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Master in Economics

Dynamics of local employment in Europe:
Is the impact of agglomeration economies time inconsistent?

Author
Magdalena Kizior

Supervisor
Ph.D. Pierre-Henri Bono

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1 Introduction

According to Starret's (1978) impossibility theorem in a world with homogeneous space, transport costs and locally non-satiated preferences, spatial distribution should be uniform. Yet, people and firms choose to agglomerate in some locations and not the others. The reasons and consequences of such choices for growth and overall economic performance have been widely discussed among both academics and policy makers. While a large part of the related literature focuses on the so-called regional $\beta-$ convergence mainly in income and output, this paper will study employment growth on regional level.

The purpose of our paper is twofold. First, we aim at delivering a new piece of evidence to one of the most fundamental debates in regional economics over the impact of different types of agglomeration economies. We will thus carefully account for different types of externalities, notably localization economies (known as Marshallian externalities, linked to specialization) and diversification economies (Jacobs externalities) and try to depict their impact on regional performance in terms of employment growth. With our analysis, we will also shed some new light on the debate on a possible time-inconsistency of externalities' impact. The conventional view states that there may be a trade-off between growth of employment, coming mostly from the specialization, and stability attributed to diversity externalities. However, no definitive conclusion has been reached. Therefore, we will first study short and long term impact of different externalities on growth in both services and manufacturing using dynamic panel data models. We will next assess their contribution in regional employment growth stability.

Secondly, while a large share of related research focused on American states or European countries, the paper tries to generalize the findings for European regions. There are several reasons for that. First, a number of cohesion policies are conducted at the European level, while pan-European research on regional employment patterns is far from abundant. Moreover, it seems appropriate to compare the findings on the topic between the US and Europe, especially given that structural determinants differ considerably. With respect to regional employment patters, those may differ in Europe especially because of a much lower labor mobility. Therefore, the paper aims at contributing to a better understanding of regional employment growth patterns across European regions and derives several policy recommendations. We make use of publicly available data (Eurostat, OECD Regional database).

The study is embedded in the research line started with seminal papers by Glaeser et al. (1992) and Henderson et al. (1995) linking growth of employment in American cities to industrial specialization of the areas. Given that opposite conclusions were reached, the debate has been opened about implications of specialization and diversity. As Combes and Overman (2003) noted in their survey, similar studies have been applied to other countries, often pointing to different conclusions. Since these discrepancies in results could be explained both by cross-country differences, time periods considered or different methodologies used, this paper tries to identify the impact of these forces on a large number of countries, with the same time coverage and compare different methodologies applied.

The methodology used is inspired by several papers related to the subject. First, we apply a similar framework to Blien (2006) who conducted a dynamic panel data analysis of the impact of different types of agglomeration externalities on employment growth in Western Germany's NUTS 3 areas from 1980 and 2001. The paper concludes positive evidence for diversity both in services and manufacturing, although stronger in the latter. Concerning specialization, evidence for mean-reversion is found, suggesting lack of explosive growth predicted by Marshallian economies. The paper itself is widely inspired by Combes (2000) who assessed specialization and diversity externalities on a very disaggregated spatial level of 341 employment areas (*zones d'emploi*) between 1984 and 1993. The paper, using cross-section analysis, finds opposite long-run impact of agglomeration economies depending on a sector considered. In services sectors a positive impact on employment growth of diversity and a negative one of specialization is found. In manufacturing industries, the impact is found to be more mixed: while for majority of sectors both types of externalities produce a negative impact on growth, some sectors are found positively affected. Another inspirational paper by Combes, Robin, Magnac (2004) made use of the very same panel data as Combes (2000) with a Panel Vector Autoregression (PVAR) model to estimate simultaneously the impact of agglomeration externalities on the number of existing plants (external growth) and size of the existing plants (internal growth). Their study allowed for distinguishing short and long term dynamics, accounting for potential non-linearities in the effects. The results conclude that no Marshallian externalities are present pointing to mean-reversion in the series. As for diversity, it is found to yield a positive impact both on the size and the overall number of plants. However, the effects of the shocks are found to be of a relatively static nature, as opposed to those suggested by Henderson(1995) for the US.

In this paper, we will pursue similar empirical strategies using data on 11 sectors present in 218 European NUTS 2 regions, available from 2000-2014. Considering serious endogeneity issues encountered in the related literature, we use dynamic panel techniques, including GMM estimation, to analyze the dynamics of agglomeration externalities on unemployment growth in European regional services and manufacturing, while accounting for human capital. We will consider both short and long-term dynamics to derive conclusions on a possible time-inconsistency of the impact suggested in the literature and assess whether the data confirms a traditional trade-off between growth and stability. We will also consider possible interactions between externalities and a specific industrial network present in the regions.

Our analysis suggests that overall agglomeration economies within European regions are important both in the short and in the long run. We find no evidence of Marshallian externalities linked to specialization, but the impact of own-sector employment shock is positive and relatively persistent. Overall density economies linked to the aggregate size of a regional market are found to have a positive impact mostly in the long-run in the two sectors. Equally, total size of the sector at the national level yields positive and significant impact on regional growth, suggesting important spillovers from other regions. However, the impact of diversity externalities differ for services and manufacturing: it is found positive in services and negative in manufacturing. Finally, combining those results with our analysis of growth instability, we find some evidence of a possible inconsistency in policies pursuing growth and stability at the regional level, notably with respect to industry sectors.

2 Literature overview

2.1 Agglomeration economies and growth: theoretical considerations

Since late 1980s the debate over the mechanisms leading to agglomeration and its consequences for economic performance attracted academics in economics and regional science. From the traditional trade economic theory's standpoint, agglomeration effects and specialization were present mainly due to technological differences in the sense of Ricardo or exogenous endowments of Hecksher-Ohlin. However, for an endogenous generation of agglomeration forces new economic geography models, started with Krugman (1991), introduced the interplay of centrifugal and centripetal forces related to cost and demand linkages. Inclusion of increasing returns to scale and monopolistic competition with taste for varieties in input use and consumption enabled endogenous creation of both specialized and diversified areas. The within-sector interactions give rise to so-called localization economies related to own-sector specialization, while between-sector interactions yield urbanization economies linked to the overall structure of the area. Firms would thus locate weighting these agglomeration and dispersion forces. Central locations would offer relatively larger customers base and wider intermediates goods' supply, but peripheral areas offer less competition and lower prices of land. Importantly, in these models transportation costs act as one of the centrifugal forces.

On the other side, urban and regional economists stressed the importance of various external, more than internal, scale economies more related to the overall production function of the entire area. Those external economies were classified by Marshall (1890) into three broad sources of agglomeration economies: Hirschman backward interlinkages between firms or entire sectors, labor market interactions, as well as technology and knowledge diffusion spillovers. The theoretical mechanisms were formally developed in Duranton and Puga

(2004) around these three categories. First one focuses on the importance of *sharing*. One of the reasons incentivizing people to agglomerate is a possibility of sharing indivisible public good (based on Buchanan (1965)). Sharing idea is also depicted in Krugman's (1991) new economic geography model. The model indeed generates endogenous agglomeration economies through sharing of a wider base of intermediate products and the taste for variety assumption. This idea of sharing, this time individual specialized skills, was also emphasized by Smith's (1776) concept of benefits of individual specialization when executing a limited number of tasks. Finally, Stahl and Walz (2001) model presents a mechanism of a better risk-sharing when agglomerated. Second micro-founded mechanism is based on *matching* and labor market friction. It is therefore found that agglomeration tends to improve quality of labor matching in the sense of Mortensen and Pissaridies (Helsley and Strange (1990)), as well improves the odds of matching, which implies in turn a lower level of unemployment. Finally, Arrow (1962) and Marshall (1890) stressed the importance of *learning* and knowledge spillovers. According to them, workers and firms learn by doing, which allows for a better spread of technology. With this respect, the overall debate opposed two different theories, giving rise to contradictory conclusions.

On one side Marshall, Arrow, and Romer (1986) advocated that specialization in the same sector of activity allows for benefitting from knowledge spillovers via firms' interactions. The larger and the more productive labor markets, the larger the spillovers. In the spirit of Krugman's trade inspired model, within-sector agglomeration also allows for lowering transportation and distribution costs as the both final demand and intermediate goods supply tend to be higher in these, often central, locations. Moreover, in their view monopolistic power has a stronger impact on economic performance than competition as it allows for efficient knowledge spillovers without appropriation. Consequently it leads to productivity growth and innovation of all firms present in each economic area.The concept, further on formally developed by Glaeser et al. (1992), is commonly called localization or, alternatively, Marshallian (MAR) externalities.

On the other one, Jane Jacobs (1969) emphasized the benefits of "diversity" of industrial activity. In the regional economics literature diversification is classically understood as "the presence in an area of a great number of different types of industries"(Rodgers (1957)) or "the extent to which the economic activity of a region is distributed among a number of categories" (Parr (1965)). According to her theory, formalized by Duranton and Puga (2001), the more diversified the structure and the more divided labor, the higher the ability of the economic structure to add new varieties and innovate in line with Schumpeterian creative destruction [1]. The underlying mechanism insists on the importance of across-sectors complementary knowledge and innovation spillovers, more than within sectors. The theory also hypotheses that competition increases innovation, by fostering innovation and technological progress, pointing to the direction of Porter (1990) [2].The mechanism described above is known as Jacobs or urbanization externalities.

However, Duranton and Puga (2000) noted that an area may be both specialized in a limited number of activities and diversified, while the process of sectoral composition of an area is dynamic. On one hand, a firm would want to enjoy the economies of scale coming from of its own sector while weighting the benefits with the costs of agglomeration related to an increased competition and congestion. On the other hand, an enterprise would want to benefit from between-sectors linkages. Consequently, as other sector would reply to a higher demand of inputs, the number of sectors present in a specialized area could increase over time. This points to a dynamic nature of sectoral composition in the regions. Indeed, the two types of externalities may turn out to be complementary and evolve in both directions, as confirmed by Huallachain and Lee (2011) . Two situations illustrate the idea. First, specialized cities are often smaller than diversified ones (Duranton and Puga 2000). This implies lower costs of land and living, as well as lower production costs on one hand. On the other, specialized areas are also found to be composed of mature industries whose demand is relatively inelastic and sector-specific shock risks are high (Duranton and Puga 2000).

[1] However, note that the original model of Schumpeter predicted that a too high innovation pattern leads to lower return on RD investment

[2] In his model, Porter (1990) however acknowledges that knowledge spillover occur faster in specialized economies.

Therefore, the existing sectors could benefit more from their localization externalities when the demand is higher and asymmetric risks are lower, namely in a more diversified structure. Symmetrically, more diversified regions are on average bigger which provide a more important and elastic demand, especially as the industries present in large and dense areas tend to be immature and thus subject to innovation processes. Moreover, portfolio theory states that sectoral diversity (or a dynamic process of diversification) enhances employment stabilities. Those benefits are offset by higher costs of living and commuting, higher wages and competition. Those centrifugal forces could be potentially moderated through own-sector positive spillovers or relocation leading to more specialization. Based on French data on firms' reallocation, Duranton and Puga (2001) found evidence of the described mechanism: large and diversified "nursery cities" act as nest of innovations, but once the project succeeds firms have tendency to move the production to the periphery to enjoy lower costs. Given the lack of obviously apparent pattern observed in sectoral structure dynamics across areas, one could hypothesize that those patterns are whether idiosyncratic or resulting from an exogenous distribution of various natural resources. Both hypothesis have been quickly discarded. First, Ellison and Glaeser (1997) in their study of American manufacturing find that when analyzing very disaggregated spatial units, the distribution of industries across the areas is too concentrated to result from a random allocation. On the other hand, Henderson (1997) in his panel data study of US manufacturing study proved existence of significant externalities when controlling for for time-invariant natural resources . Therefore areas are subject to dynamic change in their sectoral composition. The underlying mechanisms determining sectoral mix and its consequences on economics performance do not make unanimity in the theory, opening the field to vast empirical literature.

2.2 Agglomeration economies and growth: empirics

Consequently, as theory points to different conclusions regarding the impact of sectoral structure on economic outcomes, wide empirical literature burgeoned yielding often contradictory conclusions. Indeed, two seminal papers in the matter pointed to two different directions. On one side Glaeser et al. (1991) used a simple pooled cross-section method to study the impact of Jacobs and MAR externalities in American city-industries pairs. They found a positive impact of regional diversity on city employment growth and a negative one of specialization. Although his study potentially suffers from endogeneity issues, the results were replicated for other countries and time periods. On the other side of academic debate, Henderson et al. (1997) used a long panel data to conduct GMM estimations on employment in manufacturing industries in the US. He finds the opposite conclusion: only high-technologies sectors seem to benefit from diversity externalities, while a large majority of the sectors enjoy a positive impact of localization economies only. Importantly, Henderson studies long-term dynamics of agglomeration economies in the US finding that the highest effect of a shock to industrial composition acts with an important delay of around 7 to 11 years. However, although endogeneity was properly taken care of, his study is likely to suffer from misspecification bias induced by collinearity of regressors (Combes 2000). One could also think that the difference comes from not only different methodology used but also from a different the time and sectoral coverage. Henderson focuses on booming years for areas specialized in manufacturing (1970-1987) and does not include services sectors.

Most of the academic research differed in methodology used, country-coverage and time-span finding once again contradictory results regarding both the direction and the dynamics of externalities. A large part of the academic field was conducting country-specific studies using cross-sectional analysis focused on employment patterns. For instance, Attaran (1986) in his cross-sectional study of US areas found no significant evidence of a positive impact of diversity economies on neither growth or stability of unemployment. As a European counterpart, Combes (2000) applied a cross-section analysis to French areas at a very disaggregated level and found that diversity matters positively only for services. However, cross-sectional analysis could have been likely subject to some endogeneity bias, considered as the biggest challenge in the related literature. Therefore, an important part of the literature applied parsimonious panel data technics, following Henderson (1997), in order to depict the causal impact of externalities both on level and growth of employment. At the European scale, Ciccone (2002) estimates the impact of density of employment on labour productivity in relatively disaggregated regions in France, Germany, Italy, Spain and the UK. Ciccone's (2002) solution to endogeneity consists in using instrumental variables of historical regional area size, arguing that, while area is indeed positively and significantly correlated with density, regions have been administratively delimited sufficiently long ago (between 1789 and 1888) for the size to be uncorrelated with today's productivity. The study suggests that agglomeration economies present in Europe are of a roughly similar size as in the US. Other authors like Brulhart and Mathys (2008) use GMM estimations in order to make use of internal instruments present in the sample. They develop a simple theoretical model proposed by Ciccione (2002) by adding dynamics to study the impact of overall density economies in European countries both in the short and in the long-run. They find a positive impact of diversity mostly in manufacturing, while localization economies seem to play a role mostly in European services. The externalities are found to have a small long-term impact pointing to a possibly static nature of agglomeration economies in Europe. Also Blien (2006) applied GMM estimations to study employment patterns in German NUTS3 regions. He finds positive evidence of both types of agglomeration economies. Diversity in his study seems to impact positively both services and manufacturing, more however manufacturing. Moreover, he finds no evidence of MAR externalities. Also, Combes, Robin, Magnac (2004) use panel data VAR technics on French employment zones and confirm a positive impact of regional diversification on French employment growth. They notice however a relatively static nature of externalities acting in France, in opposite to importance accorded to past changes in industrial composition of regions found by Henderson(1997). Interestingly while most of the study introduced two separated indicators for specialization and diversity, Kroll (2011) followed Duranton and Puga's suggestion regarding states in-between specialization and diversity. Using German data on Kreise from 1998 to 2008 she investigated a concept of diversified specialization accounting for a potential complementarity of both effects. Using several indicators of relative specialization, they find that areas specializing in several sectors may benefit from both types of externalities.

Empirical research in the field encountered important challenges regarding regional data availability, methodological problems r which may partly explain differences in conclusions. As seen, despite important implications of industrial composition on regional growth patterns, not all the results point in the same direction. The first explanation could point into a highly country-specific nature of forces in play. However, as market-based forces operating at the regional level is likely to be similar across countries and fixed-effects components are discarded using fixed-effects data, another one points to differences in methodologies. In the extensive literature survey by Beaudry et al. (2009), they find that data used have an important effect on discrepancies in results. They find that the smaller the spatial unit used in the studies, the more often both Marshallian and Jacobs externalities are found positive and results are more significant. Moreover, studies using large spatial units and relatively broad sectoral classification tend to detect much more MAR externalities than Jacobs. Moreover, evaluating regions instead of firm level behavior, the probability of detecting Jacobs externalities are always higher, independently of the level of aggregation of data. To conclude, patterns in conclusions reached using different types of data were observed. This adds an additional point to consider when analyzing the results.

Other interesting concepts related to agglomeration externalities have recently enriched the debate about agglomeration economies. One of them is "relatedness" or "regional branching", measuring to what extent varieties produced in a region are interconnected both in terms of final products and input use (Frenken and Boschma (2007), Frenken and Van Oort (2007)) . It is thus an additional factor to be considered when assessing diversification and specification: a region may be very diversified in terms of its industrial composition, but the existing sectors may be whether linked to one another or unrelated. This in turn would have an impact on the concentration of the shocks and overall response of an economy to the disturbance due to existing input-output linkages. On the other hand, relatedness allows for more efficient knowledge spillovers, fosters innovation by enhancing creation of new combinations of varieties and improves compatibility of types of labor which fosters the reallocation. It is indeed found that on average new industries entering the regional markets are usually related to the existing ones (e.g. Klepper 2007). Traditionally the measures of sectoral relatedness have been expressed by Hirschman linkages in supply chain found in

input-output tables (eg. Fan and Lang 2000) or comparing different mixes of "occupations" used by the industries (Farjoun 1994). However, for instance Neffke (2009) used a novel indicator of relatedness in manufacturing sectors expressed as co-occurrence of varieties belonging to different industries but being present at the very same plants in Sweden. He finds a strong link between the existing structure and the probability of a new industry to enter the market. Also, it has indeed been found that a diverse region better absorbs the shock when industries require the same kind of skills (are more related) from the workers allowing for an efficient labor pooling (Diodato and Weterings (2017)). Finally, Frenken, Van Oort, and Verburg (2007) using their cross-section analysis of Dutch regions that regions where varieties are relatively more related among with each other experience higher growth rates of employment, controlling for a specialization indicator (yielding itself a negative coefficient on pure localization economies). Therefore, it seems to be an important factor to consider when assessing the impact of agglomeration economies.
Frenken, Van Oort, and Verburg (2007) insisted on labor pooling stabilising effects in diversified areas pointing to another point of disagreement in the debate on agglomeration economies.

2.3 Agglomeration economies and instability

One of the factors brought to light by the survey of Beaudry et al.(2009) is that time coverage of the sample matters a lot when assessing importance of different types of externalities reflecting a possible time-inconsistency issue. These discrepancies in results may be related to a possible time-inconsistency of the impact of externalities, as suggested by Combes (2013). The effects of specialization and diversity may be different depending on business cycle position, pointing to different conclusions and indicating a possible time inconsistency issue when deriving short and long term conclusions.This observation is related to the relationship between economic structure and stability. The main hypothesis states that the impact of different types of externalities differs depending on the business cycle: while specialization would have a positive impact on growth during the booms and negative during the downturns, the opposite would be encouraged by a diversified economy. This would in turn impact overall conclusions for the effect of specialization and differentiate them in the short as opposed to the long-run. The research on the topic once again does not provide definitive conclusions.
With this regard, two theories focusing on regional employment and stability, complementary in their conclusions, have been developed. First, from a micro perspective, Conroy, 1975 presented his portfolio theory stating that specialized areas tend to be more exposed to risks, as overall economic performance relies on a particular sector. With sector-specific shocks, risk of a severe downturn will be lower in a diversified area as all the industries experience different, not perfectly correlated, shocks. With higher risks, the variance of the "industrial portfolio' is found to be higher in specialized regions, leading to a higher instability. Thus, this line of literature focuses on variation in regional outcomes, notably employment. Conroy's empirical finding has been confirmed by Kort (1981). Using quarterly data on American metropolitan areas and improving the measure of diversification, he concluded that half of the overall variation in "regional economic instability" (REI) employment is due to diversification of industries. Importantly, Kort took into controlled for the overall size of the are, following the observation that larger areas tend to be more diversified and experience less variability. More recently, Malizia and Ke (1993) based on Canadian data and using cross-sectional analysis, showed that regions that are more stable tend to be more diverse, have lower than average growth rates, larger plant sizes and higher export intensity. On the other side, some other authors show a weak or inexistant impact of industrial diversity on stability of employment, notably Rodgers (1957); Attaran, (1986). (These relationships are stronger for regions that have low manufacturing employment than for those where manufacturing employment is larger.)

On the other hand, it has been found that diversity may reduce regional unemployment (e.g. Wasylenko and Erickson (1978). As it is not exactly in line with the portfolio theory, a new theory, called search theory has been advanced. The search theory argues that specialization indeed induces higher exposure to unemployment risk as there is a limited scope of labor pooling: possibilities are scarcer to move to other sectors not concerned by a sector-specific shock. Therefore, unemployment should be lower in diversified regions than in specialized ones. According to Thompson (1965) diversity, together with competitiveness are both acting as stabilizer: an area can easier face a shock when using its comparative advantage or absorb the shock by relocating labor across sectors. Therefore, unemployment should be lower in diversified regions than in specialized ones. Among others, this point has been confirmed by Malizia and Ke (1993), Izraeli and Murphy (2003) or Longhi (2005) accounting for institutional factors such as wage barganing. However, the question remains open as numerous studies found the opposite or found no impact at all e.g. Mizuno et al. (2006).

Given inconsistency among the findings, other factors need to be considered when assessing the benefits of diversification in terms of stability and unemployment decrease. First, benefits of diversification in terms of labor pooling seem to be conditional once again on "relatedness" in terms of compatibility between occupations: workers should be capable to execute tasks in another sector. Therefore, occupation diversity across sectors may diminish the positive impact of sectoral heterogeneity (Malizia and Ke (1993)). Moreover, as noted by Diodato and Wetering (2015), the ability to recover from a shock for firms and workers may be very different. Even if new activities developed in a given region, boosting growth, it might be the case that these are not compatible with existing skills, especially that as noted by Neffke (2011) skills required by new industries may differ a lot from those in existing industries. However, the opposite also may happen if a decline in a particular sector is followed with migration of workers to other sectors or regions. Therefore, another important factor influencing the results is the quality of network linking neighboring regions: the relative position of regions could matter when comes to connectivity. Finally, when existing activities are related by important intput-output relations, a shock producing unemployment may be much less concentrated reducing the benefits of diversification as it spreads across the existing linkages. Following a shock to particular sector, the demand for goods decreases for all the intermediates spreading the shock. Indeed, as showed by McCann and Ortega-Argiles (2013), shock is magnified when important backward linkages are present. Therefore the study of Neffke (2011) included all these important elements related to the issue, namely "embeddness" reflecting input-output relations across sectors, "skill-relatedness" index reflecting compatibility of labor and connectivity index. The issue is therefore closely related to the discussion over relatedness stated above. Moreover, some authors consider that the effect of diversification on the cycle stability remains neutral: according to Hoover and Giarratani (1984), it is less so diversification per se that makes a region stable but the nature of the existing activities: cyclically insensitive and stable sectors would therefore promote stability.

While the authors mentioned above were interested primarily in stability, a new brunch of economic literature together with international organization and policy makers has been recently born focusing on so-called regional "resilience", an interesting but still not clearly defined concept linked to stability.The notion, inherited from biology, has been defined by Holling (1973) as "ability to absorb changes of state variables, driving variables, and parameters, and still persist". It is thus incorporates the debate over the importance of agglomeration economies and human capital transmission in sustaining regional growth. Simmie and Martin (2010) distinguish three types of economic resilience, namely engineering one (capacity to return to equilibrium), ecological one (capacity to smoothly absorb the shock in the system) and adaptive one, linked to Grubhner's concept of adaptability and relating to the capacity of a system to transform itself. This line of research is linked to the evolutionary geography philosophy, stating that no stable equilibrium exists and the dynamic process of regional industrial structure is highly history-related and thus path-dependent. First line of research in the field is related to characteristics of regions considered as "resilient", such as macroeconomic stability, market efficiency, social capital (Briguglio et al., 2006).

Moreover, another line in the literature related to resilience studied the impact of industrial structure on a region's response to a shock, notably the financial crisis. Considering that the financial crisis occurred unexpectedly and spread quickly into the real economy through the banking system, it provides a natural candidate for a comparative studies related to shock-resistance and shock-absorption. Notably, Davies (2011) used correlations between unemployment, GDP and shares of specific sectors to investigate the response of a region to the great recession. She finds that regions with high share of manufacturing were more hit by the crisis in the early stages of the recession. Some authors, like Deller and Watson (2016) studies the impact of diversity on the response to the great recession taking into account regional spillovers. Others focused on comparison studies between types of negative shocks. Fingleton, Garretsen, and Martin (2012) analyzed the response in employment change during periods of growth and recovery from a different kind of crisis in the UK from 1970 until 2010 suggesting that shocks to own-region employment have a quasi-permanent nature. Spatial spillovers do not seem to play a role only to neighboring regions.

Having overviewed major findings in the related literature, one needs to retain that the results indeed vary across studies and due to data limitation most of the studies focused on particular countries only. Two explanations are possible: whether the mechanisms are indeed country-specific and very idiosyncratic or the methodology and time coverage result in such large discrepancies. Moreover, as most of the studies of a larger scope focused on the US states, our paper will try to complement existing studies by providing an analysis on a wide range of European regions. We will therefore try to depict whether a significant impact of agglomeration economies on the level of growth and its stability in European regions may be established.

The rest of the paper is organized as follows: the next section will focus on descriptive analysis of the heterogeneity among European regions. Next, we will turn to the empirical analysis divided into a cross-section analysis providing a first insight on the relationship. Secondly, we will make use of the existing panel data to assess the dynamics of the impact of agglomeration economies on employment growth. Finally, we will confront those findings with our assessment of regional instability in employment in order to investigate whether a potential time inconsistency issue occurs.

3 Regional heterogeneity within the EU

First and foremost, employment structures in Europe are highly heterogeneous. Overall employment density varies considerably across European regions. The highest level of employment per km_2 are obtained in the traditionally highly developed countries (UK, Germany, Luxembourg, the Netherlands, Belgium), as well as in capital cities metropolitan areas with the highest values reaching 1000 employees per km_2 observed in some districts of London. On the other hand, regions of Eastern Europe exhibit relatively lower level of employment density. Equally, rural regions in the Southern countries (Spain, Portugal) host relatively less employment by area. The outlier of 2 workers per kilometers squares is reached in Northern Finland for reasons related to the climate (see table 1 and graphs in the Annex).

Considering industrial composition in terms of diversity in the regions, we will apply two widely used indices in order to account for both relative and absolute industrial diversity. The first index considered is the Krugman index:

$$KI_i = -\sum_{s=1}^{S} \mid v_{is} - v_{\bar{EU}} \mid, \text{ where: } v_{is} \text{ and } v_{\bar{EU}}$$

are employment shares of a sector s in a region i and at European level, respectively [3].

It takes a value of zero when the local industrial composition reflects perfectly to an 'average' region in the EU regions and becomes negative when the area becomes less similar to the structure of reference (less diversified if we assume that the average is well balanced). One needs to notice that the value that the index is relative to a given benchmark, here European 'average' region. For instance, if the benchmark region is very specialized, a region with more balanced sectoral structure would get a low value of its index and vice-versa. The index satisfies specific baseline criteria of a diversification measures: it is comparable across activities, spatial scales and time. However, it does not satisfy the criteria of decomposability when disaggregating the index into smaller categories. For instance, if a given region is relatively more specialized in one sub-sector and less in another than the reference group, aggregating up to a sector level would decrease the specialization as both effect would cancel out. Aggregation could also blur the interpretation if some sectors grow faster than others. There could be thus a composition effect in the index amplified by a larger sectoral aggregation, as it is the case in our dataset.

Table 1: Employment density in Europe (in thous. of workers, 2014)

Cou	Nr	Mean	Median	St. Dev.	Min	Reg.	Max	Reg.
AT	9	0,3129	0,0386	0,8059	0,0289	Karnten	2,4614	Wien
BE	11	0,5177	0,1433	1,2559	0,0208	Prov. Lux.	4,2981	Bruxelles
BG	6	0,0304	0,0265	0,0154	0,0160	Severozapaden	0,0600	Yugozapaden
CY	1	0,0000	0,0000	-	0,0000	-	0,0000	.
CZ	8	0,2776	0,0573	0,6188	0,0327	Jihozapad	1,8085	Praha
DE	11	0,1981	0,2190	0,1406	0,0318	Mecklenburg-Vorpommern	0,5081	Berlin
DK	5	0,1128	0,0463	0,1554	0,0346	Nordjylland	0,3905	Hovedstaden
EE	1	0,0134	0,0134	,	0,0134	-	0,0134	.
EL	13	0,0494	0,0187	0,1058	0,0095	Dytiki Makedonia	0,4004	Attiki
ES	18	0,1436	0,0378	0,3302	0,0081	Extremadura	1,4200	Ciudad Autonoma de Ceuta
FI	5	0,25131	0,0116	0,0356	,0023	Pohjois-Suomi	0883424 ,	Helsinki-Uusimaa
FR	13	0,0875	0,0475	0,1297	0,0255	Corse	0,5090	Ile de France
HU	7	0,0617	0,0270	0,0856	0,0214	Southern Transdanubia	0,2552	Budapest
IE	2	0,0272	0,0272	1 ,019021	0,0137	Border, Midland, Western	0,0406	Southern and Eastern
IT	21	0,0718	0,0676	0,0470	0,0189	Valle d'Aosta	0,1918	Lombardia
LT	1	0,0202	0,0202	-	0,0202	-	0,0202	-
LU	1	0,1531	0,1531	-	,1531	-	,1531129	-
LV	1	0,0136	0,0136	-	0,0136	-	0,0136	-
MT	1	0,0006	0,0006	-	0,0006	-	0,0006	-
NL	12	0,2205	0,1847	0,1681	0,0523	Friesland (NL)	0,5228	Zuid-Holland
PL	16	0,0522	0,0438	0,0318	0,0216	Warminsko-Mazurskie	0,1495	Slaskie
PT	7	0,1090	0,0434	0,1476	0,0090	Alentejo	0,4311	Area Metropolitana de Lisboa
RO	8	0,1058	0,0328	0,2101	0,0239	Vest	0,6256	Bucuresti - Ilfov
SK	4	0,0808	0,0418	0,0851	0,0320	Stredno Slovensko	0,2079	Bratislavski kraj
UK	32	0,1869	0,1165	0,2271	0,0324	Highlands and Islands	1,2866	Inner London - East

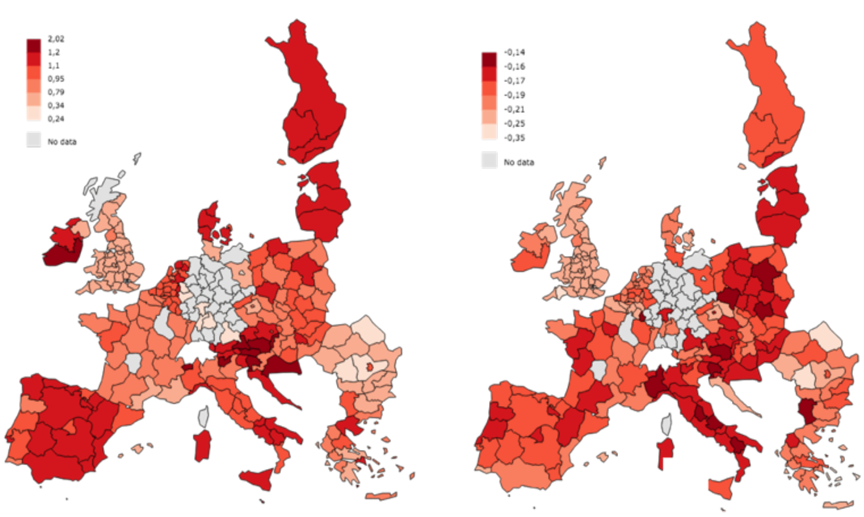
Source: OECD and Eurostat.

The second index commonly used in the literature is the inverse of the Hirschman-Herfindahl index, measuring absolute diversification:

$$HHI_i = -\sum_{s=1}^{S} {v_{is}}^2, \text{ where: } v_{is} \text{ are employment shares of a sector } s \text{ in a region } i .$$

The index takes value of zero where employment is uniformly distributed across existing sectors. Lower values reflect higher employment in some sectors than the others and thus less diversity. The index is useful when inspecting absolute diversity in industrial composition across regions, but does not inform about which sectors are present nor how it is situated relatively to the average in a country. It might be the case that in some regions only few sectors are present with equally distributed employment, while in the other employment would be spread among a wider range of activities, but still pointing at a lower diversity. However, in our case, the problem is more related to the broad aggregation on sectoral level hiding important heterogeneity among particular sub-categories.

Figure 1: Industrial diversity in the regions : Krugman index (left) and inverse HHI index (right)



Note: Krugman index is calculated relative to the shares of sectors present in the sample (European average).
Source: OECD, Eurostat.

Keeping these remarks in mind, one could notice that regions exhibit indeed a strong heterogeneity in their industrial structure. According to Midelfart-Knarvik et al. (2002)'s study covering 14 Western European countries from 1970 until 1997, on average, the lowest level of specialization and highest diversity is observed in highly developed and large countries, notably the UK, France, Germany. Smaller core countries like Belgium and the Netherlands tend to be relatively more specialized. The most specialized countries turned out to be Southern countries: Greece, Portugal, as well as Ireland. Spain on the other hand was found to be very diversified among so-called cohesion countries, while patterns in Italy were similar to small central countries. These results reflect industrial diversity relatively to a given benchmark, here Western countries only. However, adding Eastern-European countries to the sample and analyzing the patterns at the regional level, changes the benchmark quite importantly, as it can be seen in the Figure 1. One needs to notice that these patterns are mostly country-specific, as they are compared to an average European structure, not a national one. Spain remains very decentralized relatively to the EU average, together with Baltic and Scandinavian countries, reflecting potentially high shares of different types of services on the top of remaining industrial sectors. Austrian regions appears to play as reference in the EU. Indeed, in Midelfart-Knarvik et al. (2002), the country was found to diversify quickly over time, while remaining relatively specialized. Therefore, two forces seem to be in play. On one hand Austria diversified its industrial structure in recent years developing wider range of activities. On the other, entrance of Eastern-European countries, typically more specialized, pushed the benchmark towards more industry-oriented sectors. Indeed, Eastern-European countries, e.g. Romania and Bulgaria, as well as Greece, tend to be relatively specialized in traditional industries. Following the reasoning, Poland, Check Republic, Slovakia and Hungary seem to indeed reflect well European average structure. France and Italy are found to be relatively decentralized, as found in the previous studies. Interestingly, UK is found to be relatively divergent from European average, potentially reflecting high share of industrial sectors in a large part of the country, as the sectoral aggregation is quite rough.

Given that the benchmark used in our study has been modified by adding Eastern-European countries pushing the European average to be more specialized, we also present absolute HHI index of diversification. First, one needs to notice that industrial diversity becomes much more region-specific when not relating them to the European average. Typically, capital city regions appear to be very diversified reflecting large shares of different types of services present in our sample. Industrial regions (typically UK) and agriculture ones (Romania, Bulgaria) tend to appear as more specialized. Within-countries heterogeneity in industrial structure seems to be relatively important. Therefore, in our study we will study these patterns relatively to national and not European average structures.

Moreover, regional industrial structure seems to be persistent over time. Molle(1997) in his study provides a long time perspective of historical change in industrial diversity across 96 EU NUTS2 (or for some countries NUTS1) regions from 1950 to 1990. Using Krugman index, he finds that an overwhelming majority of regions became less specialized over the period. The changes are however relatively small. On the other hand, Hallet (2000) in his study used the very same data but for a larger number of regions, finding that 85 of these regions became less specialized. On the other hand, Midelfart-Knarvik and Overman (2002) present results by industry branch and find a more blurred picture: in their sample around a half became more specialized, with the rest of the regions showing a decrease.

In our sample covering a relatively short period of roughly 15 years, the changes occurred over the time period are also relatively small. In the table 2, we use absolute HHI index of specialization on a similar sectoral aggregation level and the same spatial units. It is thus possible to compare region-specific patterns across countries. We observe that roughly half of our regions diversified over time. Most of the regions concerned lie in Center and Eastern Europe, as well in the south. Although an average change in diversification index is very small, some regions seem to have experienced higher changes in their industrial structure (see table 2). Once again the biggest changes concern a few regions in Bulgaria, Poland and Romania, all typically agriculture-oriented. As on average these regions tend to have higher shares of manufacturing and agriculture then Western countries, one may interpret it as a part of a transmission mechanism and opening to services.

Table 2: Regional industrial composition in 2014

	Min	Region	Country	Max	Region	Country
Emp.	-0,355	*Ciud.Aut. de Ceuta*	ES	-0,153	*Malopolskie*	PL
	-0,344	*Ciud. Aut. de Melilla*	ES	-0,150	*Basilicata*	IT
	-0,302	*Nord Est*	RO	-0,144	*Mazowieckie*	PL
Δ Emp.	-0,048	*Reg. Aut. da Madeira*	PT	0,155	*Nord-Est*	RO
	-0,037	*Algarve*	PT	0,119	*Sud-Vest Oltenia*	RO
	-0,032	*Devon*	UK	0,103	*Sud - Muntenia*	RO
Share of serv.	0,041	*Nord-Est*	RO	0,578	*Inner London - West*	UK
	0,046	*Severen tsentralen*	BG	0,445	*Inner London - East*	UK
	0,047	*Severozapaden*	BG	0,399	*Outer London - South*	UK
Δ Share of serv.	-0,033	*Essex*	UK	0,107	*Comunidad de Madrid*	ES
	-0,032	*Overijssel*	NL	0,097	*Yugozapaden*	BG
	-0,028	*Flevoland*	NL	0,077	*Zahodna Slovenija*	SI
Share of manuf.	0,068	*Ciud. Aut. de Melilla*	ES	0,444	*Vest*	RO
	0,070	*Ciud. Aut. de Ceuta*	ES	0,437	*Severova chod*	CZ
	0,074	*Bruxelles-Capitale*	BE	0,435	*Stredna Morava*	CZ
Δ Share of manuf	-0,157	*Cataluna*	ES	0,064	*Swietokrzyskie*	PL
	-0,153	*Comunidad Valenciana*	ES	0,055	*Opolskie*	PL
	-0,129	*Comunidad de Madrid*	ES	0,054	*Mazowieckie*	PL

Note: A positive change in inverse Herfindhal index corresponds to an increase in diversity. Diversity is the highest when the index is close to 0.
Change in shares may be interpreted as changes in percentage points.
Changes in indices are computed between 2014 and 2000.
Source: Eurostat, OECD. Based on authors'calculations.

However, one needs to take these first results with caution. First, geographical aggregation matters as for a larger spatial areas it takes longer to change its industrial structure. Secondly, in general NACE classification is much more detailed for industry sectors than on services, artificially lowering specialization indices. However, more aggregated level of classification especially in industry, as in our sample, do not differentiate between lower sub-sectors' diversity, indicating broadly employment distribution across agriculture, several types of industries and different services.

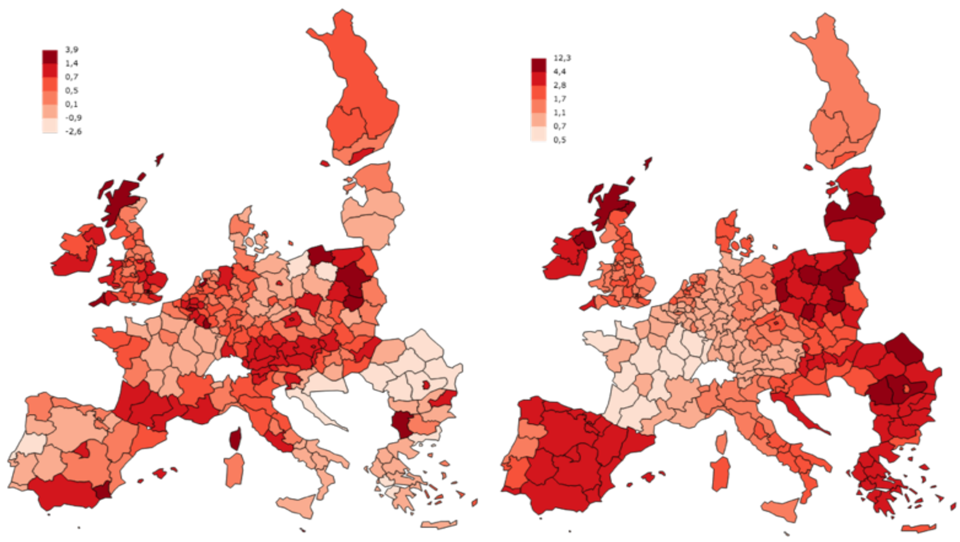
Concerning shares in manufacturing and services [4], the European regions exhibit high large heterogeneity with respect to their industrial composition. Eastern and Central European countries have a relative higher shares of manufacturing, reaching up to roughly 45 percent of existing industries in Southern Poland and Czech Republic. Services on the other hand constitute a larger share of local economies mostly in the so-called center of Europe, in proximity to the UK. The highest shares of services reach 58 percent in London agglomeration[5].

The share of manufacturing and services also experienced substantial changes over the period. First, 160 over 218 regions increased their share of services employment in total, with highest changes reaching 10 p.p. increase. The highest changes in services employment concern mostly Eastern and Southern countries, as well as the UK. Interestingly, the biggest increase in shares of services occurred in the capital cities. By the same token, majority of regions decreased their share of employment in manufacturing : only 23 out of 218 increased their manufacturing share. The biggest drop in manufacturing shares reach -15 p.p., while the highest increase roughy 6 p.p., indicating a clear pattern of a decline in European industry sector. The largest decline in manufacturing concerns Spanish and Portuguese regions.

[4] Services here are limited to business services only, including Communication (J in NACE rev.2), Financial activities (K), Real Estate (L) and Legal and Administrative services (M to N). We do not consider retail and wholesale trade (G to I), public services (O to Q) and others unclassified services as we want to focus mainly on market-based services and trade and public services are highly influenced by public interventions.

[5] See the graph in the Annex

Figure 2: Average employment growth (left) and its standard deviation deviation (right), 2000-2014



Source: OECD. Based on authors' calculations.

Moreover, regions experience very different employment growth dynamics, as depicted in Figure 2. Highest average growth rates are observed mostly in regions in central Europe (Germany, Belgium, the Netherlands) and in the UK. The observed deviations in employment growth are also relatively small pointing at a stable and important growth path, keeping in mind that those countries tend to be relatively diversified. Eastern European and Southern countries also have seen relatively high average employment growth over the period, but the variation in growth rates is more important. Poland, Slovakia and Hungary and other new member states also have seen important employment growth over the period, with several countries of the group presenting more instability in their growth rates (e.g. Poland). France and Italy on the other hand are typically confronted with smaller employment rates (especially in the South of Italy and Center and North-East of France), but also small variation in growth rates, pointing at a very stable employment series in these regions. [6]. Interestingly peripheral regions, including Eastern and Southern countries, seem to have experienced larger both positive and negative variations. As typically those regions are also relatively less diversified and relying often on tradition industries, one may indeed hypothesize a potential causal relationship between the two.

Having overviewed important heterogeneity across European regions with respect to their structural composition, the next session will try to assess whether industrial composition of the regions, along with other characteristics and agglomeration externalities types, may explain employment growth dynamics in the European regions.

4 Dynamics of agglomeration economies: empirical analysis

A central aim of the paper is to bring new insights into the discussion over the impact of agglomeration economies on a regional scale. We will benefit from the existing panel data on regional sectoral employment in Europe to study employment patterns using several estimation technics.

4.1 Data

We use publicly available data from OECD Regional Database and Eurostat. Spatial aggregation units used are NUTS2, corresponding to French *regions*, German *Regierungsbezirke* or Italian *regioni*. As explained in the extensive survey by Beaudry et al., the choice of spatial units may indeed matter when assessing agglomeration economies. The units chosen here are

[6]A similar observation may be derived when analyzing the largest peak in employment growth before the financial crisis, as well as the deepest drop in its aftermath (see the Annex)

indeed relatively large, which according to Beaudry's survey point into relatively large rejection of agglomeration economies. Indeed, it might be the case that cluster and networks of industries operate mostly at a smaller scale between local producers, but it seems unlikely for the agglomeration economies not to be found at a regional level. Given technological process in transporting technology, related fall in trade costs and globalization, the limits of areas in which firms may operate increased, making the spatial scope of agglomeration effects larger. Moreover, the choice of aggregation is suitable as a wide range of public policies are devoted to reduce regional disparities. In European Union, the so-called regional convergence policies are set both on national and European level and the attribution of funds is done based on NUTS2 level for several programs. Finally, regional specialization historically happened on larger spatial scales than very small NUTS3: due to the abundance of endowments (land, coal, access to the sea), large areas specialized in a specific good production was created. Consequently, in our opinion units chosen should not be discredited for their level of aggregation. [7] In total, our sample covers 218 NUTS 2 units in most of the countries of the EU, including both new members and core European Countries. Interestingly, the inclusion of new member states into the sample allows to derive comparisons between finding focused only on old European member states.

Employment data comes both from Eurostat and OECD Regional Database. Data covers 11 sectors of the ISIC rev. 4 classification: agriculture , forestry and fishing (A), industry other than manufacturing, including energy (B, D, E), manufacturing (C), construction (F), distributive trade, repairs, transport, accommod., food serv. activities (G to I), Employment in information and communication (J), financial and insurance activities (K), real estate activities (L), prof., scientific, techn. activities, admin., support service activities (M to N), public admin., compulsory s.s., education, human health (O to Q) , other services (R to U). The data on sectoral employment in European countries is indeed very aggregated hiding possible specialization patterns at a thiner level of sectoral agglomeration. Ideally ,we would use a more disaggregated sectoral classification (digit 2 would seem sufficient for the large spatial units we use). However, we assume that general patterns of industrial structure are still depicted in the indices of diversity used, especially as we are interested in effects of specialization/diversity relative to a country's average region. Additionally, for most of the regions in France, Germany, as well as for Cyprus and Malta, OECD statistics do not cover services sectors, which are available with the Eurostat starting from 2008. Eurostat data is expressed in NACE rev. 2 starting from 2008 only. Previous periods' regional employment is classified according to a very aggregated NACE rev. 1 classification, not possible to match with the new one. Therefore, we opt for the use of OECD data, much more complete and unified in terms of sectoral classification. Correspondence tables between NACE rev. 2 used in Eurostat and ISIC rev. 4 used by the OECD, enable us to complete the OECD dataset. [8]

Based on the existing sectoral aggregation with divide the sample into *Industry*, including industry other than manufacturing (B to E, without C), manufacturing (C) and construction (F) and *Services*, including information and communication (J), financial and insurance activities (K), real estate activities (L), prof., scientific, technical activities, admin., support service activities (M to N). Some part of the literature interested in assessing purely within-region variation and impact of industrial structure, excludes construction and energy from the sample of industry, as they are likely to be widely driven by public intervention. However, as we are interested in macro country-sector specific shocks (e.g. large public investments to a given sector reflected in size of the sector aggregation), those sectors are included. Robustness check is conducted on purely manufacturing sectors (see the annex). All the selected sectors can be considered as business and support services, subject to market economies mechanisms. For the same reason, we do not include public administration, education and other unclassified services as those are likely not to be subject to market-based mechanisms. Idem, we do not conduct the assessment of agricultural sector.

Finally, all indicators of human capital come from the Eurostat dataset, while value-added used for robustness checks with productivity comes from the OECD dataset. The

[7] Alternative specification could not be verified due to data limitation.

[8] Robustness check with the exclusion of the Eurostat data showed no change in conclusions. Estimation in the annex.

dummy used for the large events' impact and earthquakes comes from the author's calculations.

The data covers the period 2000-2014. Half of the period is covered by the years of a relative booms in European countries and high growth (especially in Southern and Central and Eastern-European countries). The sample period includes the great recession, as well as slow recovery of the European economy in the aftermath of the crisis. The advantage of the time period presented is that it represents both the period of the boom and the crisis allowing for deriving conclusions on a possible time-inconsistency impact.

4.2 Explanatory variables

Our explanatory variables aim at distinguishing between different types of externalities having a potential causal impact on growth of employment. We follow Blien (2006) with the main indicators of externalities and detail additional controls that we will use.

As discussed, the main issue in the related literature is strong endogeneity problem as explanatory variables, reflecting sectoral composition of employment in the region and its size, under realistic assumptions are highly related to unobserved shocks influencing the dependent variable. Given that we aim at investigating the impact of industrial structure on employment growth, there may be indeed large endogeneity issue. First, reverse causality may take place from the dependent variables towards industrial composition, as they are mechanically linked to each other e.g. a share of a particular sector, included in indicators of e.g. diversity, may increase whether because an increase in own-sectoral employment or a decrease in total employment. Moreover, as presented in Mathys and Brulhart's dynamic model of sectoral employment, productivity, density and employment are jointly included in the structural equation of the equilibrium. Given that we are interested in disentangling the impact of industrial structure and other types of agglomeration economies linked to productivity and density, we define our explanatory carefully, removing the mechanical part of the relationship.

- **Specialization : lagged log employment**

  Past values of log region employment in a given sub-sector of services or manufacturing, respectively, account for Marshallian externalities. If localization externalities were present, the higher the employment in a sub-sector, the larger its value in the next period. Therefore, if MAR externalities are present, the coefficient on the lagged dependent variable is expected to be higher than 1. This situation points to explosive growth following a positive shock and a potential lack of convergence across the regions. On the other hand, a coefficient smaller than 1, the series exhibits mean reversion after a shock and the return to the mean, slow if the coefficient is high. Some authors interpret high values of persistence (around 0,9) as signs of MAR externalities. Other indices of specialization are usually modeled as employment share of a sub-sector in total regional employment. However, as noted by Combes(2000), the effect cannot be distinguished from the initial employment in the sector as it is collinear with own employment and total employment in a region). This makes the interpretation very problematic especially if the effects point to different directions, as it was the case in the paper of Henderson et al. (1995). Therefore, we will not test this specification.

- **Diversity : Krugman index**

  $$div_{cdst} = -ln \sum_{s'=1}^{S} \mid v_{c,d,s',t} - \overline{v_{c,s',t}} \mid,$$
  $$\text{where: } v_{c,d,s',t} = \frac{E_{c,d,s',t}}{E_{c,d,t}} \text{ and } \overline{v_{c,s',t}} = \frac{E_{c,s',t}}{E_{c,t}}$$
  are shares of other sectors in total employment, in a region and in a country respectively.

  As explained in the previous section, Krugman index of diversity is a relative index of diversity taking a value of zero when the local industrial composition reflects perfectly to the reference region, here an 'average' region in a country. It becomes negative when a region becomes less similar to the national structure (less diversified if we assume that the average is well balanced). The indicator is computed as a sum of absolute values of deviations of regional employment shares in total regional employment from the respective national shares. The sum is computed over all the 11 sectors existing in a region, except the one considered (s)[9] . The exclusion of the own sectors allows for eliminating a part of endogeneity from the indicator. The index has the advantage of comparing within countries diversity in industrial composition. The coefficient will indicate whether a relative diversity in the industry mix with respect to the national level in particular sectors has a positive growth of employment in a given sector. It does take into account if a particular country is indeed specialized in a sector and whether the sector is present in a region.

Table 3: Basic descriptive statistics

	Min	Max	Median	Mean	St.dev
			Industry		
Emp.	3,35	13,96	10,98	10,62	1,80
Divers.	0,14	4,36	1,98	1,98	0,55
Region	5,98	15,30	13,08	12,70	1,69
Sector	3,35	16,05	13,87	13,60	1,92
Educ.	1,31	4,02	3,12	3,04	0,45
Age	3,45	3,89	3,69	3,69	0,08
Women	3,88	3,98	3,93	3,93	0,01
			Services		
	Emp.	Divers.	Region	Sector	Educ.
Emp.	0,00	13,40	9,21	8,97	2,03
Divers.	0,13	10,25	1,93	1,93	0,60
Region	6,11	15,36	13,19	12,80	1,70
Sector	0,00	16,13	12,35	12,15	2,18
Educ.	1,31	4,02	3,12	3,04	0,45
Age	3,45	3,89	3,69	3,69	0,08
Women	3,88	3,98	3,93	3,93	0,01

Note: all the variables are expressed in logs. Total number of observations is 5550 for industry and 11072 in the case of services.
Source: OECD regional database, Eurostat. Based on authors' calculations.

On the contrary, another common measure widely used in the literature is the inverse of the Herfindhal index (HHI). As previously explained, the index measures absolute distribution of employment shares. It has the advantage of being easily comparable across locations, but does not reflect a particular country-specific structure of the economy. As the benchmark in this case is a uniform distribution of employment, a region with only 2 industries with equal number of workers will have a higher rank that a region with a wide range of industries unequally distributed. As we are interested primarily in relative diversification of activities within countries, the Krugman index is chosen. [10]

- **Overall density economies: regional size**

$$reg_{c,d,s,t} = \sum_{s'=1}^{S} E_{c,d,s',t} - E_{c,d,s,t}$$

Another indicator used accounts for the overall size of the region, measured in terms of total employment in all the sectors present in a given region, except the one in consideration. This allows us to avoid a mechanical endogeneity issue. The indicator also

[9]Therefore, the sum includes all the manufacturing sectors, all the services sectors, as well as other sectors present in a region not falling into the two categories. See the discussion in the section Data.

[10]Moreover, the index is problematic for specifications in logs: effect cannot be distinguished from the total regional employment.

reflects overall regional density, given that the equation is expressed in first difference and size of the area cancels out.

The importance of the size effect has been confirmed by Ciccone and Hall (1993)'s study on regional disparities in the US, but from the theoretical point of view the overall impact of the regional size on employment dynamics remains ambiguous. First, larger employment centers allow for a more efficient spread of knowledge and technology across existing firms, in turn boosting productivity (e.g. Sveikauskas (1975)) and employment growth. However, specialized ares may be on average more productive while being comparatively smaller (Duranton and Puga (2000)). Second, larger areas also offer larger final demand markets and wider range of inputs markets. As found by Moomaw (1981) inputs use seems to be more efficiently in larger cities, possibly leading to higher employment. However, this beneficial impact of wider and more available input markets and thus higher productivity and overall economic performance may be offset by less productive sectors present in larger areas. Finally, larger and denser areas impose a harsher competition and higher price of land. Therefore, the effect of the size remains ambiguous and seems to depend on sectoral composition, productivity, as well as on the level of competition.

- **Sectoral specialization in a country: size of the sector**

$$sect_{c,d,s,t} = \sum_{d'=1}^{D} E_{c,d',s,t} - E_{c,d,s,t}$$

Finally, the last control variable related closely to agglomeration economies concerns country-specific specialization spillovers. The indicator expressed as the total size of the sector in consideration in a country, excluding the region concerned. The variable reflects all the nation-wide shocks to a particular industry accounting for possible spillovers. For instance, one could imagine possible spillovers from an important public investment on a country level to the regions, both via information and knowledge spillovers, but also through subcontracting and else (especially when the investments are made in neighboring regions). We would thus prior a positive impact of sectoral specialization at the country level. However, negative impact is not excluded as higher specialization nation-wise may also induce higher competition among the existing producers, pushing unproductive ones out of the market. Therefore, it is important to control for the overall productivity level of a region.

- **Overall productivity level**

All the previous indicators implied the direct effect of agglomeration economies on employment. However, as largely argued in the literature, it might be the case that those externalities operate directly on productivity, which in turn impacts employment dynamics. As noted by Combes and Overman (2003), this may be particularly problematic if comparative advantage in productivity generates employment saving instead of an expected employment growth. This might be the case of highly high-tech industries with very developed computerization. Indeed, as found in the study of Combes et al. (2003), higher productivity seems to positively impact employment only when the demand elasticity is high enough and labor inputs from other sectors are not substitutable. Considering large difference across countries and across regions in local productivity, presented notably in Ciccone (2002), one should include the variable to avoid a potential omitted variable bias and overestimate the impact of agglomeration economies. Although we would have a prior for a positive impact of productivity, the opposite may also occur if highly productive regions are dominated by mature and slowly-growing industries.

Moreover, one needs to notice that productivity level in most of the empirical literature is assessed by labor productivity, given the lack of TFP measures and data on capital. Some authors use wages as a proxy for productivity, but data is not available at the European scope. Moreover, it is important to noice that measuring productivity level as labor productivity requires controlling for heterogeneous skills, via proxies of human capital. Therefore, we will consider productivity as concentration of a value added by land use. It will allow us not only to avoid collinearity with other explanatory variables, namely regional size, but also to avoid issues related to skills heterogeneity. Again, we will remove own-sector's value added to remove the direct endogeneity in the relationship (as productivity seems to have a direct impact on employment (see the model of Ciccione's (2002)).

$$prod_{c,d,s,t} = \frac{\sum_{s'=1}^{S} va_{c,d,s',t} - va_{c,d,s,t}}{land\ area},$$

- **Human capital indicators**

  Finally, as pointed in the related literature, one needs to account for the level of human capital that is independent of a regional industrial structure, in order to properly identify the impact of agglomeration effects. In the simple theoretical model of a regional economy of Ciccione(2002), human capital indeed enters the structural equation of regional unemployment, together with density and productivity. It is quite intuitive as one could argue that human capital allows for a faster development of new industries, influencing in turn industrial diversity. As noted by Duranton and Puga (2004), knowledge spillovers, considered as a major source of localization and diversity externalities, mostly occur among educated workers. Moretti (2004) on its side distinguishes between direct spillovers and complementarities between skill types, both pointing to a positive effect of higher level of human capital via both channels. However, negative effects cannot be excluded: important increase of higher human capital share in a region could reflect the abandon of traditional sectors followed by an outflow of educated workers and decline in overall employment level for a sector. Not including human capital measure could thus potentially overestimate the impact of Jacobs externalities.Therefore, one needs to distinguish the two effects from each other.

  To account for these effects, we will thus use several proxies:

  - **Percentage of tertiary population**. The first indicator accounts for a percentage of total population with a higher diploma, reflecting the overall level of education in a given area. Areas with a larger share of educated areas tend to develop highly specific industries where the required skills level and prospects for further growth are potentially very high.
  - **Median age**. Median age of the population could reflect the dynamics of human capital: younger populations tend to attract new industries with high prospects of employment development. Young generation is also better educated and more operational (in terms of language skills, IT skills) than the previous one proxying overall level of human capital.
  - **Percentage of women**. Finally, one of the common controls for human capital is for women proportion in the economy. According to Eurostat, in 2015 women became more educated than men in European countries. The pattern is obviously relatively country specific, but almost all the countries (with the exception of Germany and Greece) showed similar results. What is more, according to ILO statistics, women tend to be employed widely more in services-related professions (around 80 percent of female employment) in which human capital could importantly blur the impact of agglomeration economies as on average they require higher level of education. We will include is as an additional instrument in our GMM regressions.

Finally, region-sector fixed effects control for geographical location (e.g. central regions appear to be more interconnected and benefit more firm spillovers), exogenous endowments, institutional differences varying very slowly over the considered time period.

To conclude, the variables have been carefully defined removing an important part of endogeneity. However, we consider that other unobserved factors for which we do not control may impact the results. Typically, spatial spillovers may have a direct effect on both the indices of industrial structure, density and employment (due to the outflow of workers or commuting between regions). Moreover, productivity and overall size of the region even when measured without the sector in consideration, can still be endogenous. Therefore, in our specifications, we will take it into account and instrument the variables.

Table 4: Contemporaneous correlations between level variables

	Industry						
Industry							
	Employ.	Diversity	Region	Sector	Education	Median age	Women prop.
Employment	1.0000						
Log diversity	0.1270	1.0000					
Region size	0.9412	0.0313	1.0000				
Sector size	0.7596	0.0384	0.7315	1.0000			
Education	-0.1365	0.1643	-0.0838	-0.0377	1.0000		
Median age	-0.2242	0.0381	-0.2271	-0.1117	0.2210	1.0000	
Women proportion	0.0974	0.0397	0.0788	-0.0192	-0.0992	0.1174	1.0000
	Services						
	Employ.	Diversity	Region	Sector	Education	Median age	Women prop.
Employment	1.0000						
Diversity	0.2084	1.0000					
Region size	0.8340	0.0717	1.0000				
Sector size	0.7617	0.1326	0.6224	1.0000			
Education	0.0657	0.1705	-0.1029	0.0752	1.0000		
Median age	-0.1666	-0.0160	-0.2314	-0.0404	0.2212	1.0000	
Women proportion	0.1281	0.0787	0.0805	-0.0662	-0.0998	0.1185	1.0000

Note: all the variables expressed in log.
Source: OECD regional database, Eurostat. Based on authors' calculations.

4.3 Contemporanous correlations

We also present contemporaneous correlations between the dependent variable and all the explanatory variables in log specification, both in services and manufacturing (see table 4). The correlation coefficients for both manufacturing and services suggest that the higher local employment in a sector, the higher the diversity, regional size and sector size. Moreover, as predicted employment in a sector is negatively correlated with age of the population. Also higher proportion of women is positively correlated with employment, both in industries and services, although more in services. Once again, as predicted women are predominately employed in services sectors, but there are signs for a potential positive impact of human capital spreading to manufacturing. Finally, higher level of education is positively correlated with employment in services sectors and negatively in industry, suggesting the common view that services require indeed higher labor skills types. One also needs to notice that women proportion is very weakly negatively correlated with the proportion of higher education reflecting potentially older generations' education level.

Table 5 reports correlations between first-differenced variables to eliminate the size effect. The first-differenced log of the variables may be interpreted in terms of growth rates. First, the coefficients are smaller as usually correlations in growth rates are weaker than in levels in panel data, but still important and going in a predicted direction. Impact of an increase in diversity, regional size and sector at the national level is still positive for both manufacturing and services. Increase in median age also negatively correlates with employment growth. Once again increase in education level of population is positively correlated with employment in services and negatively in industry. Increase in women proportion is negatively correlated with both services and industry, although the correlation coefficients are very weak. It indicates that while women proportion in level has a positive impact on the level of employment in services, the increase not necessarily. However, one needs to notice that changes in women proportion happen very slowly, unless exogenous shock happens. Importantly, change in women proportion affects positively growth rates of education, indicating an increasing tendency for women to be highly skilled and reflecting raise in human capital.

Having overviewed simple contemporaneous coefficients providing first supportive evidence of the relationship between employment and explanatory variables, we will thus turn to the panel data estimation.

Table 5: Contemporaneous correlations between first-differenced variables

	Industry						
Industry							
	Employ.	Diversity	Region	Sector	Education	Median age	Women prop.
Employment	1.0000						
Log diversity	0.0536	1.0000					
Region size	0.1729	-0.0239	1.0000				
Sector size	0.6667	0.0613	0.2615	1.0000			
Education	-0.0175	0.0438	0.0011	-0.0166	1.0000		
Median age	-0.0583	-0.0237	-0.1703	-0.0642	0.0025	1.0000	
Women proportion	-0.0735	0.0106	-0.1242	-0.0935	0.0546	0.2008	1.0000

	Services						
	Employ.	Diversity	Region	Sector	Education	Median age	Women prop.
Employment	1.0000						
Diversity	0.0394	1.0000					
Region size	0.1177	-0.0349	1.0000				
Sector size	0.3504	0.0107	0.1634	1.0000			
Education	0.0256	0.0371	-0.0073	0.0091	1.0000		
Median age	-0.0491	-0.0250	-0.1683	-0.0437	0.0030	1.0000	
Women proportion	-0.0149	0.0004	-0.1272	-0.0549	0.0551	0.1973	1.0000

Note: all the variables expressed in log.
Note: First-differenced variables may be interpreted as growth rates.
Source: OECD regional database, Eurostat. Based on authors' calculations.

4.4 First insight: cross-section

Before turning into panel data analysis, we first perform a cross-section regression inspired by Combes(2000) in order to get the first insight of what impact different types of externalities might have had on the long-run growth rate of employment over the sample period. The specifications study the relationship between relative growth rates of regions over the period and their industrial structure in a baseline year at the beginning of the period. Services sectors and manufacturing are separately estimated.

4.4.1 Empirical specification

The dependent variable is a difference between employment growth in sector s in a given region d along the period and the growth of the same sector at the national level. $E_{c,d,s,t}$ are the levels of employment in a sector s in a region d, while $E_{c,s,t}$ are the levels of employment in the sector at the national level.

$$y_{c,d,s} = ln\frac{E_{c,d,s,2003}}{E_{c,d,s,2014}} - ln\frac{E_{c,s,2003}}{E_{c,s,2014}} \tag{1}$$

Therefore, the estimation assesses the determinants of a higher/lower growth occurring in a particular region-industry relatively to the national average, as we are interested in why some regions grow *faster* or *slower* than the others. The variable may also reflect density growth of employment as size of the area would cancel out in the fraction. It thus implicitly controls for differences in area size of the regions. Finally, we choose 2003 as our base year, as the series for Belgium starts only in 2003. We therefore have a roughly similar lag in the effects to those used by Combes(2009), namely a lag of 11 years. As suggested by Henderson (1997) for the case of the US, dynamics of agglomeration economies differ across sectors: for MAR externalities the biggest effect occurs typically after seven years, while urbanization economies seem to be even more persistent and are significant even nine years ahead. Therefore, our specification seems to be convenient to study long-run effects of agglomeration externalities.

The independent variables are slightly modified from the initial equations estimated by Combes(2000). We include the same index of specialization accounting for MAR externalities:

$$spec_{c,d,s} = \frac{E_{c,d,s}E_c}{E_{c,d}E_{c,s}},$$

where $E_{c,d,s}$ is employment in a sector, in a region; $E_{c,d}$ is total regional employment, $E_{c,s}$ is national employment in the sector and E_c is total national employment. The index is thus simply the ratio of employment in a given sector and total employment in a region divided by the share of this sector at the national level. It reflects whether a region is more specialized in a particular sector than the rest of the national economy.

As for additional variables, alternatively to Combes, we will use Krugman index to assess the diversification in a given region, as described above, instead of a relative Herfindhal index [11]. Other explanatory variables include our indices of the sectoral size and regional size, as described above. We also account for human capital by including the three measures discussed (percentage of tertiary education, median age and women proportion). Additionally, we include country-fixed effects to remove country-specific invariant variation from our across-country sample. We also correct standard errors by clustering them at the regional level as suggested by the presence of important within-group heteroskedasticity [12] .

We thus conduct two separate estimations, one of pooled services sectors and one on manufacturing of the following form: All the variables are taken in logarithm and may be thus interpreted as elasticities.

$$\begin{aligned} y_{c,d,s,2003/2014} = \alpha &+ \beta_1 spec_{c,d,s,2003} + \beta_2 div_{c,d,s,2003} + \beta_3 reg_{c,d,s,2003} + \beta_4 sect_{c,d,s,2003} \\ &+ \beta_5 educ + \beta_6 prod + \epsilon_{cs} \end{aligned} \tag{2}$$

4.4.2 Results

Table 6 resumes the results. The overall magnitudes of elasticities are relatively low, although comparable with those found by Combes (2000). As the time period in consideration is relatively long, small elasticities may reflect that the impact of initial structural conditions in the regions on the long-term growth rates vanished over such a long period. This would be especially the case for fast-changing regions, where the initial conditions may not be as important for their growth rates. The R-squares are however correct, explaining more than 10 percent variation in employment growth rates.

We find positive impact of own sector share for both industry and services, although with small magnitudes. This suggests the existence of localization economies for both services and industrial sectors across European regions. The impact is however stronger for services, when controlling for human capital (elasticities up to 0,16). Interestingly, Combes(2000) did not find evidence of localization economies and for most of the industries or services in France the elasticities were found to be negative. This quite surprising result may be explained by country-specific growth patterns of particular sectors, with a large decline in some French industrial sectors. Given that our sample includes all the European countries, including those who have not seen a sharp decline in industrial production over the period, and controls for country-fixed effects, the effect is found to be in line with MAR externalities theory. As in new member states the share of manufacturing tends to be still relatively high (although declining), we include an interaction term between share of own sector and a dummy for new member states to test whether the impact is different. The results show that there is no significant difference in the effects, suggesting that localization externalities over the period were present both in so-called Central and Western countries and new member states.

Diversity index is found to have a slightly negative impact within the group of industry sectors and a positive but insignificant within the pooled services. This somehow confirms the general view, in line with models with differentiated inputs and outputs and monopolistic competition, that industry does not rely as much as services on diversified inputs and higher diversification may increase. Intuitively, heavy industries rely much more on specialized sets of inputs and does not require much backward linkages with other sectors. Therefore,

[11] See Combes(2000) for details.

[12] We cluster at the regional level as we follow a common procedure of clustering at a larger level (to reduce bias, but allow more variation) and we continue clustering until the change in standard errors is relatively small. See the discussion over clustering in Cameron/Miller's guide to clustering (2015)

Table 6: Sectoral cross-sections

	(1) Manuf1	(2) Manuf2	(3) Manuf3	(4) Services1	(5) Services2	(6) Services3
Share of own sector	0.0746***	0.0678***	0.0763***	0.0676*	0.159***	0.153***
	(3.29)	(2.96)	(3.19)	(1.79)	(3.99)	(3.26)
Diversity	-0.0320**	-0.0308*	-0.0278*	0.0185	0.00574	0.00741
	(-2.02)	(-1.90)	(-1.68)	(0.96)	(0.32)	(0.36)
Size of the region	0.0254***	0.0240**	0.0194*	-0.0219*	-0.0196	-0.00965
	(2.70)	(2.39)	(1.77)	(-1.73)	(-1.62)	(-0.78)
Size of the sector	0.00989	0.00770	0.00952	0.0184**	0.0168**	0.0177**
	(0.66)	(0.48)	(0.58)	(2.39)	(2.07)	(2.15)
Log of tertiary educ.		0.0326	0.0104		-0.276***	-0.217***
		(1.02)	(0.29)		(-4.47)	(-3.54)
Labor productivity			0.0118			-0.0159
			(1.36)			(-1.18)
Constant	-0.384	-0.429	-0.515*	0.0176	0.796***	0.734**
	(-1.60)	(-1.65)	(-1.86)	(0.09)	(3.05)	(2.48)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	358	332	332	713	661	598
r2	0.115	0.123	0.127	0.115	0.149	0.155

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

diversity in a region could imply that scale economies decrease, reducing in turn employment growth. Also, one could interpret the finding as a sign of a slow decline in industry employment and transition to services-oriented markets in European regions: in the areas where diversity plays an important role with potentially large services sectors, workers tend to abandon traditional industries in favor of fast-developing productive services. The finding is in line with the initial paper.

Elasticity on the indicator of the regional size, reflecting overall density economies, is found to be positive and significant for all the manufacturing specifications. According to the theory it suggests that benefits linked to larger inputs and outputs markets dominate in industry sectors over higher land prices and congestion in infrastructure. On the other hand, regional size does not seem to play an important role for services: it seems that regional size does not impacted services sectors, one controlled for human capital and appears negative and significant in one specification. It thus suggests that the opposite mechanism operates within services: important costs linked to denser areas and competition do not seem to be compensated by knowledge spillovers and networks effects.

Moreover, sector size at the national level is found to generate positive impact on employment growth but seems to matter especially for services sectors, which is quite unexpected. One would expect national specialization in a given sector would benefit more industrial sectors as those are related to very specialized markets, both in terms of inputs and outputs. Wider national specialization would thus benefit a sector through efficient input linkages, large client basis and technical knowledge spillovers. However, it might be the case that increased competition pushed less productive firms out of the market offsetting the positive impact of spillovers. Therefore, we also control for the overall productivity level at the regional level, but its impact is found to be insignificant.

Finally, somehow surprisingly, higher level of education in the initial period has a negative impact on employment growth in services and is insignificant for industry. One would expect education level to boost employment level due to an increased labor productivity and advanced technical knowledge, especially counting in services. On the other hand, it may indicate that regions who in the initial period had a very high share of educated people grew less fast that those who had to catch up. Typically, growth rates in services sectors have been on average higher in low-developed regions in the new member states where the initial level of education has been lower. Importantly, the results confirm that controlling for human capital level and distinguishing it from urbanization economies is crucial, especially for services sectors.

The results of the cross-sectional analysis are broadly in line with our priors and confirm the importance of agglomeration economies both in services and manufacturing, with a differentiated impact. The cross-section analysis provided us with small long-term elasticities of agglomeration externalities in the long-run, suggesting that a shock to industrial composition has a small impact on average growth over the long-term period. However, one needs to keep in mind that the analysis did not take into account dynamic changes to which a region is exposed to when passing through a structural change.

Secondly, it assessed the long-term impact of an average growth over the period, computed as a compound average of growth rates from 2003 to 2014, knowing however that the recession followed by a slow recovery had a great negative impact on employment growth in most of the European countries. Therefore, intermediary growth rates over the period are not accounted for. Also, if we believe that there is indeed unobserved heterogeneity in play, the above estimates could be biased. Therefore, we will now turn to the dynamic panel data analysis which could shed some light on the issues.

4.5 Dynamic panel data estimations

4.5.1 Baseline model

In order to assess the determinants of regional employment growth dynamics linked to aggregation economies, we will investigate the following ADL specification separately for industry sectors and services sectors:

$$E_{c,d,s,t} = \alpha + \sum_{i=1}^{j} \beta_i E_{c,d,s,t-i} + \sum_{i=0}^{j} \gamma_i \mathbf{X}_{\ c,d,s,t-i} + \epsilon_{cds} + \upsilon_t + \nu_{cdst} \tag{3}$$

The dependent variable is log of employment in a country c, in a region d in a given subsector s, belonging whether to services or manufacturing. E_{dst-i} are the lagged variables of the dependent variables, while X_{dst-i} includes all the others explanatory variables, including various indices of regional industrial structure, as well as other regional characteristics as explained in the previous section.ϵ_{ds} is the unobserved time-invariant area-sector specific fixed effects and υ_t captures the overall trend effect, common to all the regions and countries. Importantly, country time-invariant effects are captured via ϵ_{ds}. The classic time-variant standard error is ν_{dst}.

The very general equation with lagged dependent allows us to study not only short-term impact through coefficients on contemporaneous and lagged coefficients of explanatory variables but also estimate the long-run multipliers. This will in turn allow us to study a potential contradiction in short and long term conclusions over the impact of agglomeration economies. To understand where the coefficient come from, consider the most general case of an ADL(p,q) model:

$$\beta(\mathrm{L})E_t = \alpha + \gamma(\mathrm{L})X_t + \upsilon_t, .\text{ where:}$$
$$\beta(\mathrm{L}) = 1 - \beta_1\mathrm{L} - \beta_2\mathrm{L}^2 - ... - \beta_p\mathrm{L}^p$$
$$\gamma(\mathrm{L}) = \gamma_0 + \gamma_1\mathrm{L} + \gamma_2\mathrm{L}^2 + ... + \gamma_q\mathrm{L}^q$$

Under stationarity, the long-run coefficients can be found as:

$$E_t = \beta^{-1}(\mathrm{L})\alpha + \beta^{-1}(\mathrm{L})\gamma(\mathrm{L})X_t + \beta^{-1}(\mathrm{L})\upsilon_t \text{ , therefore:}$$
$$\mathbb{E}[E_t] = \beta^{-1}(\mathrm{L})\alpha + \beta^{-1}(\mathrm{L})\gamma(\mathrm{L})\mathbb{E}_t[X_t]$$

Knowing that $\mathbb{E}[E_t] = \mathbb{E}[E_{t-1}] = \mathrm{L}\mathbb{E}[E_t]$ and $\mathbb{E}[X_t] = \mathbb{E}[X_{t-1}] = \mathrm{L}\mathbb{E}_t[X_t]$, we can find the long-run multiplier of the following form:

$$\gamma_{\mathrm{LT}} = \frac{\gamma(1)}{\beta(1)} = \frac{\gamma_0 + \gamma_1 + \gamma_2 + ... + \gamma_q}{1 - \beta_1 - \beta_2 - \beta_3 - \beta_p} \tag{4}$$

However, one needs to notice that the long-term multipliers are computed using "delta method" approximation as a non-linear combination of the model's estimates. They are thus subject to possible noise, especially when coefficients on lagged dependent variables are high, which is our case. Also, the number of periods in our sample is relatively short. Therefore, we will also test the following constraint: $\sum_{i=1}^{j} \beta_i = 0$. If the sum of the estimates on the independent variables is not statistically significant from zero, we will consider that changes to the regressor have only short-run impact. For the explained reasons, long-run elasticities should be considered with caution.

Considering the number of lags to use, there are little indications in economic theory on the dynamics of agglomeration externalities. In most of the empirical studies different lag length were used without properly explaining their reasons of the specific choice. Henderson (1997) found that agglomeration economies dynamics vary importantly among the sectors in the US, some of them showing signs of dynamic impact and some more static. However, the lag length found was very long indicating dynamic nature of externalities in the US. However, externalities are found to be more static in Europe.Therefore, Brulhart (2008) in a similar setting suggests adopting ADL(1,1) specification as this very broad generic specification allows for testing several hypothesis. Also Combes, Robin and Magnac (2003) after a careful model selection apply a model of order 1. Indeed, ADL(1,1) allows for testing whether the model may be interpreted as a 'common factor model' where the data exhibits contemporaneous effects and autocorrelated errors (in this case $\gamma_1 = \frac{\gamma_0}{\beta_1}$, jointly for all independent variables) . In our case this would mean that the adjustment in employment occurs in the current period, but the shock is persistent (there is autocorrelation in the error term). Moreover, the data may also point into ADL(1,0) suggesting partial adjustment of the dependent variable to the shocks, late absorption and therefore a delayed effect. The underlying assumption implies that $\beta_i = \gamma_i = 0$ for $t > 1$. We will test both of the restrictions using a classic Wald test on linear restriction (for ADL(1,0)) and a non-linear Wald test for the common factor model. [13]. On its side Blien (2006) assumed ADL(2,2) model with two lags for each explanatory variables. Consequently, we tested both ADL(1,1) and ADL(2,2) models and chose ADL(1,1) model as our preferred option as longer lags of independent variables do not appear as significant (results in annex). Moreover, ADL(1,1) allows us not to impose specific restrictions on our dynamic process and enables us to test different mechanisms.

Moreover, in dynamic panel data models, the time-invariant fixed effect is fundamental. Independently of whether the unobserved heterogeneity is correlated with the explanatory variables, any estimation in cross-section or OLS based on instruments being lagged will yield biased estimates if the unobserved effects are large. Panel data allows for removing of the fixed effect by first-differentiating the equation:

$$\Delta E_{dst} = \sum_{i=1}^{j} \beta_i \Delta E_{dst-i} + \sum_{0=1}^{j} \gamma_i \Delta \mathbf{X}_{\ dst-i} + \Delta \upsilon_t + \Delta \nu_{dst} \tag{5}$$

However, as noted by Nickell (Econometrica (1981)), in the context of dynamic panel data demeaning does not solve the problem. Subtracting mean value of both dependent and independent variables creates a correlation between the lagged regressor and the transformed error, resulting in a bias estimate of the lagged dependent variable. Importantly, the bias is exacerbated when N is large and T is small, which is our case.

Therefore, the use of past values of the dependent variable starting from the second lag has been proposed. They are natural candidates for good instruments as past values are highly correlated with the lag dependent variable and uncorrelated with the error term under the assumption of independent and identically distributed errors. GMM methods offer an elegant way to depict the causal impact of the exogenous variables, while exploiting these internal instruments in a very flexible way.

[13]commands are available as post-estimation commands of xtabond2 STATA package for GMM

4.5.2 Estimation strategy and discussion of GMM

The most common estimator offering solutions to such problems is DIFF-GMM suggested by Arellano and Bond (1991). The method estimates the first-differenced data, allowing for elimination of regional unobserved time-invariant heterogeneity and instruments all endogenous variables with their lagged levels, assumed to be uncorrelated with the error term. The estimation method imposes some relatively weak assumptions to validate instruments already present in the sample. It requires that the initial conditions are pre-determinded and uncorrelated with the error term: $\mathbb{E}[E_{cds1}\nu_{cdst}] = \mathbb{E}[\mathbf{X}\ _{cds1}\nu_{cdst}] = 0$, for all $t > 2$. Intuitively this implies that employment series are long enough not to be correlated with initial employment level. Moreover, the estimator is consistent when $N \to \infty$ for T given. This is the case of our dataset counting 218 regions for 14 years. However, according to Blundell and Bond (1998, 2000) DIFF-GMM seems to perform poorly where the lagged dependent variable is very persistent (β is large and approaches unity) or when the variance of unobserved fixed effect is high relatively to the error term. If this situation occurs, the lagged levels used as instruments are only weak instruments. Given that our explanatory variables of industrial structure of regions are likely subject to slow change over time and variance of the region-sector specific fixed effect is very high, these considerations are relevant. The DIFF-GMM estimation would thus suffer from sample bias.

Therefore, another related dynamic panel estimator proposed by Arellano and Bover (1995) is recommended in these circumstances. System GMM (SYS-GMM) estimates simultaneously an equation in levels, instrumented by differences, and a second in differences instrumented by levels making use of all the possible information in the dataset. However, the estimator requires additional assumptions to hold, namely: $\mathbb{E}[\Delta E_{cds2}\nu_{cdst}] = \mathbb{E}[\Delta\mathbf{X}\ _{cds2}\nu_{cdst}] = 0$. The sufficient condition for the equation to hold is mean-stationarity excluding secular trends for all the explanatory variables. In our case may seem very stringent as an assumption given high persistence of industrial structure patterns. However, one could circumvent this difficulty by including time effects to the equation. According to Brulhart (2008), this would allow for time trends while respecting the requirement of the equation, remove time shocks common to all the countries from the error term and require only lack of diverging patterns within countries. Importantly, diverging trends within countries are not observed as noted by Combes and Overman (2004) when all the explanatory variables are expressed as deviations from their respective country means. Therefore, as the within-country dispersion of the regressors is stable, one can assume the assumption to hold for the country-demeaned data. On the other hand, the condition of mean stationarity is a sufficient but not a necessary condition. According to Brulhart(2008) following the remark of Blundell and Bond (1998), the assumption requires that the process generating the series was long enough to assume that the initial conditions are irrelevant or, on the other hand, initial errors are distributed randomly between regions. Blundell and Bond (1998) insist on important advantages relatively to DIFF-GMM in the case of small samples. The additional merits of the method lie in reducing measurement errors relatively to cross-sections widely used in the related literature: time invariant component of the error term is removed making the estimation more robust. Moreover, with lags long enough the estimator is also consistent even when time variant and region-specific (but not serially auto-correlated) measurement errors are present.

When using SYS-GMM, one needs to pay attention to the number of instruments used. By default, all past levels and differences of the explanatory variables are used as instruments to make use of all available data. However, it may lead to overfitting of endogenous variables. Especially, given that any precise methodology aiming at defining number of lags used exists, one needs to carefully choose the specification relying on existing tests of instruments validity, as well as on Arellano Bond tests for second-order autocorrelation. Instruments validity tests assess if the excluded instruments are correctly independent of the error term process. Sargan test regresses the residual form an IV regression on all instruments used. Under the null hypothesis of jointly uncorrelated instruments, the test has a chi-square distribution. The test is not robust, but not weakened by the number of instruments. Hansen test on the other hand generates J statistic that should not be too large for the instruments validity to hold. If both statistics reject the validity of instruments, estimates should be considered with extreme caution. We will thus report both statistics in our estimations.

However, no tests exist verifying the strength of the instruments and checking that they are not too weak. Weak instruments would be unreliable in predicting endogenous variables. According to Bun and Windmeijer (2007) , system GMM would be subject to the same bias as DIFF-GMM if instruments are too weak, especially when the variance of the area-sector specific fixed effects is smaller than the variance of the time-varying error term. In our case, variance of time invariant component is much higher than error term's which brings additional reassurance about instruments validity. Moreover, a standard procedure suggested by Bond et al. (2001) consists on comparing the coefficients on lag dependent variable from the GMM regression from those obtained by the same estimates in OLS and simple FE. OLS coefficients are assumed to be the upperbound and FE the lowerbound. If the coefficients from the GMM estimation lie in the interval, this indicates correct choice of the instruments. Moreover, according to Bun and Windmeijer (2007), one could also check if the first differences of the dependent variables are significant when regressing it on the lagged levels. We conduct such tests for all our specifications.

Therefore, we will estimate the equation 3 in an ADL(1,1) specification for two separate samples: pooled industry and pooled services sectors. Given potentially remaining endogeneity issue explained above, we will instrument both the lagged dependent variable and the three indicators related to industrial structure (Krugman index of diversity, size of the region and size of the sector at the national level), as well as the productivity measure included in some specifications. Following the practices suggested above, we will instrument all the endogenous explanatory variables by the lags starting from the third past period, as suggested by a persistent autocorrelation in the data. In some specifications, especially those including numerous controls, the number of lags is restricted. According to Arellano (2003b), this is analogous to a projection of a full set of instruments with constraints on coefficients to be zero. Instruments are combined through smaller sets. The method keeps all the instruments retaining all the informations provided, but impose a constraint on the coefficients of these subjects.

Moreover, all our specifications indicate correct values of Sargan and Hansen statistics. They also fulfill all the additional criteria indicating validity of our instrument set both in manufacturing and services. Following Brulhart (2008), as well as Combes, Robin and Magnac (2004), given that country and time fixed effects account for a large part of the variance in the employment series, we will demean the variables by their respective country means. As we are not interested in the effect of universal trends, we will also include time fixed effects in all the specifications to remove common time-related shocks from the error term. A contrario, as we are interested in country- and industry-specific shocks (e.g. government's intervention on particular sectors or technology shock in a particular sector) impact on local employment, we will not remove this part of the variance. We also impose quite restrictive clustered standard errors on regions, as the data exhibits important groupwise heteroskedasticity, confirmed by a modified Wald statistic of a fixed effect regression (Greene 2000). Finally, we will apply a two-step estimator that together with small sample Windmeijer's correction is found to yield more efficient results.

4.5.3 Panel data testing

Before proceeding to estimations, number of tests on the data is conducted. First, we assess stationarity of the data in first difference necessary for the further analysis. In order to assess stationarity in first-difference for our panel, we use Im-Pesaran-Shin test, suitable for large N given T and unbalanced panels. The null hypothesis that all panels have a unit root is rejected for all variables, suggesting that at least some of our panels follow stationary process. The results confirm stationarity of our variables in first-differences. Dickey-Fuller's results confirm the finding.

Moreover, Wooldrige (2002) test assesses serial autocorrelation bias in the idiosyncratic error of a linear panel data that could potentially infer with the standard errors. It suggests indeed some potential autocorrelation issues. However, one needs to notice that the test is not performing well in presence of heteroskedasticity. Finally, we performed Hausman test, testing whether fixed or random effects should be applied. The null that random effects are consistent is rejected for all our specification. We therefore performed on the favorite specification with fixed, rather than random effects.

As part of the data testing, we conduct estimations using classic pooled OLS and Fixed-effect within estimator, known to be both biased in a dynamic setting with unobserved heterogeneity. According to Bond (2002), the estimations are useful as they provide an upperbound (via OLS) and lowerbound (FE) of the lagged dependent coefficient in presence of endogeneity. Indeed, if we believe that the unobserved heterogeneity has a positive impact on our independent variables, the OLS estimator would be biased upwards. On the other hand, fixed effects estimates will be biased downward as in the transformed error term the sign on $t-1$ is negative. The results are presented in table 7 and indeed indicate a range of coefficients on lagged dependent variables between 0.983 and 0.603 for industry and 0.959 and 0.616 for services. This points to positive and persistent impact of own-sector employment, without explosive growth neither for manufacturing or services, as the coefficients are smaller than 1. The rest of the coefficients are biased, but they still confirm the findings of the cross-sectional analysis. We find significant evidence of positive impact of diversity and regional size in services sectors in the short run. For industry, the impact of diversity is insignificant and overall regional size seems to matter only with delay, pointing to the importance of a dynamic specification. Size of the sector at the national level seems to matter for both industry and services. Importantly, the short-run elasticities found are also importantly larger than the long-run found in the cross-sectional analysis before, pointing at a sharper initial effect. Finally, education is positive and significant in both OLS and FE regressions for services, which is confirming the conventional knowledge. In industry, the coefficients are very small and negative pointing to a possible across-sector labor migration due to an overall higher level of educations. The explanatory power of the models is also very high.

However, both estimators are subject to serious biases with autoregressive panel models. Therefore, the use of GMM estimator is recommended.

4.5.4 Consistent estimators: System-GMM - Baseline

As discussed in the previous section, we apply system GMM to our ADL(1,1) model of the equation 5 for both sample of services and manufacturing in order to account for dynamics of agglomeration economies while properly accounting for remaining endogeneity. The results are presented in table 8. All the lagged dependent coefficients fall within the range of coefficients suggested by pooled OLS and FE estimations, giving additional reassurance in results reliability. Moreover, all the tests point to valid Sargan and Hansen statistics. Autocorrelation tests are also reassuring for all our specifications, given that we started instrumenting with the third lag backwards. Therefore, the estimations seem to be valid based on disposable statistics.As all the explanatory variables are expressed in logs, the coefficients may be interpreted as elasticities of the growth rates.

Concerning manufacturing, our findings somehow confirm the cross-section analysis. We thus find a high and positive elasticity related to the lagged dependent variable in all the specifications, pointing towards positive and persisting impact of own-sector employment increase in the short-run. Therefore a 1 percent increase in sectoral employment growth in $t-1$ leads to an increase in today's growth rate of around 0.8-0.9 in the short run. However, the coefficient is less than 1, suggesting that no stricto sensu Marshallian externalities occur. However, very high coefficients implies that, following a shock, employment is growing faster. Some authors however interpret very high values of the coefficient as evidence of localization economies, which would be plausible especially that the coefficient is not statistically different than 1. Moreover, diversity seems to be neutral when not controlling for either education level or productivity. However, it negatively affect growth rates in the short run with the controls (M3). It suggests that across-regional differentials in both education and productivity infer in two opposite directions with the impact of diversity: highly productive regions with educated labor could indeed benefit more from spillovers from the other sectors and better absorb a potential increase in land prices or input costs. However, as indicated by the coefficient on the second lag, past shocks to diversity vanish quickly over time. This

Table 7: OLS and fixed effects

	Industry		**Services**	
	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)
L.Log of employment	0.983***	0.603***	0.959***	0.616***
	(348.17)	(19.71)	(158.93)	(22.32)
Diversity	0.00994	0.0118	0.0278**	0.0395***
	(0.95)	(1.21)	(2.00)	(2.74)
L.Diversity	-0.00505	0.00164	-0.0275*	-0.0133
	(-0.48)	(0.17)	(-1.97)	(-0.99)
Size of the region	-0.00796	-0.0144	0.313***	0.346***
	(-0.15)	(-0.27)	(3.73)	(3.75)
L.Size of the region	0.0237	0.111**	-0.265***	-0.179**
	(0.44)	(2.21)	(-3.15)	(-2.00)
Size of the sector	0.886***	0.897***	0.674***	0.661***
	(17.13)	(20.80)	(10.69)	(10.32)
L.Size of the sector	-0.871***	-0.530***	-0.633***	-0.361***
	(-16.70)	(-9.68)	(-10.18)	(-7.45)
Log of tertiary educ.	-0.00753**	-0.00232	0.0634***	0.0476***
	(-2.05)	(-0.21)	(7.02)	(2.65)
Constant	-0.199***	-2.021***	-0.922***	-2.534***
	(-4.06)	(-5.27)	(-7.07)	(-4.72)
Country FE	Yes	No	Yes	No
Observations	5158	5158	10285	10285
r2	0.999	0.863	0.996	0.574

All variables are expressed in logs. Standard errors are clustered at regional level.
t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

is confirmed by the long-term multipliers for all the specifications. Therefore, in comparison with the cross-sectional analysis accounting for dynamic change in sectoral composition made the long-term coefficients insignificant, without a change in the sign.

Regional size seems to matter only in the long-run: for all the specifications the short run coefficients are insignificant, while the inferred long-term coefficients are highly positive. They indicate a large, slightly more than proportional impact of a 1 percent increase in the overall growth rate of regional employment. The finding seems to be relatively intuitive as the effects of the overall increase in employment in a given region may take time to spread into a particular sector. An increase in total employment may be associated with lower factor costs, higher demand for products or affect a given sector via knowledge and technological spillovers that take time to realize. The effects are also quite long-lasting and cumulating, as a shock to total employment, due to e.g. migrations, can be quasi-structural. Interestingly, inclusion of productivity lowers the gains from an increase in own region in the long run. Controlling for productivity allows for distinguishing between more productive and probably faster-growing regions and those lagging behind. Therefore, it seems that the impact of an increase in own region depends importantly on the level of productivity. However, the coefficient on productivity is insignificant, suggesting that the impact of pure productivity shocks is partly absorbed in other explanatory variables. Finally, as predicted, positive and significant elasticities are found for all the specifications indicating that a shock to own-sector at the national level results in both short and cumulative long-run positive effects. It is again intuitive: a large shock to sectoral size and increase in national specialization may

Table 8: System-GMM table

	(M1)	(M2)	(M3)	(S4)	(S5)	(S6)
		Industry			**Services**	
L.Log of employment	0.870***	0.867***	0.829***	0.904***	0.909***	0.956***
	(11.84)	(12.03)	(11.39)	(12.31)	(13.74)	(13.78)
Diversity	-0.0855	-0.0767	-0.116*	0.338**	0.373***	0.367***
	(-1.29)	(-1.17)	(-1.76)	(2.24)	(3.03)	(2.85)
L.Diversity	0.0574	0.0521	0.0806*	-0.200*	-0.211**	-0.198**
	(1.20)	(1.13)	(1.67)	(-1.82)	(-2.45)	(-2.09)
Size of the region	0.00574	0.224	0.247	1.008	0.798	0.457
	(0.01)	(0.63)	(0.71)	(1.23)	(1.54)	(0.77)
L.Size of the region	0.146	-0.0684	-0.0683	-0.763	-0.544	-0.275
	(0.33)	(-0.20)	(-0.20)	(-0.99)	(-1.13)	(-0.49)
Size of the sector	0.986***	0.954***	0.949***	0.910***	0.917***	0.944***
	(10.24)	(11.85)	(11.82)	(5.59)	(5.99)	(6.85)
L.Size of the sector	-0.849***	-0.816***	-0.771***	-0.838***	-0.841***	-0.882***
	(-6.19)	(-6.92)	(-6.78)	(-4.58)	(-4.81)	(-5.65)
Log of tertiary educ.		-0.0153	-0.0127		0.00271	-0.00443
		(-0.84)	(-0.73)		(0.09)	(-0.15)
Productivity			-0.0140			0.0905
			(-0.42)			(0.75)
Constant	-0.00118	0.00173	0.00206	-0.00971	-0.00957	-0.0205
	(-0.18)	(0.21)	(0.18)	(-0.63)	(-0.63)	(-0.70)
Long term coefficients						
Diversity	-0.215	-0.184	-0.204	1.438	1.777	3.795
	(-1.04)	(-0.90)	(-1.29)	(1.41)	(1.37)	(0.69)
Size of the sector	1.051***	1.035***	1.037***	0.751	0.826	1.403
	(7.56)	(7.94)	(9.93)	(1.27)	(1.31)	(0.76)
Size of the region	1.164***	1.165***	1.044***	2.559***	2.790**	4.102
	(4.15)	(4.62)	(5.21)	(2.53)	(2.29)	(1.04)
Restriction testing						
ADL (1,0)	0.000	0.000	0.000	0.000	0.005	0.004
Common factor	0.000	0.000	0.000	0.009	0.000	0.000
Observations	4896	4768	4648	9757	9502	8250
sarganp	0.254	0.244	0.311	0.0989	0.153	0.131
hansenp	0.454	0.455	0.576	0.205	0.249	0.268
ar2p	0.000694	0.000548	0.00143	0.815	0.922	0.365
ar3p	0.362	0.330	0.452	0.318	0.378	0.509

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

indeed benefit a regional producer in a short run through larger demand offsetting higher competition effects, for a given level of productivity and human capital. However, positive knowledge spillovers occur with a delay exacerbating the effect. The coefficient on education level is insignificant, as it was the case in the cross-section analysis and its inclusion does not change the results in the short-run.

Once again when turning to services, the overall impact of agglomeration economies changes. Similarly to the cross-sectional findings, the impact on own-sector increase is positive and significant in all the specifications. The coefficients are higher than in industry sectors, suggesting higher impact of localization externalities, as found by e.g. Brulhart (2008), Blien (2006). As all the coefficients are less than 1, there are no strict signs of Marshallian economies acting in European services. However, as it is the case with industrial sample, the effect is not statistically different than 1. We can thus expect that the broad sectoral aggregation indeed lowered the elasticities, as suggested by Beaudry et al. (2013). Moreover, an increase in diversity is found to have a positive and significant impact in the short-run for all the specifications, with moderate elasticities of around 0,3 - 0,4. The effect of shocks seems quickly dampened, as suggested by the first lag of the Krugman index entering with a negative sign of a similar size. As found in the cross-sectional analysis, the effects become insignificant in the long-run which has been confirmed by a large part of the related literature.

Own-sector size has a strong and positive coefficients for all the specifications. Once again past shocks' effects vanish quite quickly as indicated by a high negative elasticity on the past values of sector size growth. Long-term multiplier is indeed insignificant. Finally, overall regional size does not seem to be significantly important in the short run, but the long run effects are important. The magnitude are very large, even more than in the case of manufacturing sectors. The finding seems plausible, as services, defined here as various business-related activities are very much tied to overall density economies as they depend on larger range of inputs and interactions. It somehow confirms the predictions of heterogenous input and output models with imperfect competition. The coefficient on percentage of tertiary education is positive, but insignificant potentially reflecting potentially a relative lack of variability in the data in a short period of 15 years.

To sum up, accounting for dynamics in effects of different types of agglomeration economies provides additional insights into long-term implications of sectoral composition changes at regional level. Our analysis indicates that shocks to industrial composition tend to be quickly dampened. Past shocks to most of the regressors impact current growth rates only within a few periods, as confirmed by the ADL(2,2) model where second lags of the independent variables are not significant. This is in line with the conclusion of Combes, Magnac and Robin (2004) who confirm a relatively static nature of externalities for the French regions. However, while a shock to diversity does not seem to have long-lasting impact on the growth rates, long-term multiplier for regional size and sector size suggest that for some types of externalities there might be a long-term positive and important impact on employment rates. The long-lasting impact would be however transmitted indirectly through persistence in own-employment: even a relatively small shock to industrial composition and thus, in turn, to own-sector employment seems to be relatively persistently transmitted over the period. We therefore checked whether the series exhibit evidence of a pure common factor restriction in which the shock would be absorbed in the current period and transmitted by autocorrelated errors. The restriction is however rejected pointing to a lasting impact of localization economies. The finding is consistent with Blien (2006) who also finds similar relationships.The results are robust to the country coverage and changes in lags specifications, as presented in the annex. Results for manufacturing only also yield similar results.

4.5.5 Consistent estimators: Interactions

However, one could also wonder whether the impact of different types of agglomeration externalities depends on the content of the industry mix. One could expect that in a predominately industrial region, impact of agglomeration externalities on services sectors could differ from those operating in a services-oriented region, as competition effects within sector might be much lower. However, in this case knowledge spillovers are also likely to be lower, leaving the impact ambiguous. Vice versa, for an industry sector the impact of agglomeration externalities could be different in a more industrial regions with a large input base and stable demand market, but also with higher competition than in a region typically services-oriented. In order to get the first insight on the prevalent forces, we add additional interaction terms between each agglomeration externality (linked to diversity, region size and

Table 9: Interaction terms

	(M1)	(M2)	(S1)	(S2)
	Industry		**Services**	
L.Log of employment	0.924***	0.912***	0.935***	0.972***
	(15.04)	(16.91)	(12.79)	(13.59)
Diversity	-0.0693	-0.0876	0.315**	0.325**
	(-0.97)	(-1.29)	(2.46)	(2.56)
L.Diversity	0.0241	0.0379	-0.170**	-0.175**
	(0.65)	(1.06)	(-2.19)	(-1.98)
Size of the region	0.170	0.141	0.656	0.365
	(0.47)	(0.38)	(1.15)	(0.59)
L.Size of the region	-0.0385	0.00445	-0.410	-0.212
	(-0.11)	(0.01)	(-0.81)	(-0.37)
Size of the sector	0.913***	0.932***	1.056***	0.943***
	(10.19)	(10.63)	(6.49)	(6.81)
L.Size of the sector	-0.840***	-0.844***	-1.020***	-0.900***
	(-7.09)	(-7.88)	(-5.24)	(-5.63)
Log of tertiary educ.	-0.0167	-0.0147	-0.0134	-0.00563
	(-0.87)	(-0.78)	(-0.46)	(-0.19)
Productivity		0.00198		0.0513
		(0.08)		(0.46)
Sector x services	0.0139	0.0137		
	(1.12)	(1.08)		
Region x services	-0.0221**	-0.0240**		
	(-2.02)	(-2.09)		
Diversity x services	0.0410	0.0529		
	(1.24)	(1.44)		
Diversity x industry			-0.0424	-0.0473
			(-1.09)	(-0.82)
Sector x industry			0.0408*	0.0310
			(1.69)	(1.26)
Region x industry			-0.0329	-0.0229
			(-1.55)	(-1.00)
Constant	0.0115	0.0162	-0.00106	-0.0109
	(1.05)	(1.45)	(-0.06)	(-0.41)
Observations	5158	5010	10285	8862
sarganp	0.528	0.660	0.454	0.127
hansenp	0.662	0.664	0.660	0.230
ar2p	0.000629	0.00156	0.962	0.348
ar3p	0.214	0.240	0.307	0.513

t statistics in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.010$

sectoral size at the national level) with a dummy taking a value of 1 if the biggest sector of a region belongs to services and industry for the sample of industry and services, respectively.

The results are presented in the table 9. The inclusion of interaction terms did not change the main results conlusions. Moreover, most of the dummies are insignificant indicating that whether the biggest sub-sector belongs to own-sector or other sectors does not seem to matter for the impact of externalities. In two cases however, the dummies are significant. Within industry sectors, the impact of the regional size on industry sector is lower when the biggest sector belong to services. The impact however does not seem to change the conclusions: regional size increase does not impact growth in the short-run, only in the long-run. The long-run coefficients are therefore slightly lower in the regions where main sector belongs to services. For the services sample, the results suggest an additional positive impact of own-sector increase at the national level when the biggest sector belongs to manufacturing. Both the short and the long run coefficients are therefore higher for these regions. The result indicates that a nation-wide shock to the overall size of the sector, yielding technological and knowledge spillovers, benefits more regions where the competition in the field is lower.

Consequently, our results indicate that industrial composition and the type of the sectors, not only their relative size, present in regional network matter indeed when evaluating impact of agglomeration externalities.

4.6 Instability of employment

Having overviewed the impact of different agglomeration externalities types on growth of employment both in the short and in the long-run, one could already conclude that there is no inconsistency between short and long-term effects: for some particular types the effect seems to be positive, but simply vanishing over time without influencing long-run growth (e.g. diversity economies). Moreover, own-sector employment has a stable, positive and persistent elasticity. However, the common prior states that specialization may have a beneficial impact during upturns and lower during downturns, while the opposite is supposed for diversity economies. This would in turn impact the overall variation in employment. To investigate the question, we will therefore study the impact of the agglomeration economies on variation of regional employment per sector. The dependent variable is standard deviation of the regional employment growth over the sample period in a given sector. The controls are the same as before, where the variable *share of own sector* corresponds to the one used in cross-section analysis[14]. We follow two different methodologies. The first one considers the impact of the changes occurring in the baseline year 2003 on the standard deviation over the entire period (following Attaran (1986)) and is our preferred option as it reflects long-term implications of industrial structure. The second one regresses averages of the indicators over the whole period following Baldwin (2003) taking into account contemporaneous impacts over the period as well. As before, we include country-fixed effects and clustered standard errors at the regional level.

The results are presented in table 10. The coefficients of interest are significant and the part of explained variation is large. First, the most important agglomeration effect decreasing variability of employment seems to be the overall size of the sector at the national level for both manufacturing and services. The result indicates that specialization at the national level reflects a probable comparative advantage in the sector which stabilizes employment growth. Indeed, one may think of several mechanisms that could justify the result. A large sector at the national level (especially given that the level of sectoral aggregation is relatively broad) is likely to develop stable input-output networks and benefit from within-sector technological spillovers providing an additional shield against sector-specific shocks. Moreover, important sectors in which a country specialized is likely to benefit from an important comparative advantage providing a stable client base and lower demand elasticity in case of a sector-specific shock. Finally, for important sectors incentives are provided for governments to protect employment in case of sector-specific shocks.

Moreover, overall size of the region also seems to have a stabilizing impact on employment growth in both industry sectors and services, which is once again intuitive. Larger markets tend to create more complex networks of sub-sectors allowing for an efficient labor pooling. Also, larger and denser markets also offer relatively higher local demand both of inputs and

[14] $spec_{c,d,s} = \dfrac{E_{c,d,s}E_{c,d}}{E_{c,s}E_c}$

Table 10: Instability

	Industry		**Services**	
	Base	Mean	Base	Mean
	(1)	(2)	(3)	(4)
Share of own sector	-0.494	-0.561	-2.683**	-3.142**
	(0.344)	(0.227)	(0.021)	(0.010)
Diversity	-0.424*	-0.356	-3.176***	-2.692***
	(0.076)	(0.191)	(0.000)	(0.000)
Size of the region	-0.592***	-0.608***	-0.878***	-0.955**
	(0.000)	(0.000)	(0.010)	(0.019)
Size of the sector	-2.837***	-3.153***	-2.067***	-2.253***
	(0.000)	(0.000)	(0.000)	(0.000)
Log of tertiary educ.	-0.448	-0.394	3.724	3.442*
	(0.459)	(0.555)	(0.105)	(0.086)
Labor productivity	-0.299	-0.256	-8.827***	-7.517**
	(0.756)	(0.800)	(0.004)	(0.012)
Country FE	Yes	Yes	Yes	Yes
Observations	332	360	656	600
r2	0.955	0.958	0.761	0.749

Dependent variable is sd. of employment growth.
Estimation 1 and 3 (*base*) are based on regressor in the base year.
Estimation 2 and 4 (*mean*) are based on regressor in the base year.
Standard errors are clustered at regional level.
p values in parentheses
* p<0.10, ** p<0.05, *** p<0.010

outputs. Finally, in larger areas efficiency of knowledge spillovers and innovation encourages growth-friendly innovation.

Specialization seems to have different impact on employment growth stability in industry and services. While own-sector share is found to have an insignificant impact in the sample of industry, it decreases variability of growth rates in services sectors in both specifications. Thus, we do not observe the assumed relationship that own-sector specialization increases employment variability in services sectors. However, it might be indeed the case that, holding diversity constant (meaning that own-sector increases when others become relatively closer to the national average share), an increase in own sector size allows for larger scale economies while still benefitting from important diversity offered by an area. The sign of the relationship is the same for industry, the impact is insignificant. This may be due to the fact that given that services sectors are mostly concentrated in diversified and urban areas and industry tend to delocalize, the baseline level of diversity level for manufacturing is not high enough to benefit from, as Kroll(2010) stated, 'diversified specialization'. Therefore, own sector specialization does not seem to play a role in industry-related sectors.

On the other hand and confirming the common view, diversity is found indeed to decrease instability in both industry and services sectors pointing once again to the beneficial impact of developed industry mix for stability of growth employment. The effects are however much larger in services sectors than in manufacturing, reflecting the fact that services sectors rely on a larger range of inputs and thus benefit more from between-sectors interactions. The insignificant impact in the second regression of industry may illustrate that a shock to diversity in a region benefit industry sectors with a delay, as indicated by the significant result of the first regression.

Therefore, as expected relative diversity is found to have a positive and significant impact on employment growth stability. However, one needs to notice that it is not the most important factor: apart from important impact of the overall sector size nationwide, an increase in productivity level seems to decrease the standard deviation of employment in business services. Indeed, more productive sectors make use of a comparative advantage and resist better to shocks. The productivity level however does not seem to play a role in industry sectors, maybe because of a different nature of the shocks abating on industrial sectors.

Finally education level does not seem to contribute to the overall variation in growth rates, with the exception of one regression on services where the variable enters with a positive sign. As regression 4 includes contemporaneous impacts of an increase in education level, it might illustrate young educated people across-region mobility, observed in Europe.

5 Conclusion

5.1 Time-inconsistency issue and policy implications

The conventional view and a large part of the literature hypothesize the link between diversity and stability, suggesting a trade-off in pursuing both growth-friendly and stability-seeking policies. According to the theory, policy makers would thus have to choose between volatile but sizeable growth and employment stability at the cost of lower growth rates. As policy makers often focus on short-run gains and there is no unanimity on the subject, our analysis of the dynamic impact of agglomeration economies on the level of employment growth and instability may provide new insights on the subject.

First, when considering the dynamics of the impact of agglomeration externalities on the level of growth, we do not find evidence of a diametrically opposite impact in the long-run with respect to the short-run. Past shocks seem to impact positively long-term growth via persistence in own-employment series, depending on the sector considered and the type of a shock. As the heart of our interest, localization economies do not seem to exhibit time inconsistency issues sensu stricte. The impact of a shock to own-sector employment seems to have a persistent positive impact both in industry and services, with a very slow return to the mean. Industrial diversity in the regions seems to impact differently the two sectors. In the short-run, an increase in diversity seems to have a positive impact on growth in services and a negative one in manufacturing. In the long-run, the effects of a shock to diversity seem to disappear in both cases, with some indications of a possible positive impact on services. Therefore, if we consider the issue at a face value of long-term growth, there is no time inconsistency in either type of agglomeration economies in both sectors.

However, the analysis of the standard deviation of employment growth points to a possible time inconsistency issue. According to the results, diversity indeed reduces the volatility of employment growth both in industry sectors and services. As stated above, diversity may imply a negative impact on employment in manufacturing in the short-run, indicating the trade-off that faces a policy-maker. While the long-term level of growth seems to be unaffected, it causes a reduction in employment in the short-run. However, one needs to note that the impact of such a shock seems to be rapidly absorbed. On the contrary, the gains from diversity on stabilization seem to take some time to materialize, as our specifications suggest. The issue does not seem to concern services as diversity increases growth in the short-run and potentially in the long run. Moreover, the impact for both industry and manufacturing are robust to the content of the industry-mix present in a region.

Therefore, the existence of a potential trade-off when conducting different types of policies, whether encouraging specialized clusters or promoting diversification and stability, seems to depend largely on an industry-mix present in a region. A growth-friendly clustering policy in manufacturing would seem to benefit both sectors through different channels, as services would enjoy gains from Jacobs externalities. Although appealing in practice, clustering policies are found in practice inefficient (Martin et al.(2008)). On the other hand, a policy enhancing stabilization through more diversified networks may be harmful to traditional industries in the short-run. Thus, the overall impact of such policies would depend on the relative weights of different types of sectors operating in the area and on their interactions.

Finally, the discussion over the trade-off between growth and specialization seems to focus mostly on implications of policies promoting diversity versus specialization. However, our analysis suggests that pursuing policies focused on nationally important sectors is dispensed of such a trade-off and seems to impact regional growth and stability much more than pure localization and diversity externalities.This is in line with the observation made by Wagner and Deller (1998) who advocated for policies targeting sectors with the highest comparative advantage. Indeed, our results suggest, that investment in nationally important industries together with efficient cohesion policies could offer an alternative solution to the existing trade-off.

5.2 Further research

The biggest challenge in the related literature is linked to endogeneity of regressors and data availability at a large geographical scale. The two issues, although not linked in appearance, are interconnected. Long panel data allows to instrument the indicators of local industrial structure with more precision by using sufficiently long lags. Long-term conclusions would yield more precise estimates of the overall impact of agglomeration externalities. However, the data on regional employment by sector is hardly available. Our study made use of all publicly available statistics on regional employment in Europe, but longer series on exist [15] It would be thus useful to complement the research on the subject with this respect. Moreover, another important improvement could be linked to the sectoral aggregation of data. According to Beaudry et al.(2013), using larger sectoral aggregations lowers the probability of finding positive impact of agglomeration economies, notably in terms of localization externalities as those may be operating at a lower sectoral level. This is indeed our case. Moreover, the indices of sectoral diversifications are obtained on a relatively broad definition of a sector, potentially hiding large variation at a lower level. Thus, a large data collection work with cooperation with national authorities could improve the precision of the findings. Concerning data availability, competition indices, typically Herfindhal-type ones based on firm-level data, could be added to account for Porter's externalities. As found in a large part of the literature, competition has a significant impact on employment dynamics in this context (Combes (2000), Combes, Robin, Magnac (2004)). However, to proceed with such improvement on European level, an extensive dataset work would be required, considering the lack of ready-to-use data. Therefore, in order to improve the estimations on a large set of countries, data collection work is needed.

By the same token, use of a more disaggregated data , although linked with tedious data mining, could open the door to the studies of interlinkages between sectors and their relationships. As input-output data at regional level are not available, micro data disaggregated at a very low sectoral level could proxy such relationships using indications on relative proximity of sub-sectors aggregated under the umbrella of a higher level of classification.

Alternatively, one could account for spatial spillovers across neighboring regions to investigate whether region-specific shocks spread across local units. To this aim, a number of studies included weighted indices accounting for neighboring regions. However, as found by Brulhart and Mathys (2008) for a set of European NUTS 3 regions, these spillovers do not have a large impact. However, it might be the case that they were not correctly specified. Some authors construct spatial weighting matrices and use spatial Durbin Model e.g. Watson and Deller (2017) in their study assessing the impact of the great recession. Their results indeed suggest that sectoral diversity of neighboring regions plays a role of a buffer during economic crisis. Inclusion of such effect would be particularly interesting, especially as it would allow for studying of a a potential border effect.

[15] For instance, Cambridge Econometrics has indeed longer series at roughly the same level of sectoral aggregation.

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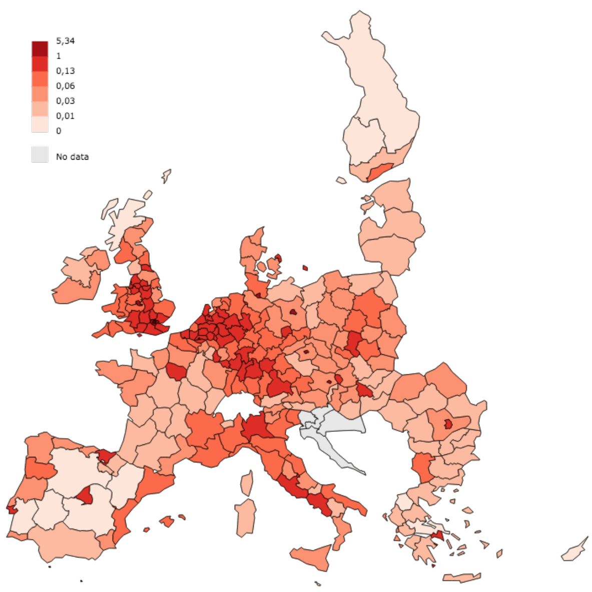
7 Annex

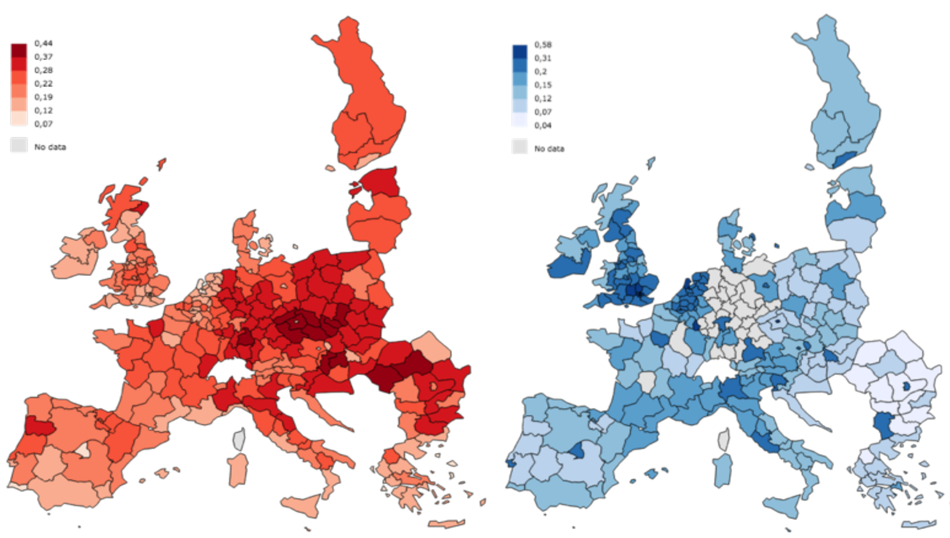
7.1 Descriptive statistics - graphs

Figure 3: Density of employment, 2014



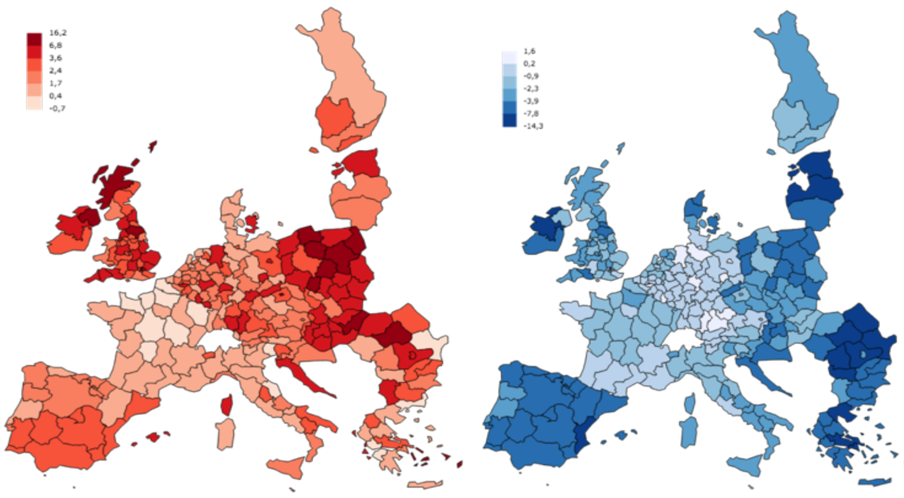
Source: OECD. Based on authors' calculations.

Figure 4: Share of manufacturing (left) and share of services (right) in total employment, 2014



Source: OECD. Based on authors' calculations.

Figure 5: Largest peak in employment growth (left) and largest drop (right), 2000-2014



Source: OECD. Based on authors' calculations.

7.2 GMM robustness checks

Table 11: OLS and fixed effects: ADL (2,2)

	Industry		**Services**	
	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)
L.Log of employment	0.878***	0.657***	0.775***	0.565***
	(38.29)	(23.59)	(31.25)	(17.98)
L2.Log of employment	0.111***	-0.0223	0.196***	0.0769***
	(4.88)	(-0.95)	(8.36)	(4.07)
Diversity	0.0132	0.0128	0.0321**	0.0454***
	(1.34)	(1.28)	(2.27)	(2.67)
L.Diversity	0.00357	0.00951	-0.0271	-0.0121
	(0.28)	(0.84)	(-1.64)	(-0.78)
L2.Diversity	-0.0125*	-0.00933	-0.00492	0.00172
	(-1.70)	(-1.23)	(-0.55)	(0.18)
Size of the region	0.00637	0.0118	0.275***	0.333***
	(0.12)	(0.21)	(2.77)	(3.19)
L.Size of the region	0.145**	0.131**	-0.177	-0.126
	(2.29)	(2.35)	(-1.31)	(-1.09)
L2.Size of the region	-0.141***	-0.0604*	-0.0632	-0.0252
	(-3.81)	(-1.67)	(-0.97)	(-0.42)
Size of the sector	0.841***	0.861***	0.668***	0.646***
	(24.13)	(24.29)	(10.16)	(9.51)
L.Size of the sector	-0.696***	-0.520***	-0.466***	-0.327***
	(-13.06)	(-10.59)	(-6.58)	(-5.16)
L2.Size of the sector	-0.136***	-0.00736	-0.172***	-0.0399
	(-4.64)	(-0.26)	(-3.62)	(-1.03)
Tertiary educ.	-0.00631	0.00821	0.0487***	0.0414**
	(-1.65)	(0.61)	(5.98)	(2.10)
Constant	-0.108***	-1.762***	-0.677***	-2.724***
	(-2.69)	(-4.59)	(-6.19)	(-4.22)
Country FE	Yes	No	Yes	No
Observations	4768	4768	9502	9502

All variables are expressed in logs. Standard errors are clustered at regional level.
t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 12: OLS and fixed effects: ADL (2,2)

	Industry		**Services**	
	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)
L.Log of employment	0.878***	0.657***	0.775***	0.565***
	(38.29)	(23.59)	(31.25)	(17.98)
L2.Log of employment	0.111***	-0.0223	0.196***	0.0769***
	(4.88)	(-0.95)	(8.36)	(4.07)
Diversity	0.0132	0.0128	0.0321**	0.0454***
	(1.34)	(1.28)	(2.27)	(2.67)
L.Diversity	0.00357	0.00951	-0.0271	-0.0121
	(0.28)	(0.84)	(-1.64)	(-0.78)
L2.Diversity	-0.0125*	-0.00933	-0.00492	0.00172
	(-1.70)	(-1.23)	(-0.55)	(0.18)
Size of the region	0.00637	0.0118	0.275***	0.333***
	(0.12)	(0.21)	(2.77)	(3.19)
L.Size of the region	0.145**	0.131**	-0.177	-0.126
	(2.29)	(2.35)	(-1.31)	(-1.09)
L2.Size of the region	-0.141***	-0.0604*	-0.0632	-0.0252
	(-3.81)	(-1.67)	(-0.97)	(-0.42)
Size of the sector	0.841***	0.861***	0.668***	0.646***
	(24.13)	(24.29)	(10.16)	(9.51)
L.Size of the sector	-0.696***	-0.520***	-0.466***	-0.327***
	(-13.06)	(-10.59)	(-6.58)	(-5.16)
L2.Size of the sector	-0.136***	-0.00736	-0.172***	-0.0399
	(-4.64)	(-0.26)	(-3.62)	(-1.03)
Tertiary educ.	-0.00631	0.00821	0.0487***	0.0414**
	(-1.65)	(0.61)	(5.98)	(2.10)
Constant	-0.108***	-1.762***	-0.677***	-2.724***
	(-2.69)	(-4.59)	(-6.19)	(-4.22)
Country FE	Yes	No	Yes	No
Observations	4768	4768	9502	9502

All variables are expressed in logs. Standard errors are clustered at regional level.
t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 13: System-GMM table: ADL(2,2)

	(M1)	(M2)	(M3)	(S4)	(S5)	(S6)
		Industry			**Services**	
L.Log of employment	0.841***	0.799***	0.866***	0.780***	0.582**	0.619**
	(4.55)	(4.76)	(4.44)	(2.69)	(2.16)	(2.01)
L2.Log of employment	0.0853	0.112	0.0405	0.144	0.281	0.249
	(0.54)	(0.78)	(0.24)	(0.65)	(1.31)	(0.94)
Diversity	-0.0999**	-0.112**	-0.122**	0.190*	0.208**	0.259**
	(-2.10)	(-2.26)	(-2.51)	(1.76)	(2.10)	(2.03)
L.Diversity	0.0648*	0.0793**	0.0865**	-0.00742	0.0382	0.0583
	(1.73)	(2.16)	(2.33)	(-0.05)	(0.27)	(0.31)
L2.Diversity	-0.00469	-0.00120	0.00149	-0.0785	-0.111	-0.123
	(-0.39)	(-0.11)	(0.13)	(-1.00)	(-1.49)	(-1.11)
Size of the region	-0.297	0.0234	0.0657	0.802	1.010**	1.203
	(-0.88)	(0.09)	(0.28)	(1.10)	(2.32)	(1.42)
L.Size of the region	0.472	0.154	0.119	-0.643	-0.407	-0.609
	(1.35)	(0.57)	(0.48)	(-0.48)	(-0.61)	(-0.49)
L2.Size of the region	-0.0866	-0.0793	-0.0938	0.0622	-0.248	-0.235
	(-1.34)	(-1.37)	(-1.57)	(0.07)	(-0.46)	(-0.34)
Size of the sector	0.877***	0.887***	0.866***	0.906***	0.835***	0.871***
	(6.86)	(7.25)	(7.15)	(4.81)	(4.57)	(4.04)
L.Size of the sector	-0.662***	-0.664***	-0.694***	-0.842***	-0.661***	-0.729**
	(-2.95)	(-3.18)	(-3.05)	(-2.99)	(-2.75)	(-2.59)
L2.Size of the sector	-0.135	-0.130	-0.0733	0.00487	-0.0641	-0.0339
	(-0.93)	(-0.99)	(-0.50)	(0.03)	(-0.33)	(-0.12)
Log of tertiary educ.		-0.00657	-0.00620		0.0180	0.00254
		(-0.36)	(-0.32)		(0.50)	(0.07)
Productivity			-0.00889			0.157
			(-0.32)			(1.18)
Constant	0.00395	0.000289	0.00236	-0.0101	-0.0107	-0.0374
	(0.74)	(0.04)	(0.33)	(-0.67)	(-0.82)	(-1.00)
Long term coefficients						
Diversity	-0.536	-0.375	-0.358	1.372	0.985	1.473*
	-0.87	(-0.99)	(-1.09)	0.91	(1.59)	(1.75)
Size of the sector	1.187***	1.043***	1.047***	0.909	0.804**	0.824
	(2.75)	(5.80)	(6.29)	(1.11)	(1.95)	(1.43)
Size of the region	1.093***	1.099***	0.967**	2.919	2.583***	2.718***
	4.62	3.77	(3.14)	(1.45)	(2.64)	(3.20)
Observations	4896	4768	4648	9757	9502	8250
sarganp	0.0810	0.0689	0.231	0.164	0.101	0.291
hansenp	0.319	0.365	0.536	0.380	0.463	0.463
ar2p	0.0989	0.0389	0.150	0.544	0.195	0.413

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 14: SYS-GMM table: OECD data only

	(1) Manuf1	(2) Manuf2	(3) Manuf3	(4) Serv1	(5) Serv2	(6) Serv3
L.Log of employment	0.837***	0.835***	0.825***	0.903***	0.913***	0.956***
	(11.56)	(11.97)	(11.53)	(13.43)	(15.41)	(13.78)
Diversity	-0.102	-0.0939	-0.102	0.334**	0.344***	0.367***
	(-1.52)	(-1.41)	(-1.53)	(2.36)	(3.12)	(2.85)
L.Diversity	0.0717	0.0665	0.0730	-0.207*	-0.205**	-0.198**
	(1.41)	(1.38)	(1.50)	(-1.85)	(-2.43)	(-2.09)
Size of the region	-0.00911	0.216	0.248	1.183	0.973*	0.457
	(-0.02)	(0.56)	(0.66)	(1.44)	(1.70)	(0.77)
L.Size of the region	0.185	-0.0387	-0.0666	-0.936	-0.738	-0.275
	(0.43)	(-0.10)	(-0.17)	(-1.20)	(-1.36)	(-0.49)
Size of the sector	0.986***	0.954***	0.951***	0.886***	0.895***	0.944***
	(10.59)	(11.68)	(11.53)	(5.31)	(5.88)	(6.85)
L.Size of the sector	-0.820***	-0.788***	-0.772***	-0.814***	-0.821***	-0.882***
	(-6.08)	(-6.85)	(-6.92)	(-4.44)	(-4.83)	(-5.65)
Log of tertiary educ.		-0.0139	-0.0128		0.00947	-0.00443
		(-0.72)	(-0.69)		(0.34)	(-0.15)
Productivity			-0.0107			0.0905
			(-0.32)			(0.75)
Constant	-0.00264	-0.00000415	0.00194	-0.00702	-0.00922	-0.0205
	(-0.37)	(-0.00)	(0.15)	(-0.44)	(-0.59)	(-0.70)
Observations	5054	4888	4888	10073	9743	8862
sarganp	0.384	0.364	0.253	0.142	0.192	0.131
hansenp	0.527	0.483	0.478	0.224	0.267	0.268
ar2p	0.00161	0.00127	0.00133	0.705	0.787	0.365
ar3p	0.412	0.382	0.401	0.358	0.414	0.509

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 15: SYS-GMM: New and core EU countries table

	(1) Manuf_core	(2) Manuf_new	(3) Serv_core	(4) Serv_new
L.Log of employment	0.831***	0.681***	0.905***	0.887***
	(10.97)	(3.04)	(10.86)	(4.14)
Diversity	-0.0336	-0.163	0.311***	0.272
	(-0.49)	(-1.57)	(3.03)	(0.74)
L.Diversity	0.0501	0.104	-0.210***	-0.148
	(1.05)	(1.31)	(-3.62)	(-0.73)
Size of the region	0.423	0.345	0.321	1.375
	(1.42)	(1.08)	(0.58)	(1.02)
L.Size of the region	-0.251	0.0381	-0.119	-0.825
	(-0.76)	(0.15)	(-0.23)	(-1.05)
Size of the sector	0.880***	0.902***	0.941***	0.577
	(12.61)	(8.68)	(8.86)	(0.63)
L.Size of the sector	-0.729***	-0.610**	-0.909***	-0.354
	(-8.98)	(-2.33)	(-8.18)	(-0.39)
Log of tertiary educ.	-0.0129	-0.0283	0.00331	-0.00135
	(-0.69)	(-0.41)	(0.13)	(-0.01)
Productivity	-0.0507	0.0755	0.0636	0.313
	(-1.15)	(0.85)	(0.50)	(0.69)
Constant	0.00428	-0.0237	-0.0143	-0.0952
	(0.44)	(-0.68)	(-0.60)	(-0.70)
Observations	3730	1280	7202	1660
sarganp	0.0264	0.334	0.466	0.0262
hansenp	0.0569	0.446	0.280	0.781
ar2p	0.0699	0.00600	0.0268	0.169

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 16: SYS-GMM: manufacturing only table

	(1) Manuf1	(2) Manuf2	(3) Manuf3
L.Log of employment	0.993***	0.944***	0.989***
	(13.23)	(16.52)	(17.83)
Diversity	0.0780	0.0447	0.0859
	(1.37)	(0.70)	(0.89)
L.Diversity	-0.0409	-0.0118	-0.0279
	(-1.03)	(-0.30)	(-0.38)
Size of the region	-0.140	0.248	0.400
	(-0.30)	(0.44)	(0.90)
L.Size of the region	0.179	-0.195	-0.410
	(0.40)	(-0.34)	(-0.89)
Size of the sector	1.031***	0.870***	0.679***
	(4.33)	(2.61)	(3.01)
L.Size of the sector	-0.974***	-0.811**	-0.640***
	(-3.99)	(-2.55)	(-2.89)
Log of tertiary educ.		-0.00544	0.00623
		(-0.15)	(0.19)
Productivity			0.00467
			(0.13)
Constant	0.00658	0.000912	-0.00156
	(0.78)	(0.06)	(-0.09)
Observations	2604	2521	2271
sarganp	0.0716	0.0760	0.0420
hansenp	0.417	0.265	0.304
ar2p	0.203	0.183	0.354

t statistics in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.010$

Table 17: SYS-GMM: Before and after crisis table

	(1)	(2)	(3)	(4)
	M_before	M_after	S_before	S_afer
L.Log of employment	0.824***	0.865***	1.083***	0.929***
	(4.67)	(11.82)	(6.21)	(10.31)
Diversity	-0.0389	-0.0740	0.215*	0.299
	(-0.54)	(-1.29)	(1.75)	(1.32)
L.Diversity	0.0177	0.0690*	-0.0844	-0.214*
	(0.31)	(1.85)	(-1.07)	(-1.91)
Size of the region	0.228	0.00730	-0.745	0.788
	(0.51)	(0.02)	(-0.90)	(0.92)
L.Size of the region	0.0509	0.0887	0.899	-0.661
	(0.13)	(0.28)	(1.14)	(-0.78)
Size of the sector	0.985***	0.941***	1.184***	0.489*
	(7.84)	(13.02)	(12.20)	(1.83)
L.Size of the sector	-0.754***	-0.819***	-1.151***	-0.433
	(-3.74)	(-10.19)	(-6.07)	(-1.48)
Log of tertiary educ.	-0.0222	-0.0195	-0.0383	-0.0119
	(-0.66)	(-0.78)	(-0.63)	(-0.27)
Productivity	-0.0407	0.0163	-0.0862	0.142
	(-0.68)	(0.39)	(-0.34)	(0.86)
Constant	0	0.00332	-0.00507	-0.0165
	(.)	(0.31)	(-0.06)	(-0.47)
Observations	2636	2728	4748	4757
sarganp	0.0348	0.0169	0.0517	0.000419
hansenp	0.0609	0.264	0.216	0.0303
ar2p	0.691	0.00161	0.289	0.364

The estimations are based on a very short sample period.

Before sample covers 2001-2008, after 2008-2014..

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010