Changes in regional knowledge bases and its effect on local labour markets in the midst of transition: Evidence from France over 1985–2015

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Abstract
In the 2000s, the European labour market experienced a number of significant changes including the transition to a more knowledge-intensive economy as well as the introduction of various economic policies (e.g. Eurozone, subsidized jobs, and social tax cuts). In times like these, the role of knowledge, which is essentially the driving force of innovation and thus promoting technological change and economic growth, is shifting due to new labour market conditions. The present study aims to explore how processes of local knowledge bases have been altered in this transformative environment and how these have impacted on local employment growth. The investigation considers three different knowledge bases in conjunction, incl. knowledge size, knowledge creation, and knowledge application. The study is based on an econometric analysis of a panel of 94 France NUTS-3 regions covering the period 1985–2015, utilizing patent data from European Patent Office (EPO) Statistical Patent Database (PATSTAT), and regional data from European Regional Database (ERD). The result shows that the role of knowledge for employment growth has indeed changed towards more specialized inputs in applications while the importance of greater knowledge size remains still important.

Keywords Regional knowledge bases · Local labour market · Employment growth · Transition · Quantile regression

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Introduction

In the last decades, the European regional economy has experienced several changes including global crises such as the recent COVID-19 pandemic or the economic recession around 2009, all of which are events of far-reaching consequences and that have caused a significant impact on both the national and local economies. These global crises, which brought a shock that led to the decline of the economy, were inevitable even for leading European countries such as Germany, the United Kingdom, and France. Besides these global economic trends in parallel also other changes have taken place, including the rise of knowledge-intensive industries and novel economic policy approaches, all which brought further changes to European regional economies, especially with respect to the local labour markets. Especially, the influence of knowledge-intensive industries, those with high intensive usage of technology and human capital, has been increased globally. While a global crisis creates a great shock to the economy, structural changes in a local labour market are usually more likely related to endogenous-driven transformations (Jung & Choi, 2006).

The most significant change affecting local employment over the past decades has been the transformation to a knowledge-based economy. Resulting from advancements in information communication technologies (ICT), knowledge-intensive industries have grown dramatically and thus reshaped regional economies, not only in Europe but also in regions all over the world. A transition to a knowledge economy led to significant changes in labour market structures. Firstly, the demand for college-educated workers with complementary skills (Hope & Martelli, 2019) and higher hourly wage rates (Acemoglu & Autor, 2011; Jung & Choi, 2006) has increased. In addition, automation has replaced many existing routine-focused occupations. The increasing automation of occupation further compounded the wage dispersion (Hope & Martelli, 2019), and it raises concerns that knowledge-based development may in fact lead to so-called ‘jobless growth’ rather than to contribute to employment growth at the regional level (Döpke, 2001). Strohmaier and Rainer (2016) show that the broad diffusion of ICT affected growth significantly only after 2000, owing to technical change, substitution, and capital deepening and it can be associated with skill-induced wage dispersion. Thus, the transition to the knowledge economy mainly occurred before and after 2000 and not only changed the labour market, but also broaden the gap between firms, industries, and regions.

Another important change in this timeframe, and that impacted local employment, relates to the economic transition that started around the early 2000s, i.e. the introduction of the Euro currency among the members of the European Union in 1999. The Eurozone aims to reduce transaction costs, and to eliminate exchange rate uncertainty, all which should accelerate single marketization. In addition, since its inception, it brought about downward stabilization of inflation vulnerability and has contributed to increasing mutual investment between EU countries (Barr et al., 2003). Besides the benefits of the currency zone among European countries, it also weakened the self-correcting mechanisms for all
membered countries, especially for western European countries where wages and employment conditions are negotiated by labour-management agreements and where wage flexibility is relatively low. In this regard, European countries have implemented employment policies such as subsidized jobs and social tax cuts (Bergeaud et al., 2016; Cette et al., 2017; Gabriel & Macron, 2014), however, the downturn in local employment did continue over the past couple of decades. In sum, many European regions faced a new competitive environment and a single large market, all of which required different strategies for local employment.

In the present investigation, France serves as a representative case of these far-reaching changes that occurred in the United Kingdom, Germany, Italy, the Netherlands, Finland, Sweden, Norway, and Japan (see Bergeaud et al., 2016). Table 1 shows the proportion of employment for various industry sectors in France. Here, the values are obtained by taking an average of NUTS-3 employment data. While employment in agriculture and manufacturing decreased, the rest of industry sectors, especially knowledge-intensive industries (financial & business service and wholesale, retail, transport, accommodation & food services, information and communication) increased.

Figures 1 and 2 show the negative impact of the previously outlined economic transition on local labour markets, i.e. the decreasing trend of employment growth among the French NUTS-3 regions. Figure 1 shows the average employment growth changes of French NUTS-3 regions between 1985–1999 and 2000–2015. Average employment growth in 2000–2015 is calculated without 2008 and 2009 to avoid overestimation. Here, regions below the “0” line on the x-axis are the ones with negative employment growth in 1985–1999 while regions below the “0” line on the y-axis are the ones with negative employment growth in 2000–2015. From this, we can easily notice that more regions are experiencing a negative employment growth rate after 2000. Figure 2 compares the employment growth rate before and after the year 2000, and also one without 2008 and 2009, i.e. the years of the pan-European financial crisis. Except for a few regions, the employment growth in the majority of France regions decreased. Along with the transitions that took place around 2000, these observations show that the local employment condition in French regions is not in a good shape.
Regions are key territorial units for an economic system perspective where endogenous forms of development through an innovative milieu and regional knowledge are key factors for regional economic development (Huggins & Izushi, 2013). Local knowledge is a vital component of regional innovation system that has an important role in regional development (Cooke, 2004). Schimke et al. (2013) argue that local endowment with knowledge is indeed a driving factor of the employment growth of local firms. Moreover, the role of knowledge externalities across local actors in opportunities for entrepreneurs to start a new business has been emphasized via the knowledge spillover theory of entrepreneurship (Audretsch & Lehmann, 2005). Colombelli (2016) finds that local knowledge stock, variety, and similarity induce the creation of innovative start-ups in Italian regions that lead to employment dynamics.

In times of transition, the role of knowledge in determining local employment growth is shifting. The labour market conditions caused by the transition require different knowledge bases and new ways of innovation to achieve regional growth. Eliasson (2006) states that labour market risks are changing such that entrepreneurial ability, intellectual flexibility, and the ability to learn efficiently from experience will become ever-increasing competitive advantages for actors. The examination of the changes in the contribution of local knowledge is an important topic to be discussed for employment growth. However, the literature has considered the two separately at the regional level.

This study aims to explore how processes of local knowledge bases have been altered in this transformative environment and how these have impacted on local

Fig. 1 Employment growth change in French NUTS-3 regions between 1985–1999 and 2000–2015 (except 2008 & 2009)
Changes in regional knowledge bases and its effect on local employment growth. The investigation is based on an econometric analysis of a panel of 94 France NUTS-3 regions covering the period 1985–2015, utilizing patent data from European Patent Office (EPO) Statistical Patent Database (PATSTAT), and regional data from European Regional Database (ERD). Our findings provide implications for the effects of local knowledge on employment dynamics vary in different situations. We also suggest regional policy implications for overcoming the limitation of realizing knowledge effect in small economic scale regions.

Note: Author’s calculation using EPO PATSTAT

Fig. 2 French NUTS-3 regions’ average employment growth change
The various contributions of this study are as follows. First, the investigation takes advantage of a number of knowledge domain aspects that have not been previously employed in regional studies. Specifically, the study considers three different knowledge features in conjunction, incl. knowledge size, knowledge creation, and knowledge application. In regard to knowledge size, the knowledge stock is measured via a permanent inventory method of patent applications. Knowledge creation and knowledge application indicators, which capture the degree of diversity observed in local knowledge base, are then measured by employing three distinctive indicators, i.e. the distribution of local knowledge domain production (knowledge diversity), and through the backward citation found in patent documents (knowledge originality) as well as the forward citations in these (knowledge generality).

Second, the investigation explores how regional knowledge bases contribute to regional employment growth in times of transition. Due to the introduction of the Euro in 1999, many European regions faced a new competitive environment and had to quickly adjust and adapt to these significant changes. Moreover, the rapid development and increasing significance of ICT-related technologies further accelerated the transition into a knowledge-intensity economy that already started in the late 1990s. Thus, in addition to changes in the institutional environment, in the early 2000s also changes in the technical knowledge environment, and in particular how local knowledge could potentially influence regional employment growth patterns, took place. Taking advantage of the full set of technical knowledge indicators and regional economic data that covers a 30-year period it is possible to investigate the transitions between 1985–1999 and 2000–2015, and then to compare the results. From the comparison of knowledge effects on local employment growth between the two periods, how knowledge role adapts to the new changes and resilience to external shocks are discussed. Furthermore, through this approach it is then possible to obtain a more intuitive interpretation of the role played by regional knowledge bases on regional economic prosperity at different times. These insights will be highly relevant also in the contemporary context where most European regional economies experience a further wave of transitions due to the advent of novel technologies such as Artificial Intelligence, Industry 4.0, along with further institutional and organizational changes that most likely will occur due to the ongoing pandemic crises, Brexit, etc.

Third, the heterogeneous impacts of local knowledge are considered at different points of the conditional distribution of employment growth. Although the important role of knowledge has been highlighted in many relevant studies, the way and level of how knowledge is utilized may differ significantly from region to region. In this regard, quantile regression is used as an estimation strategy to model the outcome based on the conditional distribution of employment growth (Antonelli & Gehringer, 2016; Crespo-Cuaresma et al., 2011). By doing so, the relationship between local knowledge and employment growth is tested in order to verify whether such a relationship holds at different quantiles of the cross-regional employment growth distribution.

The structure of this study is as follows. Section 2 presents the data and methodology. Section 3 describes the main results and Sect. 4 discusses the findings. Finally, Sect. 5 concludes this work.
Data and methodology

Data

For empirical analysis, an integrated data set covering the France NUTS-3 regions is constructed by combining EPO PATSTAT and European Regional Database (ERD) provided by Cambridge Econometrics. EPO PATSTAT provides the overall information on patent records such as year of application, inventor’s address, technology classification, citations, etc. Patents, the outcome of research and development investment (R&D), have been regarded as good indicators for technological capabilities (Jaffe & Trajtenberg, 2002) to characterize regional economies (Kedron et al., 2020; Rocchetta & Mina, 2019). Due to this fact, patents have been used to investigate the relationship between regional knowledge and employment growth (Rocchetta & Mina, 2019). To build France NUTS-3 regional knowledge data set, we firstly collected all lists of patents that were invented by the inventor whose address is located in France. Each region’s knowledge is measured based on the fractional approach. Fractional approach measures count for 1/n in each of the locations if a patent contains n investors from n different places. For instance, if a patent has four investors from four different NUTS-3 regions, the patent only counts for 1/4 in each region. Once the France NUTS-3 level knowledge data set is constructed, we combined ERD by the NUTS-3 code and year. From this, we extracted employment, population, value-added, and population density all at France NUT-3 level. Overall, the final dataset includes a total of 94 NUTS-3 regions from 1985 to 2015.

Variables

Dependent variable

This study aims to investigate the effect of regional knowledge on the local labour market. In our empirical analysis, employment growth displayed by the France NUTS-3 regions has been used. The evaluation of differential employment effect has been regarded as an efficient measure for analyzing resilience (Martin, 2012; Rocchetta & Mina, 2019). In this respect, exploring how local labour markets are affected after the recessionary shocks can highlight the significant role of local knowledge in resilience. Employment growth is measured by the log difference in the number of employees per population:

$$\text{Employment growth}_{it} = \log \left( \frac{\text{Employment}_{i,t}}{\text{population}_{i,t}} \right) - \log \left( \frac{\text{Employment}_{i,t-1}}{\text{population}_{i,t-1}} \right)$$  \hspace{1cm} (1)$$

Independent variable

Our independent variable, local knowledge, is measured using the patent information. Using the inventor’s address, the patent information has been used to measure the local knowledge (Boschma et al., 2015; Colombelli, 2016; Kogler et al., 2017).
To consider both the accumulated quantity of knowledge and a variety of knowledge, three aspects of local knowledge are considered: knowledge size, knowledge creation, and knowledge application. Firstly, the size of knowledge is measured by the knowledge stock. The local knowledge stock represents the size of technological knowledge produced in each region. Due to the absence of regional level R&D intensity, accumulated R&D investment, patent has been regarded as a plausible proxy for measuring the stock of local knowledge. Instead of using the total count of the accumulated patent application, we use a permanent inventory method:

$$K_{\text{STOCK}}_{i,t} = P_{i,t} + (1 - \delta)K_{\text{STOCK}}_{i,t-1}$$

(2)

where $P$ is the inventor share of patent application in the regions $i$ at time $t$, and $\delta$ is the rate of 15% of obsolescence. 15% obsolescence rate is determined by following the work of Hall et al. (2005), and also is the widely accepted value. As the knowledge in each region is measured by the patent application made by the local inventor, the knowledge stock measured by the inventor share of the patent application represents local knowledge stock accumulated in a region.

For knowledge development measures, knowledge diversity and knowledge originality are used. Knowledge diversity, representing the variety of local knowledge stock in each region, is measured by using subclass cooperative patent classification (CPC) information that has been used by the local inventors for a patent application in a given year. While CPC has been used as a common indicator for measuring knowledge diversity, various diversity indices have been used due to the lack of consensus on the selection of diversity index. Regarding this issue, we use the Rao-Stirling index (Eq. 3), which measures the diversity with consideration of disparity among the components (Stirling, 2007). Rao-Stirling is calculated by summing the product of proportion of each component ($p_x$ and $p_y$) and the “distance” between the pairs ($d_{xy}$). Especially for technology diversification, Kim et al. (2019) showed that Rao-Stirling is specialized in addressing hetero-centred diversification. Accordingly, knowledge diversity at a regional level is calculated as described in Eq. (4). Considering the time-lag occurs in patent application and accumulated nature of knowledge, knowledge diversity is measured by using the accumulated patents in the past three years. $K_{\text{DIV}}_{i,t}$ indicates knowledge diversity in region $i$ accumulated during $t-2$, $t-1$, and $t$.

$$\text{Rao} - \text{Stirling}_{xy} = \sum_{xy} d_{xy}p_xp_y$$

(3)

$$K_{\text{DIV}}_{i,t} = \sum_{i}^{t} \text{Rao} - \text{Stirling}_{i,t}$$

(4)

While knowledge diversity captures the diversity of local knowledge stock, knowledge originality measures the knowledge diversity of backward citations (Eq. 5) (B. Hall et al., 2001). Knowledge originality illustrates the degree of knowledge diversity that local knowledge is referencing. Referring to the path-dependent nature of knowledge, the new knowledge-concentrated on limited knowledge sources is more likely to be similar to the existing ones. On the other
hand, if the local knowledge is referencing a diversified technological field, then it is more probable that the local knowledge becomes unique. In this regard, we may assume that a region with a greater value of originality index has more knowledge with originality.

\[
KORG_{i,t} = \sum_i (Rao - Stirling_{i,\text{back},t})
\]

Lastly, knowledge application is measured by the generality index (B. Hall et al., 2001). The knowledge generality is measured by the diversity of the forward citations (Eq. 6) and shows how much knowledge referencing the local knowledge is diversified. The greater value of generality index indicates that the local knowledge is more “generalized” knowledge that can be implemented in the diverse knowledge area. Both originality and generality indices have been used in previous empirical studies to measure the diversity of patent citations (Falk & Train, 2017; Gompers et al., 2005; Layne-Farrar & Lerner, 2011), but have not yet been applied to the regional studies.

\[
KGEN_{i,t} = \sum_i (Rao - Stirling_{i,\text{forward},t})
\]

To clarify the way of measurement, Fig. 3 illustrates the concept of knowledge diversity, originality, and generality from a regional perspective. For instance, Paris (2010) is the list of patents-CPCs developed by Paris inventors in 2010. Based on this, the list of Paris (2010)’s backward and forward cited patents and their CPCs are obtained. From these three patent-CPC lists, KDIV, KORG, and KGEN are measured.
Control variable

A set of control variables are included to control for other factors that could affect employment growth: labour productivity growth, employment in manufacturing industry, and population density. Labour productivity growth is measured by the log difference in the value-added per worker. Since differences in industrial composition and development across regions affect employment growth, we control for employment in manufacturing measured by the log of the number of employees in manufacturing (Wang & Chanda, 2018). Because the employment in manufacturing exhibited skewness, a natural log transformation is utilized. Population density is measured by the population divided by the area of the local region.

Estimation strategy

For the estimation of local knowledge effects, quantile regression (QR) is adopted. Regarding regional inequality, not only the size of knowledge but also the way knowledge involves in economic activity differ by the region. For instance, the regions with greater economic growth are more likely to have greater knowledge and knowledge-intensive industrial environment. In this sense, QR allows us to estimate the effect of explanatory variables along with the entire conditional distribution of the employment growth variable. As regional inequality and industrial heterogeneity exist among regions, QR is a more convincing estimation strategy to allow heteroscedasticity assumption. (Antonelli & Gehringer, 2016; Crespo-Cuaresma et al., 2011; Egbetokun, 2015).

The QR model for $\theta^{th}$ quantile between 0 and 1 is as follow (Antonelli & Gehringer, 2016; Koenker & Hallock, 2001):

$$Q_\theta(y_{it}|X_{it-1}) = X'_{it-1}\beta_\theta$$

where $y_{it}$ is dependent variable (employment growth) in region $i$ at time $t$. $X'_{it-1}$ includes the sets of explanatory variables including both independent and control variables as listed in the same region at time t-1, and $\beta_\theta$ is the estimated coefficients. In this study, estimation is performed at different ranges including 10%, 30%, 60% and 90%.

Results

Descriptive statistics

In our sample, 94 French NUTS-3 regions from 1985 to 2015 are included. The description of all variables and correlation matrix are elaborated in Tables 2 and 3. As shown in Table 2, knowledge measures are highly skewed for two reasons. First, innovation activities are uneven across the regions, because it depends on the industrial features. Since not all regions are actively participating in
knowledge-intensive activities, a large gap reflects the difference in the types of industrial activities among regions. Secondly, innovation activities are an accumulated outcome, which cannot be obtained immediately. Thus, the gap between regions is not easily narrowed down and it often gets bigger over the years. Due to this fact, the contribution of knowledge to economic growth in each region may be operated differently. To verify our hypotheses, therefore, quantile regression is an appropriate method.

### Multivariate analysis

In this subsection, the results of the QR using the sample between 1985–1999 and 2000–2015 are presented. Here, two econometric models are estimated (Eqs. (8) & (9)) to avoid multicollinearity among knowledge diversification variables. Tables 4 and 5 present the estimation results of Eqs. (8) and (9), which are about the employment growth model with knowledge stock and knowledge diversity, and knowledge originality and generality, respectively. The two models are estimated in various quantiles, i.e. 10% (low-growth regions), 30%, 60%, and 90% quantiles, of the distribution of yearly growth rates. We can observe that the effects of local knowledge on employment growth vary at different quantiles.
Table 4 Quantile regression estimation of Eq. (8) (KDIV)

|          | 1985–1999 |          |          |          | 2000–2015 |          |          |          |
|----------|-----------|----------|----------|----------|-----------|----------|----------|----------|
|          | 10%       | 30%      | 60%      | 90%      | 10%       | 30%      | 60%      | 90%      |
| KSTOCK   | -0.115*   | -0.019   | 0.126*** | 0.337*** | -0.030    | -0.004   | 0.108*** | 0.186*** |
|          | (0.067)   | (0.036)  | (0.045)  | (0.062)  | (0.044)   | (0.029)  | (0.027)  | (0.036)  |
| KDIV     | -0.004    | -0.016   | -0.023   | -0.082***| -0.053    | 0.046*   | -0.024   | 0.005    |
|          | (0.069)   | (0.026)  | (0.025)  | (0.011)  | (0.113)   | (0.019)  | (0.019)  | (0.035)  |
| LP.GR    | -0.017    | -0.019   | -0.01    | 0.024    | -0.003    | -0.003   | 0.000    | -0.003   |
|          | (0.036)   | (0.018)  | (0.023)  | (0.024)  | (0.004)   | (0.004)  | (0.004)  | (0.005)  |
| EMP.MANUF| 0.348***  | 0.154*** | -0.14*   | -0.365***| 0.211***  | 0.069    | -0.132***| -0.346***|
|          | (0.103)   | (0.057)  | (0.07)   | (0.089)  | (0.052)   | (0.046)  | (0.044)  | (0.056)  |
| POP.DEN  | -0.063*** | -0.036***| -0.045*  | -0.011   | -0.017    | -0.004   | 0.004    | 0.016*** |
|          | (0.019)   | (0.005)  | (0.019)  | (0.010)  | (0.026)   | (0.011)  | (0.013)  | (0.006)  |
| Constant | -2.288*** | -1.031***| 0.208    | 1.426*** | -0.592    | -0.203   | 0.781*** | 1.796*** |
|          | (0.464)   | (0.202)  | (0.190)  | (0.156)  | (0.525)   | (0.158)  | (0.161)  | (0.283)  |

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All specifications include year effects
Table 5  Quantile regression estimation of Eq. (9) (KORG and KGEN)

|            | 1985–1999 |          |          |          | 2000–2015 |          |          |          |
|------------|-----------|----------|----------|----------|-----------|----------|----------|----------|
|            | 10%       | 30%      | 60%      | 90%      | 10%       | 30%      | 60%      | 90%      |
| KSTOCK     | -0.127*** | -0.03    | 0.115*** | 0.329*** | -0.024    | -0.007   | 0.115*** | 0.190*** |
|           | (0.063)   | (0.039)  | (0.043)  | (0.061)  | (0.032)   | (0.027)  | (0.027)  | (0.033)  |
| KORG       | -0.013    | -0.008   | -0.035*  | -0.099***| -0.017    | 0.048**  | 0.012    | 0.070    |
|           | (0.084)   | (0.032)  | (0.021)  | (0.030)  | (0.064)   | (0.021)  | (0.016)  | (0.043)  |
| KGEN       | -0.002    | 0.009    | 0.029*   | 0.032    | -0.027*** | -0.021   | -0.044***| -0.056*  |
|           | (0.098)   | (0.028)  | (0.016)  | (0.025)  | (0.006)   | (0.017)  | (0.012)  | (0.031)  |
| LP.GR      | -0.009    | -0.022   | -0.018   | 0.032    | -0.002    | -0.003   | -0.001   | -0.005   |
|           | (0.037)   | (0.019)  | (0.022)  | (0.026)  | (0.004)   | (0.004)  | (0.004)  | (0.005)  |
| EMP.MANUF  | 0.386***  | 0.155**  | -0.134** | -0.372***| 0.214***  | 0.105**  | -0.128***| -0.317***|
|           | (0.089)   | (0.060)  | (0.068)  | (0.094)  | (0.045)   | (0.045)  | (0.037)  | (0.053)  |
| POPDEN     | -0.064*** | -0.034***| -0.04**  | -0.009   | -0.019    | -0.003   | 0.002    | 0.011    |
|           | (0.018)   | (0.005)  | (0.020)  | (0.017)  | (0.025)   | (0.010)  | (0.012)  | (0.007)  |
| Constant   | -2.318*** | -1.051***| 0.211    | 1.55***  | -0.661*   | -0.364** | 0.695*** | 1.506*** |
|           | (0.342)   | (0.243)  | (0.189)  | (0.230)  | (0.392)   | (0.166)  | (0.149)  | (0.325)  |

Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

All specifications include year effects.
In Table 4, the results of knowledge stock and knowledge diversity effects are illustrated. In 1985–1999, the effect of knowledge stock on employment growth is significantly positive in above 60% quantiles. The coefficient of knowledge stock in the 90th quantile (0.337) is greater than the 60% quantile, showing that its effect is greater in high employment growth regions. In the regions where employment growth is low, especially those below 10% quantiles, knowledge stock shows a negative and significant effect. Although the level of significance is below 10%, this tells us that the knowledge size is not always an effective way of promoting regional growth, and may differ depending on the regional condition. While the result of knowledge stock remains more or less the same to the latter period, that of knowledge diversity changes. In the earlier period, knowledge diversity shows a negative effect on employment growth only in the 90% quantile. In 2000–2015, however, the significant coefficient of knowledge diversity is only observed in the 30% quantile.

In the following table (Table 5), the effects of knowledge originality and knowledge generality are explored. Before 2000, knowledge originality causes a negative and significant effect on employment growth in above 60% quantiles while the lower quantiles are also negative but not significant. Similar to the case of knowledge diversity, this relationship also becomes no longer valid in the latter period. Again in 2000–2015, the positive and significant effect of knowledge originality is observed in the 30th quantile. On the other hand, knowledge generality is not much effective in the earlier period. Except for the 10% quantile, it shows positive coefficient, but only significant in the 60% quantile. Due to the low significance level, we may conclude that knowledge generality is not a significant knowledge feature for promoting employment growth. After 2000, however, the coefficient of knowledge generality is turned out to be significant except 30% quantile but with negative signs. Similar to this, knowledge originality also causes a negative and significant effect on employment growth above 60% quantiles.

**Discussion**

Prior to the main discussion, the difference between the two periods can be explained with the geography map (Figs. 4, 5, and 7) and trend (Fig. 6). Figure 4 and 5 illustrate the average employment growth of France NUTS-3 regions in 1985–1999 and 2000–2015, respectively. The regions with darker colour show the positive employment growth while the lighter colour shows negative employment growth. As shown, in 1985–1999, employment growth was positive in most regions. Especially the NUTS-3 regions of IL-DE-FRANCE (FR1), PAYS DE LA LOIRE (FR5), and AUVERGNE-RHÔNE-ALPES (FR7) have shown a greater employment growth. In 2000–2015, however, the majority of regions have faced negative employment growth. The highest average employment growth rates are observed in regions like
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Alpes-Maritimes (FR823), Bouches-du-Rhône (FR824), and Var (FR825), but it was below 0.4.

The negative trend of employment growth after 2000 is more clearly observed in Fig. 6. In Fig. 6, the mean value of employment growth (dotted line) and each year’s range of minimum and maximum employment growth (bar line) are elaborated. The trend of employment growth is presented separately with blue lines with standard deviation with grey colours. Regardless of the financial crisis in 2008–2009, employment growth is already started to decrease after 2000 while the increasing trend was observed before 2000. An interesting observation is that the dispersion of employment growth becomes smaller and stable. This shows that the...
The gap of employment growth between regions is narrowed down and most of local labour markets are suffering from the low employment growth. From this, we can observe that employment growth shows different patterns before and after 2000 and may assume that changes in the role of knowledge also have been altered in relation to these changes.

To observe how local knowledge has changed over time, Fig. 7 displays the average value of our knowledge indicators in the prior and latter periods of the France NUTS-3 regions. The regions with darker colour show the greater values while the lighter colour shows the opposite. Considering the range of knowledge indicators in each period, the maximum value of knowledge stock increased, but that of other knowledge
indicators did not change much. However, when taking this into at a regional level, it shows that the value of all knowledge indicators increased throughout the regions. While knowledge production was focused on certain regions, this reflects that knowledge has become more important in the recent period in most regions.

Table 6 summarises the key findings from the previous section. First of all, the effects of knowledge stock were valid only in regions with high employment growth. As both knowledge and production systems become more advanced and complicated, there has been no such a dramatic boost of economic growth like in the earlier industrial revolution (Gordon, 2014). While earlier technology innovation could have promoted both labour productivity and employment in any circumstances, the recent ones enhance economic growth along with the complementary intangibles such as organizational capital, human resources, etc. (Biagi & Parisi, 2012; Corrado et al., 2013). Thus, the accumulated knowledge in the high employment growth region can become more influential for regional growth because it is more likely to have a better environment for economic activities. Our finding result not only supports the fact that the knowledge size is still an effective means for promoting employment growth but also explains the different effects of knowledge depending on the local economy.

Second, the effects of knowledge creation (KDIV & KORG) and knowledge application effects were changed. In the case of knowledge creation, the knowledge diversification in high employment growth regions is negatively associated with the employment growth before 2000, and both became no longer valid after 2000. Before 2000, developing specialized technologies and less original technologies were important for employment growth, especially in high employment growth regions. Developing such technologies mean that the inventors are not just simply engaged in similar R&D activities, but rather advanced technologies. To obtain the benefit of developed advanced technologies, a greater number of relevant human resources that can participate are needed, and this could be made when a better economic environment is provided. After 2000, however, knowledge creation aspect becomes not much important in any circumstances.

Third, creating new knowledge that can be “less” generally used is found to be causing a positive effect on employment after 2000. The more a region produces

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1 By definition, positive (negative) sign of KDIV indicates developing diversified (specialized) technology; positive (negative) sign of KORG indicates developing more original (less-original) technology; positive (negative) sign of KGEN indicates the more generally (specifically) used technology.
knowledge with low knowledge generality value, it possesses knowledge with more specialized in usage that can be only used by a few. If a region’s produced knowledge is less applicable to be used, then it is more likely to be used in where it has been originally developed rather than others. This will make the knowledge become more attached to the local industry and as an outcome, knowledge could contribute to the creation of new jobs within the region. Figure 8 illustrates the trend of forward citation proportion by within and outside regions to provide supporting evidence for this argument. As shown, the proportion of forward citation within the regions started to increase in 2000 while the proportion of forward citation outside regions were decreasing. The increased usage of local knowledge by the local inventors since 2000 implies that knowledge is getting more localized and the knowledge generality measure reflects more about the diversity of local application. This could be a possible explanation for our argument that the specialization of knowledge application leads to employment growth.

Conclusion

The present study explored how the effect of regional knowledge on employment growth has changed before and after the year 2000 by focusing on the case of French NUTS-3 regions. To the best of our knowledge, the long-term examination of growth considering local knowledge features in conjunction with economic performance has not been discussed empirically at a detailed regional level previously. In particular, the investigation introduced new proxies for measuring local knowledge, including knowledge originality and generality, both of which have not been considered in this context in the relevant literature. Using QR techniques, the changes in
the role of local knowledge are not only compared across two periods but also examined at various levels of employment growth.

Our findings provide implications for sustainable regional growth along the following themes. First, throughout the 30 years of observation, the gap of knowledge effect between regions has not been narrowed down much as only the high growth regions were privileged to obtain the benefit of knowledge. Although the importance of knowledge has been largely emphasized by many researchers, only the regions with greater growth rates managed to take advantage of more advanced knowledge. This reflects one side of regional inequality showing a difference in the knowledge environment for both development and application. Apparently, the greater knowledge size is a comparative advantage of a region but does not guarantee economic success at the same time. The reason is that as knowledge development and knowledge application have become more complicated, or complex, over time, the need for a supportive environment for knowledge activity is increasing. In order to enhance the contribution of local knowledge to the regional economy, regional support for building a better environment for creating and adopting new knowledge outcomes is recommended.

Second, the activation of specialized knowledge in a region is needed for employment growth. Developing specialized knowledge in an application deals with the type of knowledge that is expected to be developed. This is clearly distinguished from the diversification of knowledge creation, which is often discussed in the existing studies, because it reflects more the reality by showing the diversity of knowledge that is actually being used, not the diversity of knowledge that is being developed. Although the development of knowledge that is applicable in a specialized field may narrow down the field the knowledge can contribute to, on the flipside this can also create more employment opportunities in other related fields in a region via spillover effects.

Third, extending the second implication, our finding aligns with the smart specialization strategy but sheds light on the importance of knowledge application. Smart specialization, which deals with policy-prioritization based on the relevant size of a technological domain (McCann & Ortega-Argilés, 2015) does not simply just refer to increasing the specialization of a regional economic structure, but points to the need to identify and to leverage regional strengths for more growth opportunities (Balland et al., 2019; Kogler et al., 2017; McCann & Ortega-Argilés, 2015). In this sense, the relatedness of knowledge has been regarded as an important indicator as it allows regions to boost what they are specialized in (Balland et al., 2015; Xiao et al., 2018) and it even contributes to overcoming the diversification dilemma (Balland et al., 2019). The specialization of knowledge application not only supports the main argument of smart specialization but also extends this argument by highlighting the value of knowledge development for a specialized purpose.

Lastly, the changed effect of knowledge on employment growth tells us how local knowledge development strategy should be addressed to adapt to the new transitions. The new transitions assumed in this study indicate not just an external shock like a financial crisis, but a shift of labour market due to economic and technological factors. Although most of the regions were found out to be suffered from low employment growth after transition, diversifying knowledge creation and specializing
knowledge application are suggested to recover the local labour market. In this respect, such regional policy or institutional supports are recommended especially in a situation where a global pandemic threatens the labour market of all regions.

The overall contribution of the present study is to advance relevant discussions regarding the role of knowledge for regional growth. While we were only concentrating on the relationship between local knowledge and employment growth, the linkage among local knowledge, employment growth, and productivity growth should be explored in more detail in further studies. Furthermore, extending the present investigation to other EU regions would certainly further the generalization of the argument put forward here.

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