spatial correlation in the error term.

$$\begin{aligned} Growth_{i,t+4} &= a_0 + \alpha_1 RelVar_{i,t} + \alpha_2 UnrelVar_{i,t} \\ &+ \alpha_3 Control_{i,t} + \theta_1 RelVar_{w_i,t} + \theta_2 UnrelVar_{w_i,t} \\ &+ \theta_3 Control_{w_i,t} + u_{i,t} \qquad (1) \\ \text{and } u_{i,t} &= \lambda u_{w_i,t} + \varepsilon_{i,t}, \end{aligned}$$

where $Growth_{i,t+4}$ refers to employment change in area i between year t and year t+4, $RelVar_{i,t}$ and $UnrelVar_{i,t}$ respectively refer to related variety and unrelated variety in area i in year t, w_i denotes the index of the neighbourhood of the employment area i. a_0, α_1, α_2 and α_3, θ_1, θ_2 and θ_3, the neighbourhood interaction effects, and λ, the interaction effect among the errors, are unknown parameters to be estimated, and finally ε is a vector of disturbance terms. In addition to our variables of interest, *Control* is a set of control variables selected because of their importance in the dynamics of employment. To capture urbanisation economies, we control for the employment density.[8] The underlying hypothesis is that urbanized areas promote local knowledge spillovers, linkages and imply a wide offer of local public goods (Combes, 2000; Mameli *et al.*, 2008; Paci & Usai, 2008). We expect that employment density will increase employment growth. We also control for the local level of human capital, measured by the share of highly-skilled white-collar workers in the labour force in the area.[9] The availability

6. The decomposability of entropy measure involves that five-digit entropy is equal to the addition of related variety (weighted sum of five-digit entropy within each two-digit sector) and unrelated variety (two-digit entropy).
7. If we interpret these results with the maps of related variety and recent employment growth in mind, certain similarities can be observed for high values, especially in southeast-central France (Lyon, Issoire, Annecy and Bourg-en-Bresse) west (Nantes and Les Herbiers) and south-western regions too (Bordeaux, Bayonne, and La Teste-de-Buch).
8. Employment density is calculated as the logarithm of number of employees working in establishments located in the labour market area per square kilometre (km²).
9. This variable is measured as the percentage of upper-level employees (or highly skilled white-collars) working in establishments located in the labour market area. Upper-level employees correspond to cadres et professions intellectuelles supérieures, *the third group in the most aggregated (level 1) classification of professions and socio-professional categories (PCS). For more detail, see the composition of this group: https://www.insee.fr/fr/metadonnees/pcs2020/groupeSocioprofessionnel/1?champRecherche=true*

Figure II – **Employment growth, related variety, and unrelated variety**



Source: INSEE, CLAP 2004-2015. Authors' calculation.

of a highly skilled labour force in a region is often found to be crucial for local employment growth, as this population is expected to help innovation activities and growth (Paci & Usai, 2008; van Oort *et al.*, 2015). Recently, in a study on 204 European regions, Content *et al.* (2019) stressed that educational level captures the ability and the skills to detect and exploit potential business opportunities. The spatial weight matrix W used in the econometric estimation is the row standardized inverse spatial distance matrix (with a cut-off point).[10]

3.2. Econometric Results

This section presents the findings for our estimations over the three periods (pre-crisis, crisis and post-crisis). The diagnostics for spatial dependence obtained for the OLS version of the model are reported in the bottom portion of the result tables. Whatever the period, the Moran' I index from the regression residuals is highly significant. The spatial models were estimated using a maximum likelihood estimator with White robust standard errors. Calculating the Variance Inflation Factor (VIF) for our regressions returns a score below 2.77, which infers that multicollinearity is not a severe issue in our findings, as suggested, for instance by O'Brien (2007). The overall significance of our estimations is good, and the R-squared for spatial models ranges from 9% to 31%.

The results are presented separately for three periods: the pre-crisis period (2004-2008), the crisis period (2008-2012) and finally the post-crisis period (2011-2015). We further consider the presence of heterogeneous patterns and provide estimates separately for rural areas and urban areas.[11] We also provide estimates when labour market areas of Île-de-France (IDF) region are excluded. The IDF region is indeed very specific because of its considerable weight in employment in France (almost 23% in 2015).

The separate analysis of rural and urban areas makes sense as rural and urban areas can differ in many dimensions, such as economic production structure, human capital, institutions, history, territory, geography, etc. Some papers in the literature have dealt with this issue. For instance, Duranton & Puga (2005) stress that large cities are specialised in business services while industry takes more place in rural areas. Van Oort *et al.* (2015) investigated 205 small, medium and large European regions and only observed a positive association between related variety and employment growth in small and medium places.

3.2.1. Pre-Crisis Period Results

Table 2 reports the estimated direct and neighbourhood effects of related and unrelated variety on local employment growth. The local and to a lesser extent the neighbourhood related variety is positively correlated with employment growth during the period 2004-2008 (model 1). This is in accordance with previous studies showing a positive relation between related variety and employment dynamics (Frenken *et al.*, 2007; Wixe & Andersson, 2017; van Oort *et al.*, 2015). Firms can mediate this relation, as pointed out by Cainelli *et al.* (2016) in their micro-level analysis, higher related variety increases firm innovativeness and, consequently, productivity, resulting in higher employment growth rates. Our finding is robust to the use of another spatial weight matrix (see models 1 and 2 in Table S2 in Online Appendix). However, local unrelated variety does not seem correlated with employment growth. This last finding is also observed by Cortinovis & van Oort (2015) in their study of 260 NUTS-2 regions in Europe. The neighbourhood unrelated variety seems however to exert a negative influence on local employment dynamics.

When adding control variables (model 2), we found that the density of economic activity, as a proxy for urbanisation economies, and the level of qualification have a negative and a positive influence, respectively. These results are in line with most of those found in the literature on regional growth (Frenken *et al.*, 2007; Hartog *et al.*, 2012; Deidda *et al.*, 2006). Combes (2000) considers that this negative coefficient of the density of the local system reflects congestion effects (high land rent, congestion of infrastructures and transportation, etc.) that produce negative externalities on local employment growth. As for skilled labour, in a comprehensive analysis of 784 local labour markets in Italy, Paci & Usai (2008) stress that a higher number of educated labour forces in a region fosters innovation and knowledge spillovers and, therefore, local growth. Finally, we find that the higher the qualification of jobs in neighbouring areas the lower the employment growth.

When we decompose related and unrelated varieties following the R&D intensity of sectors,

10. We define labour market areas as neighbours when the distance between them is smaller than 67.5 km, using the inverse distance between areas as weight. This latter is inversely related to the distances between the units. If the distance between units is larger than 67.5 km, this weight is set to zero. As in most applied studies, the inverse distance matrix is row-standardized (each element in row i *is divided by the sum of row* i*'s elements) so that the impact of neighbouring areas is equalized.*

11. Labour market areas are classified as urban or rural according to their population density. Areas with a level of population density equal to or greater than the first quartile (47.91) are considered urban, the others rural.

we found that both high-tech and low- and medium-tech related varieties are positively correlated with employment growth (model 3). This finding is in some way in contrast with the result of Hartog *et al.* (2012), who show only a positive effect of related variety among high-tech sectors in Finland. Model 3 also shows that the greater the high-tech unrelated variety, the lower the employment growth.

The low- and medium-tech unrelated variety in the surrounding areas reinforces the negative effect on employment.

Table 2 – **Employment growth over 2004-2008**

Dep. Var. : Employment growth 2004-2008	Model 1	Model 2	Model 3	Model 4 (rural areas)	Model 5 (urban areas)	Model 6 (without IDF region)
Characteristics of the area in 2004:						
Related variety	0.047*** (0.013)	0.039*** (0.014)		0.078*** (0.030)	0.029** (0.014)	0.051*** (0.014)
Unrelated variety	−0.014 (0.017)	−0.017 (0.017)		−0.140*** (0.038)	0.030* (0.017)	−0.024 (0.017)
Density		−0.013** (0.005)				
Share of highly-skilled white-collars		0.714*** (0.121)				
High-tech related variety			0.213** (0.095)			
Low- and medium-tech related variety			0.044*** (0.015)			
High-tech unrelated variety			−0.065** (0.027)			
Low- and medium-tech unrelated variety			−0.017 (0.019)			
Characteristics of the neighbourhood areas in 2004:						
Related variety	0.015 (0.025)	0.010 (0.025)		−0.048 (0.060)	0.045* (0.027)	0.046 (0.029)
Unrelated variety	−0.064** (0.026)	−0.055** (0.026)		−0.031 (0.064)	−0.076*** (0.026)	−0.080*** (0.029)
Density		0.011 (0.007)				
Share of highly-skilled white-collars		−0.490** (0.202)				
High-tech related variety			0.118 (0.227)			
Low- and medium-tech related variety			0.046 (0.032)			
High-tech unrelated variety			−0.093 (0.058)			
Low- and medium-tech unrelated variety			−0.084** (0.038)			
Constant	0.269*** (0.095)	0.242** (0.107)	0.339** (0.168)	0.771*** (0.260)	0.0953 (0.121)	0.331** (0.130)
lambda	0.346*** (0.078)	0.377*** (0.075)	0.338*** (0.079)	0.645*** (0.181)	0.281** (0.110)	0.357*** (0.080)
Observations	304	304	304	76	228	285
Moran’s I	6.725***	7.043***	6.706***			
R^2	0.133	0.206	0.135	0.309	0.115	0.123
Likelihood	490.660	507.180	491.993	106.285	415.011	460.255
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors are shown in parentheses. ***, **, * = significance at 1%, 5% and 10%, respectively
Source: INSEE, CLAP 2004-2015. Authors' calculation.

We observe a positive association of related variety with employment growth in rural and urban areas (models 4 and 5), as well as in all areas after excluding the 19 employment areas of the IDF region, 10 of which are rural and 9 urban (model 6). Concerning neighbourhood effects, related variety is positively associated with employment growth in urban areas (model 5) and unrelated variety is negatively associated with employment growth in all models except the fourth, which focuses on rural areas.

3.2.2. Crisis Period Results

Table 3 provides the same results as Table 2 for the period 2008 to 2012, i.e. during the global crisis. The table shows that related variety in the neighbourhood is positively associated with employment growth (model 1), leading us to consider that the crisis increased interdependence between labour market areas (Cousquer, 2022). This evidence confirms that when cognitive proximity between related sectors in an area with that of its neighbourhood is not too small, it raises opportunities and interactive learning between sectors that ultimately promote employment growth. This empirical relevance is in accordance with that of Boschma & Iammarino (2009), which illustrates the importance of extra-regional knowledge on employment when it comes from industries that are related but not similar to those present in the region.

Moreover, the level of unrelated variety in the neighbourhood seems to be negatively associated with employment growth. Model 3 suggests that this association is driven by high-tech unrelated variety in neighbouring areas. Concerning other neighbourhood interactions, the level of low- and medium-tech related variety has a positive effect on employment growth.

When we distinguish between rural areas (model 4) and urban areas (model 5), we find that unrelated variety is positively associated with employment growth only in urban areas. Regarding the neighbourhoods, our results show a positive association of related variety and a negative association of unrelated variety with local employment in urban areas, and no significant association in rural areas. This last result is also verified when we exclude the IDF region from the analysis (model 6).

3.2.3. Post-Crisis Period Results and Intertemporal Comparisons

The estimations of our models for the post-crisis period (Table 4) are close to those of the pre-crisis period. Concerning direct effects, we find three similarities between the two periods: overall related variety, low- and medium-tech related variety, and the share of highly qualified jobs are positively linked with employment growth. In the case of neighbourhood effects, we found only one common feature, which is a negative association of unrelated variety with employment growth. In addition, during the post-crisis period, we found a negative association of unrelated variety in the neigbourhood and a positive association of low- and medium-tech related variety in the neigbourhood with the local employment growth. This last result is also observed during the crisis period.

Concerning urban areas, we find exactly the same results as in the pre-crisis period for the local related variety. For the neighbourhood effects, related variety plays a positive role and unrelated variety a negative one (model 5), as in the crisis. In model 6, which excludes the Île-de-France region, we obtain the same results as in model 5 for neighbourhood effect.

To sum up, concerning the direct effects over the three periods, we find that related variety is positively correlated with employment growth before the crisis, that its role becomes insignificant during the crisis period (2008-2012) but becomes significantly positive again in the post-crisis period. It seems that during the crisis, specialisation in related sectors implies less flexibility to areas to adapt their products and reconvert their economic activities. In that vein, Steijn *et al.* (2023) state in a comprehensive study on great historical depressions that crises significantly reduce the pace of diversification. The unrelated variety does not appear to play a role in our study.

When we distinguish among high-tech sectors and low- and medium-tech sectors for each type of variety, we find that both related variety in the high-tech and related variety in low- and medium-tech sectors are positively correlated with employment growth.[12] Only the unrelated variety in the high-tech sector is linked with a slowing down of employment during the period 2004-2008. This result is in contrast with that of Cortinovis & van Oort (2015), who found a negative impact of unrelated variety in low-tech regions when controlling for the regional level of technological progress. During the crisis, neither related, nor unrelated variety influence directly employment variation, a result

12. For Hartog et al. *(2012), the positive and significant effect of related variety among high-tech sectors in Finnish regions can be explained by the ability of high-tech sectors to produce radical innovation and thus introduce new products on the market.*

Table 3 – **Employment growth over 2008-2012**

Dep. Var. : Employment growth 2008-2012	Model 1	Model 2	Model 3	Model 4 (rural areas)	Model 5 (urban areas)	Model 6 (without IDF region)
Characteristics of the area in 2008:						
Related variety	0.012 (0.010)	0.007 (0.011)		0.000 (0.020)	0.014 (0.012)	0.013 (0.010)
Unrelated variety	0.0017 (0.012)	−0.006 (0.012)		−0.061** (0.027)	0.015 (0.013)	−0.002 (0.012)
Density		0.002 (0.003)				
Share of highly-skilled white-collars		0.134* (0.081)				
High-tech related variety			0.017 (0.067)			
Low- and medium-tech related variety			0.008 (0.012)			
High-tech unrelated variety			−0.003 (0.019)			
Low- and medium-tech unrelated variety			0.010 (0.015)			
Characteristics of the neighbourhood areas in 2008:						
Related variety	0.070*** (0.024)	0.074*** (0.026)		0.025 (0.042)	0.064** (0.025)	0.064*** (0.024)
Unrelated variety	−0.073*** (0.024)	−0.060** (0.025)		−0.049 (0.044)	−0.078*** (0.024)	−0.067*** (0.024)
Density		−0.008 (0.006)				
Share of highly-skilled white-collars		0.024 (0.192)				
High-tech related variety			0.126 (0.168)			
Low- and medium-tech related variety			0.050* (0.027)			
High-tech unrelated variety			−0.092** (0.043)			
Low- and medium-tech unrelated variety			−0.036 (0.033)			
Constant	0.168 (0.115)	0.146 (0.126)	0.018 (0.158)	0.461** (0.190)	0.134 (0.117)	0.166 (0.116)
lambda	0.515*** (0.065)	0.516*** (0.065)	0.510*** (0.066)	0.676*** (0.165)	0.470*** (0.094)	0.531*** (0.066)
Observations	304	304	304	76	228	285
Moran’s I	9.500***	9.803***	9.424***			
R^2	0.099	0.118	0.106	0.253	0.086	0.096
Likelihood	620.110	623.381	620.938	144.560	478.332	586.857
Prob > chi2	0.016	0.015	0.081	0.026	0.001	0.036

Notes: Standard errors are shown in parentheses. ***, **, * = significance at 1%, 5% and 10%, respectively
Source: INSEE, CLAP 2004-2015. Authors' calculation.

maintained when we distinguish low-and-medium-tech sectors from high-tech sectors varieties.

A change occurs in the post-crisis period where we estimate a positive association of related variety in low- and medium-tech sectors and of unrelated variety in high-tech sectors with employment growth. Analysis by territory type (rural vs. urban) shows that the effect of related variety is driven by both urban and rural areas during the period 2004 to 2008. Surprisingly, there is a negative association of unrelated

Table 4 – **Employment growth over 2011-2015**

Dep. Var. : Local employment growth 2011-2015	Model 1	Model 2	Model 3	Model 4 (rural areas)	Model 5 (urban areas)	Model 6 (without IDF region)
Characteristics of the area in 2011:						
Related variety	0.018** (0.009)	0.015* (0.009)		−0.002 (0.018)	0.027*** (0.010)	0.014 (0.009)
Unrelated variety	0.009 (0.011)	−0.002 (0.011)		−0.009 (0.026)	0.008 (0.012)	0.011 (0.011)
Density		−0.000 (0.003)				
Share of highly-skilled white-collars		0.196*** (0.070)				
High-tech related variety			−0.057 (0.064)			
Low- and medium-tech related variety			0.027*** (0.010)			
High-tech unrelated variety			0.029* (0.017)			
Low- and medium-tech unrelated variety			0.002 (0.013)			
Characteristics of the neighbourhood areas in 2011:						
Related variety	0.046** (0.019)	0.037* (0.020)		0.050 (0.037)	0.047** (0.021)	0.047** (0.020)
Unrelated variety	−0.040* (0.021)	−0.039* (0.021)		−0.062 (0.040)	−0.050** (0.023)	−0.046** (0.021)
Density		−0.002 (0.005)				
Share of highly-skilled white-collars		0.178 (0.155)				
High-tech related variety			−0.009 (0.155)			
Low- and medium-tech related variety			0.045** (0.023)			
High-tech unrelated variety			−0.029 (0.036)			
Low- and medium-tech unrelated variety			−0.034 (0.029)			
Constant	0.015 (0.093)	0.057 (0.099)	0.004 (0.133)	0.233 (0.153)	0.048 (0.107)	0.035 (0.093)
lambda	0.406*** (0.073)	0.398*** (0.074)	0.407*** (0.073)	0.332 (0.208)	0.465*** (0.095)	0.402*** (0.075)
Observations	304	304	304	76	228	285
Moran's I	7.172***	6.851***	7.238***			
R^2	0.089	0.127	0.095	0.112	0.101	0.093
Likelihood	660.047	666.543	661.229	151.829	512.374	620.069
Prob > chi2	0.004	0.000	0.022	0.307	0.000	0.009

Notes: Standard errors are shown in parentheses. ***, **, * = significance at 1%, 5% and 10%, respectively
Source: INSEE, CLAP 2004-2015. Authors' calculation.

variety with employment growth in rural areas during the crisis, that is not persistent in the post-crisis period. Related variety in urban areas also seems to be positively associated with employment growth except during the crisis.[13] This result is in line with those by Cortinovis & van Oort (2015). Relatedly, Firgo & Mayerhofer

13. The bounce ability of urban counties is also verified in the study of Talandier & Calixte (2021) on the effects of the 2008 economic shock on French territories. However, in a similar study on the US case, Grabner & Modica (2022) observe effects for both rural and urban areas, with a particularly large effect for urban ones.

(2018) find in their study on Austria that employment benefits more from diversity in related fields in urban regions. However, this work, which was conducted over a large period (2000-2013), does not include the context of the crisis in the analysis.

The investigation of the neighbourhood effects tells us that, except for rural areas, related variety is positive correlated with employment growth during the crisis. However, this correlation seems less marked during the post-crisis period. Unrelated variety exerts a negative influence across the three periods studied (with a more intense influence during the crisis) both in urban areas and areas outside of the IDF region.

When considering the R&D intensity of economic activities, we find a positive association of related variety in the low- and medium-tech sector with employment growth during the crisis and post-crisis periods (the association being smaller during the post-crisis period). A negative association of unrelated variety is found in the low- and medium-tech sectors from 2004 to 2008 and in the high-tech sectors from 2008 to 2012.

The separate analysis of urban areas clearly shows positive association of neighbourhood related variety and a negative of neighbourhood unrelated variety with employment growth during the three periods. These associations are stronger during the crisis (from 2008 to 2012). This confirms the potential important role for related variety in the neighbourhood in mitigating the effects of the crisis. For the three periods, the association of related variety and unrelated variety with employment growth was only present in urban areas. It seems that when an employment area is characterised by a low intensity of forms of variety, neighbouring territories help to compensate for this deficit. This compensatory effect only applies to urban employment areas; rural employment areas do not benefit.

As a robustness check, we have estimated the same models for the three periods using a different specification of the spatial weight matrix, namely the square inverse distance neighbourhood matrix. The latter is supposed to be more robust in differentiating between neighbouring and distant areas since using square values increases the relative weights of the nearest ones. The coefficients of our key variables were found to be very similar to our main estimations in terms of significance and scale (see Tables S2 to S4 in Online Appendix).

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This article aimed to investigate the relations between varieties – related and unrelated – and employment growth at the labour market area level in France mainland between 2004 and 2015. Its main contribution is to improve our understanding of how different forms of industrial variety relate to local employment growth; this is achieved, on the one hand, by developing a new perspective that considers the local and neighbourhood nature of industry relatedness, and on the other hand, by exploring crisis times and ordinary times.

While empirical results show that local industrial diversity is correlated with local employment dynamics, two questions arise, particularly for public decision-makers. The first is whether and how local industrial diversity can be increased. It seems more straightforward and less costly to support the entry of a sector related to existing activities than creating an unrelated industry. The second question concerns how public policy should deal with the interactions between territories, if local growth is influenced by industrial variety in the neighbourhood. From this perspective, various institutional frameworks could be explored. For instance, the 'policy network' concept, which focuses on relations between interest groups in the broad sense and evokes a form of coordination between national and sub-national levels, could find a wider field of application. Another promising development is rooted in multi-level governance as an alternative to hierarchical government, which implies a mode of negotiated relations between institutions at different institutional levels or as the interweaving of political networks within formal government institutions.

While empirical evidence suggests that the higher the industrial diversity the higher the local growth, and under the hypothesis that this relation is of cause and effect, a pivotal question for policymakers is whether diversity can be deliberately enhanced and, if so, through what means. A common assumption might be that supporting the entry and emergence of related sectors would be more straightforward and cost-effective than introducing unrelated sectors. However, empirical findings challenge this assumption, indicating that the benefits of an unrelated sectoral structure might be more economically advantageous. In addition, policymakers should also pay attention to the policies adopted in the neighbourhood to bring consistency to public action at the regional level.

To provide some answers to these questions, future research should focus on analysing how knowledge flows between related sectors on the one hand, and between unrelated sectors on the other hand, as well as on the public policies that would make it possible to increase these flows. The diversity of situations should also be addressed insofar as, since Jacobs' externalities are based on innovation, require a certain level of absorptive capacity to favour their effect on growth. The idea is that a larger regional knowledge base enhances the ability to absorb knowledge from various related and unrelated sectors, resulting in a more significant effect on employment growth (Fritsch & Kublina, 2017). Therefore, it would be essential to develop policies that not only support regional diversification but also enhance absorptive capacity to maximize the benefits of knowledge flows across sectors.

Our results suggest several avenues for future research. First, using the NAF hierarchical industry classification system, or its equivalent at the European level NACE, to calculate related and unrelated variety measures is disputable. This classification is primarily based on product relatedness, which assumes that industries belonging to a given sub-category make products that are closer to the ones made in the other sub-categoris of the same parent category than to the ones made in other sub-categories. (Hartog *et al.*, 2012). However, such categorisation may fail to account for knowledge externalities and technological proximity between industries (Boschma *et al.*, 2012). Another suggestion consists in using other sectoral taxonomies, such as the one of Pavitt (1984) which is based on technology and identifies four groups (science based industries, scale intensive industries, specialized suppliers industries, and supplier dominated industries), or Neffke & Henning's one (2008) which adopts a novel characterisation technique based on the place of manufacture of the products. The study of Wixe & Andersson (2017) stresses the importance of two other dimensions of variety resting upon the respective relatedness of education and occupation of employees, that could be taken into account in further researches. The argument is that information and knowledge transfers primarily involve individuals. Finally, a third promising research field is the investigation of the channels through which related variety leads to employment growth. In a recent study based on a novel pan-European regional survey, Content *et al.* (2019) show that entrepreneurship may be a possible transmission mechanism via which spillovers between related sectors lead to the creation of new jobs and, thus, to employment growth. ☐

Link to the Online Appendix:
www.insee.fr/en/statistiques/fichier/8305261/ES544_Amdaoud-Levratto_OnlineAppendix.pdf

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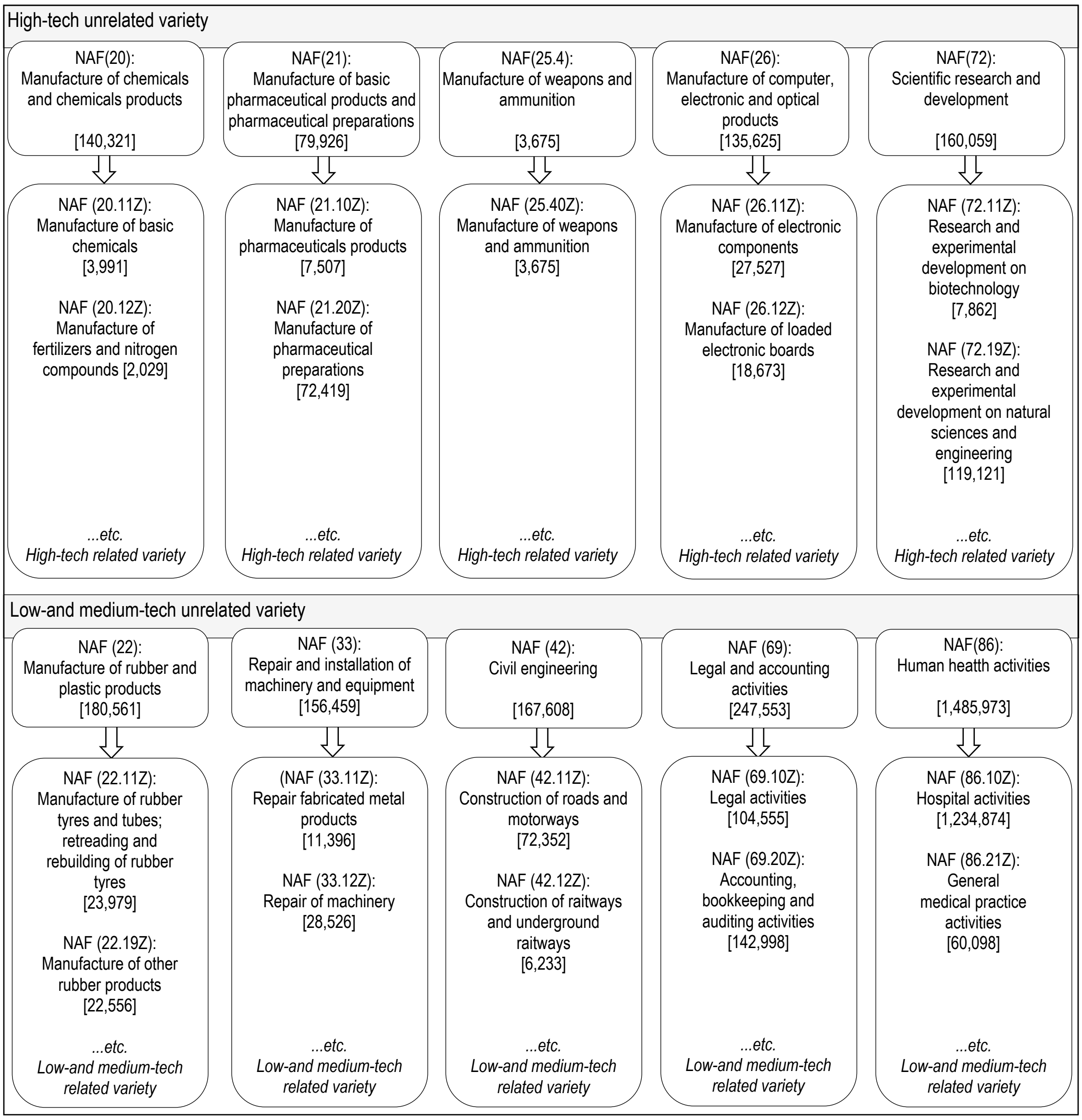
Figure A1 – **High-tech related and unrelated variety vs. low- and medium-tech related and unrelated variety**



Note: The values between brackets are employment at national level in 2011, they are obtained from CLAP information system. They are used to illustrate, on one hand, how related variety is decomposed in high-tech related variety and low- and medium-tech related variety and, on the other hand, how unrelated is decomposed high-tech related variety and low and-medium-tech unrelated variety. The figure is just an excerpt; all sectors are not represented.
Source: INSEE, CLAP 2011. Authors' calculation.