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Cluster presence and economic performance: a new look based on European data

Christian Ketels[a] and Sergiy Protsiv[b]

ABSTRACT

This paper takes a fresh empirical look at how cluster presence matters for economic performance. It analyses a new data set developed for the European Cluster Observatory to assess the impact of clusters on industry-level wages and regional prosperity. It is found that industry-level wages are associated with industry- and surrounding-cluster agglomeration levels to a similar degree. For regional prosperity, cluster portfolio strength is found to matter, while the specific mix of clusters is insignificant once business environment conditions are accounted for. The data show a meaningful relationship between clusters and economic outcomes, independent of other locational qualities.

KEYWORDS
clusters; productivity; prosperity; regions; competitiveness

JEL O40, R12, R58
HISTORY Received 3 September 2018; in revised form 16 June 2020

INTRODUCTION

Almost three decades after a new set of contributions established the role of clusters for modern economies (e.g., Becattini, 1990; Porter, 1990) discussions on their nature and, even more controversially, their impact continue (Chatterji et al., 2014; Kerr & Robert-Nicoud, 2019; Norman & Venables, 2004). In this paper we exploit a new European data set to take a fresh empirical look at how cluster presence and specialization matters for economic performance. We look both at the industry level, that is, how being located in a strong cluster drives industry-level performance, and at the locational level, that is, how the presence of strong clusters is systematically associated with a location's prosperity level. We explore the role of clusters in the context of other factors identified as location-specific drivers of economic performance. In particular, we assess the role of clusters relative to the role of agglomeration in narrow industries on industry-level wages, and of clusters relative to both the quality of the broader business environment and the specific set of industries and clusters present in a location on location-wide prosperity. Overall, our data provide clear evidence of a meaningful relationship between the presence of clusters of related industries and economic outcomes. Clusters play a role alongside and independent of these other locational qualities; they all need to be taken into account for a comprehensive understanding of a location's economic performance.

We can draw on significant advances over recent years in the measurement of clusters. Clusters were in the past often operationalized in idiosyncratic ways, for specific locations and sectors or with regards to specific research questions, leading to criticism that clusters were a 'fuzzy' concept (Martin & Sunley, 2003). Or they used broad categories from industrial classification systems (e.g., Frenken et al., 2007) that were not grounded in the conceptual idea of clusters.

We apply a new set of benchmark cluster definitions (Delgado, Porter, & Stern, 2016) that deals with these issues. It defines clusters of related industries based on an empirical analysis of co-location patters, similarities of skill needs and input–output relationships, identifying those groupings of industries into cluster categories that are most coherent in terms of relatedness measures. These definitions were applied in the United States, the European Union (EU) and several additional countries. The European part of these data, available on the EU Cluster Portal,[1] forms the basis of analysis. The data behind the US-based cluster definitions were combined with

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European co-location patterns to create a set of 51 cluster categories that both match the original US categories and reflect the European industrial location and economic activity definitions (Ketels & Protsiv, 2014).

The primary cluster strength indicator is the employment location quotient (LQ), which captures the concentration of related industries in a region and the opportunities for interaction it entails. The LQ measures the degree that an industry is over-represented in a particular region relative to the industry's overall distribution in Europe. We use the LQ directly in the industry-level analysis, where it is measured both for narrow industries and the 51 cluster categories. In the region-level analysis we use a combined cluster strength measure that captures the share of a region's employment in strong clusters, where a cluster is 'strong' if it is in the top 20% by LQ in its industry. We also define measures of regional cluster strength that look at the role of all strong clusters within the broader composition of the regional economy.

Overall, we find that the presence of strong clusters of related industries is significantly related to economic outcomes, playing a meaningful role in the context of other locational factors. The composition of clusters and industries, however, seems to be endogenously driven by the underlying quality of a location's business environment rather than having an independent effect on regional prosperity. The findings are consistent with much of the existing literature but add important new insights in the two areas we study.

More specifically, in the industry-level analysis we find both narrow industry- and wider cluster-level agglomeration to have a significant and quantitatively comparable positive effects on industry-level wages, with elasticities broadly in the range of the previous literature. In the region-level analysis, we introduce a new measure – the share of strong clusters in a region's payroll – in the analysis. We find higher values of this measure to be associated with higher prosperity, particularly when accounting for a range of other business environment and locational factors. We also find that while the specific set of industries and clusters present in a location has a high correlation with prosperity when introduced alone, this effect disappears once controls for business environment quality are introduced.

LITERATURE REVIEW

The study builds on two streams of research within economic geography: one related to industry- and one to location-specific outcomes. At the industry level an important set of contributions looks at the effect of specialization and density, that is, the relative and absolute size of an industry in a location on its performance (for overviews, see Combes & Gobillon, 2015; Feldman, 2000; and Glaeser et al., 2010). Rosenthal and Strange (2004) survey the earlier literature and find the elasticity of productivity with respect to industry size to be between 3% and 8%. More recent studies using detailed individual-level data and controlling for endogenous labour quantity and quality (Combes et al., 2010; Mion & Naticchioni, 2009) suggest that the magnitude of these estimates needs to be revised further, with their preferred estimate of the effect of density on wages close to 2%. Martin et al. (2011) find similar effects of specialization on firm productivity (somewhat smaller on wages). They see these positive externalities largely internalized in existing location patterns so that moving individual firms from one location to another has very small effects. Greenstone et al. (2010) find larger effects of relocations for larger size investments. A related literature looks specifically at the impact of cluster presence on innovative performance (e.g., Feldman, 2000), a topic we do not cover here.

Most of these papers look at clusters as local concentrations of specific industries, not of groups of related industries. The most common approach is to differentiate between the narrow industry presence and the overall density and/or diversity of industries (e.g., Basile et al., 2017; Neffke et al., 2011). A new literature takes a different approach, looking at industry-level employment growth as a function of both the strength of a narrow industry and of the strength of the cluster of related industries around it (Delgado et al., 2014). They find a combination of industry-level convergence effects, that is, more specialized industries adding jobs more slowly, and related-industry cluster effects, that is, industries with a strong presence of related industries adding jobs faster. Spencer et al. (2010) develop different cluster definitions to find similar results for Canadian data. Aharonson et al. (2014) show that firms located in strong clusters generate significantly more patent applications than firms in locations without similar presence of related industries.

At the location level, a broad range of studies look at clusters as well as at many other potential drivers of prosperity differences across locations (for wider discussions, see Beaudry & Schiffauerova, 2009; Ketels, 2013; and Rodríguez-Pose, 2013). Porter (2003) finds that having economic activity concentrate in strong clusters is significantly more important for prosperity levels than being active in industries that across locations tend to pay high wages. Spencer et al. (2010) report similar findings for Canadian data. Martin et al. (2011) find cluster presence to matter more in groups of related industries that use skills extensively.

Rodríguez-Pose and Comptour (2012) find cluster presence to matter for regional innovation and growth if other factors – which they call a 'social filter' – are in place. This view is related to the recent literature on economic complexity that finds industry mix (measured through the profile of exported goods) to be strongly associated with prosperity levels (Hausmann & Klinger, 2006; for a different perspective, see Lederman & Maloney, 2012).

MODELS AND HYPOTHESES

The effects we want to capture are present at both the scale of individual industries and of regions as a whole.

Cluster-level effects

In a first step, we analyse the impact of agglomeration in specific sectors on their economic performance, specifically the level of wages. The analysis distinguishes the effects of agglomeration at the industry and the cluster level on industry-level wages. In separating these two elements we follow the approach taken by Delgado et al. (2012). They analyse US data to study employment growth, contrasting the effects of convergence in highly specialized narrow industries from the effects of divergence based on linkages across related industries within a cluster. We look instead at wages, where we expect both industry and surrounding cluster effects to work in the same direction.

The baseline set of relationships we want to estimate can be formulated as:

$$\begin{aligned} \mathrm{WAGE}_{\mathrm{REG,IND}} = {} & \beta_{\mathrm{IND}}\mathrm{LOC}_{\mathrm{REG,IND}} \\ & + \beta_{\mathrm{CLU}}\mathrm{LOC}_{\mathrm{REG,CLU}} + \beta_{\mathrm{BE}}\mathrm{BE}_{\mathrm{REG}} \\ & + \text{controls} \end{aligned}$$

where each observation is a four-digit industry–NUTS-2 region combination; $\mathrm{WAGE}_{\mathrm{REG,IND}}$ is the log of the average wage in this industry–region; $\mathrm{LOC}_{\mathrm{REG,IND}}$ is the log location quotient (LQ) within the four-digit industry; $\mathrm{LOC}_{\mathrm{REG,CLU}}$ is the log location quotient of the *remaining* four-digit industries belonging to the same cluster category; and $\mathrm{BE}_{\mathrm{REG}}$ is a measure of the quality of the regional business environment, and controls include industry and region fixed effects.

Agglomeration at the sector level has been shown to affect measures of productivity (Ciccone & Hall, 1996) and innovation (Audretsch & Feldman, 2004; Moretti, 2019). We analyse whether this relationship also holds for wages, and test at what level of sectoral scope – narrow industry or broad cluster – agglomeration matters. Narrow industries could capture the very industry-specific skill and technology advantages in a region, while broader clusters could generate benefits from deeper relationships with specialized suppliers and service providers in related industries.

Hypothesis 1: Locations with larger relative employment at both the industry and surrounding cluster level are expected to report higher levels of industry-level wages.

Better business environment conditions might enable workers to achieve higher levels of productivity, and thus be correlated with higher levels of wages and prosperity (e.g., Klaesson & Larsson, 2009). The impact on wages is not a given; labour mobility across locations could work to eliminate wage differences across regions. Better business environment conditions could even impact the benefits of sectoral specialization for wages looked at under hypothesis 1. The intuition is that stronger business environments enhance the positive spillovers in clusters, and thus increase raise the returns to a given level of specialization.

Hypothesis 2: Locations with higher business environment quality are expected to report higher levels of industry-level wages.

Hypothesis 3: The impact of higher specialization at the industry and surrounding cluster level on industry-level wages is increasing in business environment quality.

Region-level effects

In a second step, we broaden our view to the regional level and analyse how cluster presence might affect overall regional prosperity. The analysis aggregates cluster-level data into regional cluster strength indicators. We distinguish between the different aspects of the cluster portfolio in a region that might matter:

- The role of strong clusters in the regional economy.
- The specific mix of clusters in which the region has a strong position.

We identify clusters as 'strong' based on their employment LQ, following the traditional literature (Haggett, 1965). We characterize cluster mix by looking at a standardized measure of wages paid in the relevant clusters across regions.

The baseline model on the regional level is formulated as:

$$\begin{aligned} \mathrm{GDP}_{\mathrm{REG}} = {} & \beta_{\mathrm{PORTFOLIO}}\mathrm{PORTFOLIO}_{\mathrm{REG}} \\ & + \beta_{\mathrm{MIX}}\mathrm{MIX}_{\mathrm{REG}} + \beta_{\mathrm{BE}}\mathrm{BE}_{\mathrm{REG}} + \text{controls} \end{aligned}$$

where the observations are now NUTS-2 regions; $\mathrm{GDP}_{\mathrm{REG}}$ is gross domestic product (GDP) per capita purchasing power parity (PPP); $\mathrm{PORTFOLIO}_{\mathrm{REG}}$ captures the strength of the regional cluster portfolio (share of wages paid to employees in strong clusters); $\mathrm{MIX}_{\mathrm{REG}}$ captures the cluster mix (the bias of a region towards high-wage clusters); $\mathrm{BE}_{\mathrm{REG}}$ is an indicator of business environment; and controls include spatially lagged log GDP per capita PPP as well as dummies for the capital region and Eastern Europe.

We then look at a range of hypotheses that capture the relationship between cluster presence and regional economic performance, including their relationship with each other and other regional controls.

Hypothesis 4: Locations with stronger cluster portfolios are expected to report higher levels of prosperity.

Hypothesis 5: Locations with a regional cluster mix biased towards higher wage clusters are expected to report higher levels of prosperity.

Hypothesis 6: Cluster portfolio strength and cluster mix are expected to be both independently associated with higher prosperity levels after controlling for business environment quality.

When it comes to causal identification, finding valid instruments for industry- and cluster-specific effects remains elusive (unlike strong progress in urban and regional contexts in Ahlfeldt et al., 2015; and Greenstone et al., 2010). We thus follow much of the existing literature on clusters (e.g., Delgado et al., 2012) and focus on the measures of association; causal identification is something left for future work to tackle.

DATA AND METHODS

The empirical analysis draws at its core on a new comprehensive data set of cluster indicators across 28 European countries from the European Cluster Observatory. We add regional performance and business environment data from Eurostat, the European Observation Network for Territorial Development and Cohesion (ESPON) and the European Social Survey (ESS). The complete data set used for this paper can be requested from the authors and is also available through the European Cluster Observatory.[2] The majority of the data come from national statistical offices and are based on annual enterprise surveys, censes and registers (Structural Business Statistics – SBS). The data used in here come from the period 2011–14, with some variation depending on the country. The two key variables used throughout are the number of employees in full-time equivalents and the average wages per full-time equivalent (see Appendix A in the supplemental data online for details on definitions and normalizations).

For some of the analyses below we use the industry data directly, but most of the time they are aggregated into cluster categories, using the cluster category definitions developed in the US cluster mapping project (Delgado, Porter, & Stern, 2014) and then translated into the respective European industry classifications (Ketels & Protsiv, 2014). In the first step, the cluster definitions classify all industries as either 'traded' or 'local'; traded industries are those that empirically are concentrated in a few locations, while local industries are present at roughly the same relative share everywhere. In a second step, traded industries are grouped into 51 cluster categories based on co-location, similarity in skill use, and input–output relationship. These 51 traded cluster categories are the focus of our analysis. Appendix A in the supplemental data online provides the allocations of four-digit NACE industries to cluster categories as used in this paper. Cluster category employment is the sum of employment of all constituent industries in a region. Cluster category wage is the average wage of constituent industries in the region weighted by full-time equivalents.

Table 1 indicates large size differences across cluster categories. This is partly due to the poor granularity of service sector industry classifications, which drive the 'business services' cluster category to be by far the largest source of employment among traded clusters. The data also reveal large wage differences across cluster categories. This is consistent with large differences in skill and capital intensity across industries. Finally, the data show that there are strong differences in the geographical footprint across cluster categories. All have employment unequally distributed across locations; this led to their classification as 'traded'. But in some cluster categories overall activity is highly concentrated in a few locations while it is more widely dispersed in others. This is likely to be reflective of differences in the nature and strength of local externalities and of the relative importance of transportation costs for the products and services provided.

While the core of our data set is cluster specific, we have also collected several regional indicators on cross-cutting dimensions. First, we construct an indicator of the overall strength of a region's cluster portfolio. The core indicator of cluster strength calculates the share of payroll from traded clusters in every NUTS-2 region that is accounted for by strong clusters. While some previous studies have instead looked at the share of all traded industries in regional employment or value added (e.g., Martin et al., 2011), we see only strong clusters achieving the critical mass that would leave us to expect cluster effects to be visible. In the identification of strong clusters we follow the methodology used by Delgado et al. (2012). Within each cluster category we assign the 'strong' status to the top 20% of clusters ranked by LQ within this category. Given the 263 regions included in our analysis, at most 52 clusters within each category will be classified as strong. This quantile-based cut-off is preferable to a fixed LQ threshold (such as 'LQ > 2') because it adjusts to the different distributions of LQ magnitudes within cluster categories. We also require strong clusters to be within the top 80% of all clusters in a category ranked by employment to remove very small, potentially spurious clusters.[3]

The regions with strongest cluster portfolios are most prevalent in Finland, Sweden, Germany, Poland and Portugal (Figure 1, top). The UK, France and Spain exhibit wide variation in cluster strength between their respective capitals and the rest of the countries (Aberdeen in the UK being an exception due to the high share of highly paid oil and gas employees). Countries associated with decentralization, such as Germany and Italy, are among the few where the strongest regions are outside the capital.

Next, we construct an indicator of a region's cluster mix, capturing whether a region's cluster portfolio is biased towards clusters that across regions tend to pay higher wages. Table 1 shows that European average wages by cluster category differ significantly. However, the data do not immediately indicate whether these differences reflect underlying differences in productivity potential across cluster categories, or whether they are driven by some cluster categories being predominantly located in lower wage locations. To tackle this issue of uneven distribution of industries across regions, we look at the variation in wages across industries within regions, regressing log wages for regional industries on industry and region fixed effect. Figure 2 shows how for individual cluster categories the average EU wage differs from the wage level normalized by the effect of location. Financial services are an example of a cluster category where wages benefit from employment being predominantly in high wage locations; for apparel the opposite is the case.

We then compute a region's cluster mix indicator by weighting the cluster-specific wage level coefficients by

Table 1. Cluster categories; descriptive statistics.

Cluster category	Total employment	Median cluster employment	Average wage (€)	Normalized wage (€)[a]	Share of payroll in the top 10 locations (%)
Financial services	1,026,883	1637	€51,386	€38,413	45.9%
Aerospace vehicles and defence	361,255	205	€44,914	€41,288	1.5%
Upstream chemical products	301,780	545	€43,057	€43,328	6.8%
Insurance services	1,032,328	1986	€42,992	€39,878	9.7%
Oil and gas production and transportation	322,075	440	€42,280	€48,467	1.2%
Biopharmaceuticals	539,739	1000	€42,011	€42,757	1.8%
Communications equipment and services	751,239	1606	€40,612	€37,889	3.6%
Video production and distribution	211,886	208	€36,544	€23,572	4.9%
Electric power generation and transmission	420,570	1042	€35,867	€54,140	3.6%
Information technology and analytical instruments	1,090,188	2287	€35,355	€35,143	4.6%
Music and sound recording	31,085	30	€34,556	€20,957	4.4%
Business services	8,554,987	18,620	€34,396	€30,444	4.2%
Tobacco	48,833	135	€32,824	€44,339	5.7%
Downstream chemical products	548,657	1185	€32,594	€35,300	2.6%
Production technology and heavy machinery	2,322,306	5210	€32,160	€35,278	2.9%
Automotive	2,509,493	4146	€30,710	€34,730	11.4%
Education and knowledge creation	3,193,573	2684	€30,113	€33,424	4.3%
Upstream metal manufacturing	1,095,047	2219	€29,460	€34,665	2.0%
Marketing, design, and publishing	1,506,897	2370	€29,035	€23,963	2.4%
Medical devices	446,416	927	€28,912	€26,812	6.7%
Water transportation	586,290	976	€28,681	€33,313	0.9%
Paper and packaging	578,743	1670	€28,634	€32,962	2.1%
Lighting and electrical equipment	967,482	2305	€27,800	€32,813	3.0%
Distribution and electronic commerce	6,123,454	15,210	€27,121	€29,101	6.3%
Appliances	220,207	255	€25,408	€32,010	3.1%
Plastics	1,333,428	3684	€25,081	€30,901	5.1%
Construction products and services	1,125,178	3128	€24,670	€34,200	2.6%
Food processing and manufacturing	1,905,380	5537	€24,655	€31,204	5.0%
Metal mining	34,716	23	€24,469	€43,251	5.5%
Metalworking technology	2,219,450	5988	€24,090	€29,291	2.4%
Printing services	623,706	1633	€24,080	€28,161	4.1%

(Continued)

Table 1. Continued.

Cluster category	Total employment	Median cluster employment	Average wage (€)	Normalized wage (€)[a]	Share of payroll in the top 10 locations (%)
Vulcanized and fired materials	807,112	1787	€23,914	€31,040	2.5%
Transportation and logistics	4,670,553	13,071	€23,725	€28,171	9.0%
Downstream metal products	680,373	1582	€23,468	€30,393	3.5%
Non-metal mining	211,180	560	€23,019	€32,941	3.6%
Performing arts	500,148	961	€22,607	€23,109	5.1%
Agricultural inputs and services	278,787	165	€22,093	€23,496	3.1%
Recreational and small electric goods	397,713	861	€21,830	€25,248	3.4%
Environmental services	590,976	1635	€20,620	€33,086	4.5%
Coal mining	263,531	37	€20,222	€41,834	3.5%
Forestry	409,840	494	€19,403	€26,060	8.2%
Hospitality and tourism	3,675,552	7139	€18,029	€20,492	8.6%
Livestock processing	807,519	2196	€17,984	€25,012	1.9%
Fishing and fishing products	200,121	135	€17,937	€26,160	4.6%
Textile manufacturing	713,164	1196	€17,709	€24,517	2.5%
Leather and related products	79,677	73	€17,463	€21,933	2.3%
Jewellery and precious metals	77,901	99	€17,335	€20,064	2.8%
Wood products	811,679	2158	€17,008	€22,886	4.1%
Furniture	805,049	1844	€16,593	€22,994	1.7%
Footwear	294,381	192	€11,884	€23,433	2.4%
Apparel	736,409	613	€9,554	€20,418	8.4%

Note: [a]Normalized wages remove the bias in cluster category average wages that are driven by their employment being concentrated in regions that on average have higher/lower wages than the average region. Both insurance, and oil and gas pay high average wages. But for insurance this partly reflects that fact that insurance jobs are biased towards higher wage locations, while for oil and gas the wages are high despite a biased of these jobs towards lower wage locations. See also Figure 2.

the location-specific employment shares. Higher values thus indicate that a region is relatively more specialized in clusters that across locations pay higher wages. Figure 1 (bottom) shows how the cluster mix effect differs across European regions.

The cluster mix indicator tends to be higher in regions that focus on manufacturing or extraction industries, for example, selected regions in the Czech Republic, France, Germany and Sweden, and some natural resource-extracting regions in Poland and Romania. This is due to jobs in these sectors usually commanding higher salaries, potentially driven by higher capital and skill intensity. Regions specializing in low-wage sectors such as tourism score low on this indicator even if they are located in overall prosperous countries, for example, the Alpine resorts in Austria and Italy.

In addition, we used the regional competitiveness index (RCI) 2016 (Annoni et al., 2017), a composite index of regional business environment quality that incorporates economic fundamentals (macroeconomic stability, infrastructure, etc.), human capital (education and labour market efficiency), technological readiness, and business sophistication. This index applies the approach of global competitiveness index (Schwab & Sala-i-Martín, 2017) to European regions. The majority of the data behind the report come from the period 2011–14, which coincides with the period on which our cluster data is based, though some specific indicators postdate the dependent variable. To test the robustness of the results against the chosen business environment measure, we repeated our analysis using the 2013 edition of the RCI and the business environment measure from Franco et al. (2011). We achieve qualitatively the same and quantitatively very similar results.

Finally, we are using the standard regional measures such as GDP per capita, population, area, and others, which we all sourced from Eurostat.

RESULTS

Clusters and industry-level wages

Industry-level wages differ significantly across and within industries. The analysis focuses on the role of agglomeration and cross-cutting locational factors to explain the

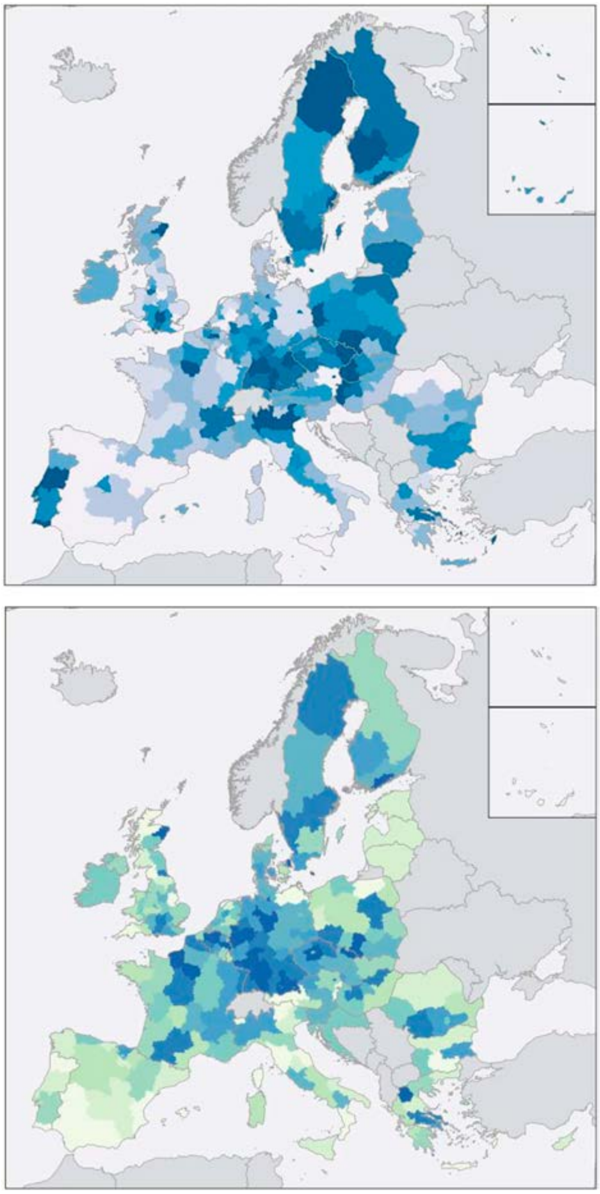

Figure 1. Indicators of cluster strength: (top) cluster portfolio strength (share of payroll accounted for by strong clusters) across European regions; and (bottom) cluster mix (bias towards cluster categories with higher wages) across European regions.
Note: Colours refer to deciles of the corresponding variables such that darker colours indicate higher values.

within-industry variations across locations. See Appendix A in the supplemental data online for details about the extent to which both industry-level wages and agglomeration differ across locations. All analyses include industry and region fixed effects, addressing the possible challenges to comparability across nations (price deflators, social contributions by employers, pensions, etc.) and industries (e.g., seasonality, share of part-time workers). Given this specification, average wage in an industry can be interpreted as a proxy for industry-level labour productivity.

We build a series of regression models with average wages per four-digit industry as the dependent variable[4] and controls for region and industry effects. We use a log–log model specification that allows us to focus on the relative changes in wages with respect to the relative change in explanatory variables. Industry fixed effects pick up systematic differences across industries driven by capital and human capital intensity and other factors. Regional fixed effects capture all region-specific factors beyond cluster presence and business environment quality not specifically included in our models.

The results are presented in Table 2, with the base model including only the fixed effects of regions and industries (each observation represents a four-digit industry in a NUTS-2 region). Region and industry properties together explain 81% of the variation in wages (with regions accounting for 73% and industries for 8% when used separately). To test our core hypothesis, we include first the log of LQ[5] in a given NACE four-digit industry (model 2) and second also the log of the LQ in other related industries in the relevant cluster (model 3). The corresponding coefficients at both the industry and cluster level are highly significant; *hypothesis 1 is confirmed*. The elasticity of wages with respect to localization in an industry is approximately 3% (model 2), in line with recent estimates in the literature. Given the observed large variation in localization the implied productivity effect is more than 30% in the densest locations. Adding employment in the rest of the cluster to the equation leads to a drop in the coefficient of industry localization to 2.2%, while cluster strength has the elasticity of 3.0% (model 3).[6] This suggests that the presence of strong related industries is at least as important for productivity as the narrow specialization within an industry.[7]

These results indicate a clear relationship between wages (as an indicator of higher labour productivity) and the presence of strong local agglomerations in sets of related industries. They also show that while some of these effects play out at the level of narrow industries, the strength of related industries in clusters is of at least equal relevance. These factors are a meaningful statistical driver of wage differences across locations: an industry that is twice as large as expected (LQ = 2) located in a cluster that is also twice as large would be expected to be 3.5% more productive. An extremely specialized industry (LQ = 10) located in a similarly strong cluster would be expected to have 12% higher productivity.

In a second step, we investigate the link between cross-cutting regional business environment quality and industry-level wages and their relationship to industry- and cluster-level employment.

Since the measures of business environment quality are available only at the regional and not the cluster level, they cannot be used in a model estimated by ordinary least squares (OLS) including regional dummies. However, such estimation is possible in the framework of hierarchical (or multilevel) linear models (HLM) (Gelman & Hill, 2007). Essentially, in the HLM framework[8] the regional effects are modelled as latent random variables, so we can use the observed variables available on the regional level (such as business environment quality) to improve our estimation of both regional effects on productivity and the

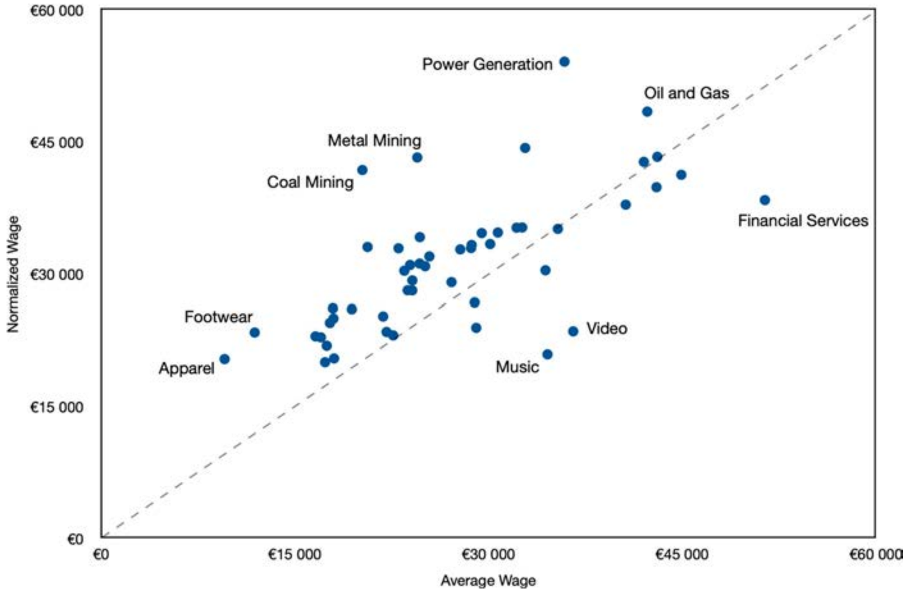

Figure 2. Average wage versus wage normalized by location effect.

region-specific effects on the impact of localization on productivity.

Model 4 in Table 2, which incorporates the business environment quality indicator as a region-level predictor, reveals that local business environment conditions are an extremely important predictor of wages, *confirming hypothesis 2*. This is also fully in line with the strong role of regional controls in models 1–3 – the regional effect is, indeed, to a large degree a reflection of region-specific business environment quality. Of the variance in industry-level wages explained by regional factors, the incorporation of the business environment indicator explains 67%.[9] Importantly, the relation between industry-level employment levels and wages is not affected by the introduction of this new indicator. Model 5 incorporates the effect of other industries within a cluster and again gives results similar to model 3: the presence of a strong cluster is at least as strong as the specialization of the narrow industry itself.

The effects of both clusters and the business environment are strong, though it is hard to gauge their relative importance from regression coefficients due to different scales and distributions of the two variables. For a better comparison, we can look at the expected increase in wages when we move from the median level of a variable to the third quartile of its distribution, based on the coefficients from model 5. The corresponding increase in business environment quality index (0.06–0.42) implies a

Table 2. Effects of localization on industry-level wages.

	1 OLS	2 OLS	3 OLS	4 HLM	5 HLM	6 HLM	7 HLM
log(industry localization)		0.030[a]	0.022[a]	0.024[a]	0.017[a]	0.024[a]	0.017[a]
		(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
log(cluster localization outside industry)			0.030[a]		0.041[a]		0.041[a]
			(0.002)		(0.006)		(0.006)
business environment				0.812[a]	0.798[a]	0.815[a]	0.792[a]
				(0.034)	(0.034)	(0.035)	(0.034)
log(industry localization)*business environment						−0.001	
						(0.004)	
log(cluster localization outside industry)*business environment							0.012[a]
							(0.005)
R^2 (OLS)	0.806	0.807	0.808				
Adjusted R^2	0.804	0.806	0.807				
REML criterion				56,055	54,063	56,063	54,066

Notes: [a]Significant at $p < 0.01$.
The number of observations is 77,130. All ordinary least squares (OLS) regression results report clustered standard errors. All models contain fixed effects for industries and fixed (random) effects for regions in OLS (hierarchical (or multilevel) linear models – HLM). The restricted maximum likelihood (REML) criterion is useful for model comparison and is a measure of 'deviance'. Smaller is better, but there is no absolute baseline value since it depends on the number of observations.

33% improvement in wages. The corresponding change in narrow industry specialization (0.68–1.43) would lead to a 1.3% increase and the change in cluster strength (0.85–1.33) – to a 1.7% increase. This is consistent with the previous results that regional conditions still account for the majority of the difference in wages across Europe.

As an additional robustness check, we have tested whether population density as a regional predictor is a missing variable behind the effects of either business environment or industry/cluster-level employment agglomeration. While density had a small significant effect when added as the only region-level predictor, combining it with business environment indicators renders it irrelevant for determining productivity.[10] Since none of the variables comprising our business environment indicator has a component tied to density, we can infer that whenever urbanization economies exhibit positive effect, it mostly serves as a proxy for a stronger business environment. This is consistent with findings that explain higher productivity in cities mainly by sorting effects, that is, higher skilled individuals co-locating in urban areas, rather than positive externalities of size effects (Gibbons et al., 2014). In general, there is likely to be a complex causal pattern between density, business environment and productivity that we do not fully explore here.

In model 6 we then test whether the specialization–wage relationship is affected by the quality of the business environment. The small and insignificant interaction term between these two variables shows that there is almost no relationship between the two factors beyond their direct effects; *hypothesis 3 is rejected*.

From model 7 we see that there is a significant positive interaction effect of broader specialization combined with attractive business environment. The effect is not large in quantitative terms, but hints at a possibility of an additional channel for the impact of cluster-level localization on wages.

Overall, these results indicate that cluster strength has an independent positive relationship with wages. This impact is quantitatively meaningful and stronger for clusters than for narrow industry specialization alone. The results also indicate that clusters are not endogenous to business environment quality but are an independent driver of economic performance. This differentiates clusters from other locational factors like urbanization that work through their relationship with business environment quality.

Cluster portfolios and regional prosperity

We now move to the level of regions and investigate how the presence of strong clusters is related to regional prosperity. We analyse whether the finding that cluster strength at the individual industry level associated with higher wages translates to cluster strength at the regional level being associated with higher prosperity. We use PPP-adjusted GDP per capita as the standard measure of prosperity due to its high quality and standardization across countries.[11]

There are significant differences in regional prosperity levels across Europe, both within and across countries. We study how both cluster-specific and cross-sectoral locational factors are associated with these differences. Apart from cluster strength and business environment quality we also look at a third potential driver of performance: cluster (or sectoral) mix. This allows us to identify whether the impact of cluster presence works through the particular mix of clusters present in a location, or through their location-specific performance independently of their generic characteristics.

All models in this section control for standard regional characteristics such as population size and area. Additionally, we incorporated the indicators for the capital regions, for Eastern European regions, as well as the inverse-weighted dependent variable to capture the key deviations of residuals from randomness and to be consistent with the literature (Dettori et al., 2012). See Appendix A in the supplemental data online for more details.

Model 1 regresses cluster portfolio strengths on regional prosperity. It shows a significant and positive relationship between the two (Table 3); *hypothesis 4 is confirmed*. This result is consistent with our cluster-level analysis before and with other work that regresses measures of cluster development, including survey evidence, with locational prosperity (e.g., Ketels & Protsiv, 2013).

Model 2 uses the cluster mix instead and finds significant correlation with prosperity; *hypothesis 5 is accepted*. This relationship does not hold, however, once either cluster portfolio strength or the quality of business environment is included (models 3 and 5, respectively). This result contrasts with Hausmann and Klinger (2006) who find differences in industry mix as revealed by a country's export portfolio to be strongly correlated with prosperity levels. An important candidate to explain this difference is that they define their industry mix indicator directly from a regression of industry-level exports on country-level prosperity, while we control whether or not countries with a strong position in a specific industry tend to pay generally higher wages.

In the next step, we introduce cross-sectoral locational characteristics in the analysis. Model 4 shows that business environment quality has a strong impact on regional prosperity. Cluster portfolio strength remains significant and positively associated with regional prosperity even after introducing business environment quality. Cluster mix remains insignificant (model 5), when introduced alongside business environment quality and cluster portfolio strength (model 6); *hypothesis 6 is rejected*.

In our preferred model specifications (model 4), we find cluster portfolio strength to be associated with regional prosperity with a coefficient estimate of around 0.3. Thus, our estimation suggests each percentage point increase in the share of strong clusters in a region's payroll to be associated with an increase in GDP per capita of approximately 0.3%. Given that our regional cluster portfolio strength indicator differs significantly across regions, we can compare the effect of moving from the first to the third quartiles of regions in cluster portfolio strength. In our data set this move corresponds to moving from 30% to 59% of payroll from traded employment to be accounted for by

Table 3. Effects of cluster portfolio strength on gross domestic product (GDP).

	1 OLS	2 OLS	3 OLS	4 OLS	5 OLS	6 OLS
Cluster portfolio strength (share of payroll in strong clusters)	0.359[a] (0.072)		0.303[a] (0.075)	0.298[a] (0.067)		0.287[a] (0.070)
Cluster mix		1.029[a] (0.276)	0.675[b] (0.282)		0.473 (0.272)	0.149 (0.276)
Business environment quality				0.222[a] (0.033)	0.221[a] (0.035)	0.216[a] (0.034)
R^2	0.715	0.703	0.721	0.758	0.743	0.759
Adjusted R^2	0.708	0.696	0.713	0.752	0.736	0.751

Notes: [a]Significant at $p < 0.01$; and [b]significant at $p < 0.05$.
The number of observations is 263. All regressions control for population density and urban–rural characteristics by including log(population) and log(area) as predictors. All models also include national capital indicator, Eastern indicator and spatially lagged log(GDP per capita PPP).

strong clusters, corresponding to a 9% increase in prosperity. A similar interquartile shift in business environment quality corresponds to 24% higher prosperity, suggesting both cluster portfolio strength and business environment quality are important factors in understanding prosperity differences.

An important corollary of our results is that cluster portfolio strength has explanatory power beyond business environment quality or other spatial characteristics; it has an independent relationship with prosperity levels. Clusters exists also in regions that have weaker business environments and as a result lower prosperity levels. This makes clusters a potential platform for organizing upgrading efforts even when significant weaknesses exist in these other dimensions.

Cluster mix, conversely, seems to reflect the level of economic development in a region and adds little information to explain prosperity beyond the general business environment conditions. While locations at different levels of prosperity differ systematically in their industry composition, these differences are more likely to be a symptom of higher competitiveness and business environment quality, not a driver.

CONCLUSIONS

The purpose of the paper is to extend the literature on the impact that the presence of clusters has on economic performance. The analysis contributes in particular to disentangling the role of cluster presence from the impact of other relevant factors, in particular economies of scale in narrow industries, the quality of cross-cutting business environment conditions and, for region-wide analysis, of the particular cluster or industry mix in a region. The existing literature has tended to focus on showing that clusters or the specific cluster/industry mix of a location matter for economic performance but has usually not put this relationship into the context of such other factors.

We are exploiting a new, comprehensive data set on the presence of clusters across European regions. The core data set leverages a set of cluster definitions initially developed in the United States, and then applied to the member countries of the EU as well as a range of other countries. Apart from the cluster data we also use a data set capturing regional performance and business environment conditions, much in line with similar efforts elsewhere in the literature (Annoni et al., 2017).

We find that cluster presence is significantly and positively related to industry-level wages. This extends the findings of Delgado et al. (2012) on job creation, showing that agglomeration both within narrow industries and within the surrounding clusters of related industries relates to performance. This finding underpins the importance of understanding clusters as groups of related industries, not just as the concentration of economic activity in a specific field.

We also find that the cluster effect remains meaningful and significant once business environment quality, a very powerful driver of performance, is accounted for. Cluster strength thus has an independent relationship with economic outcomes, it is not simply an endogenous reflection of business environment conditions.

For our regional analysis we introduce two new measures. First, we define the strength of regional cluster portfolios as the share of traded cluster payroll account for by strong clusters, operationalized as the cluster categories in which the specific region ranks within the top quintile of European regions by LQ, subject to some size cut-offs. This measure captures how much value creation in a region is driven by clusters in which the location has achieved critical mass. Second, we construct a cluster mix indicator to capture the degree to which the specialization pattern of a location is biased towards economic activities that tend to pay higher wages. This measure shows the prosperity benefit a location might gain from is mix of clusters.

We find that regional prosperity is positively and significantly associated with our measure of cluster portfolio strength. Clusters are an important factor in understanding regional performance. Again, this relationship continues to hold when accounting for business environment quality. Clusters exist at all stages of economic development, and the specialization in strong clusters is helping locations at all levels of business environment quality to support higher levels of prosperity.

We also find that cluster mix has no independent relationship to prosperity levels once business environment quality is accounted for. While more prosperous regions specialize in higher wage cluster categories than less prosperous regions, this reflects the more sophisticated business environment that these locations provide, not an independent effect of these regions focusing on generically higher wage cluster categories. Put differently, being active in generally high-wage clusters provides no prosperity benefits to a location if it does not also offer a high-quality business environment. This puts the findings of a strong relationship between industry mix as measured by exports and prosperity into a different light: what you export is less important than how well you do in whatever you export (Hausmann & Klinger, 2006; Ketels, 2019; Lederman & Maloney, 2012).

These findings are relevant for policy-makers. First, clusters are an important dimension to understand the underlying competitiveness of a location. Second, clusters have to be seen within a broader contact of locational competitiveness that importantly also includes business environment quality. This integrated perspective was already introduced by Porter (1990) but has been lost in an often misleading debate between cluster-specific and general business environment-focused policies. Third, cluster strength is a factor that is in its relationship to economic performance complementary to business environment quality. While other factors, in particular density and industry mix, are endogenous to business environment quality, cluster strength represents a distinct factor with its own impact on wages and prosperity. This makes cluster-based efforts a tool that can be applied at all stages of economic development, not only in already highly advanced locations (Ketels, 2013, 2019).

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NOTES

1. See https://ec.europa.eu/growth/smes/cluster/observatory/.
2. See http://ec.europa.eu/growth/industry/policy/cluster/observatory_en/.
3. We explored three different types of cluster portfolio measures. First, we counted the number of strong clusters per region. This was straightforward but treated clusters with very different overall size equally. Second, we calculated the share of regional traded employment in strong clusters. This took account of size differences across clusters, but weighted labour-intensive cluster categories more strongly than others. Third, we calculated the share of regional payroll earned in strong clusters. This was driven by both employment and wages and was thus most directly linked to value creation by strong clusters in the region. These three indicators are strongly related and performed quite similarly in the analysis, hence we only report the results obtained with the most conceptually convincing one: share of payroll in strong clusters in overall regional payroll in traded industries.
4. We restrict our attention to traded industries with at least two industries constituting the cluster category (to make comparisons with 'other industries in this cluster' possible, this excludes the aerospace, leather, music and tobacco cluster categories). Additionally, we only consider observations with at least 10 employees and filter out the top and bottom 0.5% of observations based on average wage to focus on the middle 99%. This censoring is done to combat the naturally high variance of ratio-like indicators for small values of the denominator, since small changes in employment due to, for example, rounding can result in very large or very low average wages. These procedures bring the total sample size to 77,130.
5. The LQ is a standard measure of specialization in an industry and is computed as the ratio of two shares: share of employment in an industry in a given region and share of employment in an industry in all regions. Values > 1 imply higher specialization in an industry compared with the baseline. In the models in this section, all the factors beyond employment in a region/industry combination are captured by fixed effects and enter additively. Thus, given observations on all region–industry pairs we would obtain identical results whether we employ log(LQ) or log(employment). Since in fact some industry–region pairs have been filtered out, we chose to use the LQ measure since it captures the specialization aspect the best.
6. As a robustness check we also repeated the analysis removing two very large cluster categories, business services and distribution. The results were slightly stronger in all cases, though the relative importance of industry and cluster localization was reversed, confirming that these two variables are highly correlated.
7. We also tested similar models but using two- and three-digit industries as the grouping (i.e., 'other industries' would refer to other industries from a respective two- or three-digit industry). We found that the effect on the three-digit level is negligible (the coefficient for the main localization variable is unchanged). The models on the two-digit level are similar to those on cluster categories, though with a lower magnitude of the coefficient.
8. We use lme4 package for the R environment (Bates et al., 2014) to compute HLM estimates.

9. If we regress the regional fixed effects in model 3 on business environment.
10. The specific results are not reported here, but are available from the authors upon request.
11. We also repeated the analysis using the average regional wages computed from the same sources as the industry-level data. The results were similar to the reported figures for GDP, but have exhibited a lot of non-random patterns at the country level. This has suggested that there are substantial issues with wage data comparability across countries due to differences in definitions and we opted instead for the standard GDP per capita measure. Wage comparability is not an issue in the previous section because of the presence of regional and industry fixed effects that capture the related data collection and definition idiosyncrasies.

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