Firm heterogeneity in productivity across Europe. What explains what?

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Abstract This paper analyses the TFP heterogeneity of a sample of manufacturing firms operating in seven EU countries (Austria, France, Germany, Hungary, Italy, Spain and UK). TFP data refer to 2008. The empirical setting is based on the multilevel modelling which provides two main results. Firstly, we show that TFP heterogeneity is largely due to firm-specific features (85% of TFP variability in the empty-model). Interestingly, we find that some key-drivers of TFP (size, family-management, group membership, innovations and human capital) influence heterogeneity in productivity with the expect sign, but do not, on the whole, absorb much of firm-TFP variance, implying that differences in productivity are due to sizable yet unobservable firm characteristics. Secondly, as far the role of localization is concerned, we demonstrate that country-effect is more influential than region-effect in explaining individual productivity. Net of the country-effect, the localisation in different European regions explains about 5% of TFP firm heterogeneity. When considering the case of three individual countries (France, Italy and Spain), location in different regions explains 5.3% of TFP heterogeneity in Italy, while this proportion is lower (3.6%) in France and higher (9.9%) in Spain.

Keywords: TFP heterogeneity, firm-behavior, localization, European countries, multilevel model

JEL classification: C30, D22, L60, R15

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1. Introduction

The presence of wide and persistent gaps in income in the EU has been a long-debated issue. The significant disparities are evident from data on GDP per-capita, which in 2011 ranged from values of more than six to less than one across EU members. Bulgaria has the lowest GDP per-capita in the EU28, being 11700 euro per-capita (in Purchasing Power Standards) at less than half of the EU28 average. The Netherlands and Ireland have GDP per-capita values which are about 30 percent above that average, while Luxembourg leads the group, with 66700 euro per inhabitant. Mediterranean countries (France, Italy, Portugal and Spain) are below the EU average. The dispersion in GDP per-capita become even more apparent when regions are used as unit-of-analysis. In such a case, GPD pro-capita ranges from the highest values of Inner London (80400 Euro per inhabitant in 2011) and Luxembourg (66700 Euro) to the lowest GDP per-capita (less than 10000 Euro) for twelve EU regions (data are from the Eurostat website, as at 12th May 2014).

While these stylized-facts include the effects of recent EU enlargements, they have given rise to an intensification of institutional interest and academic research aimed at explaining their dynamics and causes. On one hand, the EU emphasizes the benefits from integration and highlights how the regional policies have been effective in reducing the economic divide across the EU (EU Commission, 2007). On the other hand, many scholars provide convincing econometric evidence that no convergence process has occurred across the EU, as the single factor or multifactor productivity dispersion has remained constant over time (Bartkowskaa and Riedla 2012; Caggiano and Leonida 2013; De la Fuente 2002a; 2002b; Di Liberto and Usai 2013; Tamàs-Borsi and Metiu 2015). This long-term pattern of growth across EU is relevant not only to verify what the theory predicts (the observed paths suit more endogenous growth theory than neoclassical modeling), but also to give voice to the skepticism on the EU cohesion policies which served, at best, as a mechanism of redistribution (Boldrin and Canova 2001; Aiello and Pupo 2012).

A common feature of this literature aimed at explaining why economic growth is not uniform across EU is the use of aggregated data, although the nexus between firm-heterogeneity and aggregated-productivity is becoming the main concern of some recent studies. These studies exploit the firms' heterogeneity at micro-level as a source of the aggregate growth and focus on individual European countries.[1]

[1] For instance, Altomonte and Colantone (2008) calculate several compositional effects of multinational enterprises and demonstrate that the regional disparities observed in Romania over the 1995-2001 period depend on the interaction between firm-level dynamics and the initial market conditions. Aiello et al. (2011) used a panel of Italian firms to decompose the output growth into factor accumulation, technological change, efficiency and scale effects over the 1998-2003 period. They found that efficiency change (technological catch-up) explains much of the output growth observed in Italy, as a whole, and in the two macro-areas (North and South) of the country, separately. The connections

The present work contributes to the debate on the EU economic divide by proposing an alternative view of firm heterogeneity. The underlying idea is that firms differ from each other in several ways - such as size, approaches to production, different technological strategies and firm-specific learning processes (Bloom and Van Reenen 2010; Ortega–Argilés et al 2011; Teece *et al.* 1997). Such heterogeneity in firm-specific behavior would thus be expected to translate into heterogeneity in performance. While firm-heterogeneity is certainly driven by differences in individual factors, it may also be due to between and within-country effects: the location of a firm in different areas across Europe would contribute to individual productivity. Location is thus an important factor in determining enterprises' outcomes. This is not surprising since an extensive literature shows that the higher the endowments of a given area, the greater the benefits for local firms (see, i.e., Baldwin and Okubo 2006; Krugman 1991; Ottaviano 2008; Rodriguez-Pose 2009; Vernon Henderson *et al.* 2001).

Following this line of reasoning, we expect to find a substantial heterogeneity in productivity when comparing individual firms and when grouping them by geographical area. However, even when heterogeneity is detected, some issues remain unsolved. For instance, when focusing on the EU there is no evidence, to our knowledge, about the role played by individual variables and by location in explaining firms' heterogeneity in performance. The main distinguishing feature of this study, therefore, lies on the following questions. How much of the difference in firm performance can be attributed to individual heterogeneity and how much of this difference reflects territorial conditions around Europe? Are country-effects larger than regional ones? And, do firm-specific factors help in predicting individual productivity?

In order to answer these questions, we proceed by using data on firms operating in the seven countries (Austria, France, Germany, Hungary, Italy, Spain and in the United Kingdom, henceforth, EU7-EFIGE countries) included in the "European Firms in a Global Economy: internal policies for external competitiveness" (EFIGE) dataset (Altomonte and Aquilante 2012). When focusing on these countries, the influence of being located in different regions will be investigated, net of sector and country-effects. Furthermore, a deep-analysis of the impact of region-effects within a given country will be carried out by considering three individual nations (France, Italy and Spain). The key variable used in this study is the Total Factor Productivity (TFP), as estimated - within the EFIGE project - by using the Levinsohn and Petrin (2003) approach.[2]

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between micro and aggregate industry productivity have been surveyed by Foster et al. (2001) and Van Biesebroeck (2003).

[2] As regards the choice to use TFP, it is worth pointing out that a vast literature demonstrates how the economic divide observed across countries and regions is mainly due to differences in TFP instead of differences in physical and/or human capital deepening. This issue has been initially demonstrated by the seminal studies of Hall and Jones (1999), Klenow and Rodriguez-Clare (1997) and Caselli (2005). Unlike the literature on TFP divide, we consider the firm rather than the region (or the country) as the unity-of-analysis. This choise allows us to address various empirical issues

The empirical setting we propose is consistent with the type of issues to be addressed. Because firms are embedded in regional and national systems, data have a hierarchical structure, which is properly handled by multilevel models (Goldstein 2003; Luke 2004). The advantages of using a multilevel instead of a single-equation framework are numerous, which we summarize here (details are in Heck and Thomas 2000; Hox 2002; Mass and Hox 2004; and Srholec 2010). The first benefit is that the multilevel models combine different levels of data aggregation and relate them in ways that render the simultaneous existence of distinct level-one (firm) and level-two (region) equations explicit. In this respect, multilevel allows the evaluation of whether, and to what extent, space matters in determining firm performance. In fact, besides testing hypotheses at different levels, multilevel models yield a decomposition of TFP variance and hence provide highly informative outcome related to the quantitative measure on "how much" location and individual factors explain of TFP heterogeneity. Furthermore, with respect to single-equation models, multilevel exploits the structures of data and properly addresses the issue of error correlation across firms operating in the same region. Moreover, the inference is made by distinguishing between sample size at the different levels of data aggregation.[3] Another advantage is that multilevel models address both ecological and atomistic fallacies, because they take firm and regional levels into account simultaneously.[4] Finally, they offer the possibility of identifying different sources of disparity in individual productivity.

All these methodological advantages render the multilevel models attractive also from an economic perspective, because they address how the "micro, middle and macro" (Schumpeter 1934) spheres of economic systems evolve and interact in any process of growth. The originality of the approach lies on the fact that the hierarchical interactions between agents and external growth-factors are not studied in an exhaustive way yet (Raspe and von Oort 2011; Srholec 2010). For instance, the endogenous growth models pay much attention to proving the existence of increasing returns due to knowledge spillovers between firms and other organizations (Romer 1986; Aghion and Howitt 1992). However, they are macro models and focus on aggregate patterns, although they have micro-foundations. Again, the evolutionist scholars explain that the environment plays a

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related to the fact that firms are nested in regions (cfr § 4). Moreover, firms is the proper level of analysis to verify whether the regional environment affects the individual innovative performance (Beugelsdijk 2007).

[3] This represents an important statistical advantage over single-equation models, which are too limited to handle hierarchical structures of data. Indeed, in a single-equation model, the inference is based on the entire sample size and this entails a high risk of type I errors because the variance of the level-two coefficients is underestimated (Bickel 2007). There is another potential bonus entailed in the unbiasedness of results. Indeed, in many economic problems, the groups differ in size and in such unbalanced set-ups, multilevel assigns greater weight to large groups than small ones.

[4] The ecological fallacy occurs when a result obtained at an aggregate level is not automatically confirmed after replicating the analysis on an individual basis. Hence, micro-founded analysis is preferable since it controls for any potential aggregation bias. On the contrary, working with micro-data leads to the opposite issue related to the absence of any link between individual-level and group-level relationships (atomistic fallacy) (Raspe 2009; Raspe and van Oort 2011).

dominant role in influencing firms attitude to innovation, even though the micro-macro interactions are one-way, flowing from individuals to aggregates (Dosi and Nelson 2010). This implies that the "overall" patterns are just those from aggregations, while any other important environmental factor is left out of the analysis (Castellacci 2007). The link between this literature and the multilevel approach is in the basic idea that each firm is embedded in a specific economic system. The implication of this is that productivity is understood as a systemic-shared issue, which cannot be addressed without modeling the interactions from micro to macro level, and vice-versa, as multilevel does (Baldwin and Okubo 2006; Beugelsdijk 2007). Hence, multilevel represents an important contribution in the empirical studies of firms performance aimed at understanding the essential links between micro and macro patterns (Aiello et al. 2014; Raspe and van Oort 2011; Srholec 2010; 2015).

Despite its advantages, the multilevel approach has been applied to firm productivity only in few papers. For instance, Raspe and van Oort (2011) link firm productivity to the knowledge-intensive spatial contexts in the Netherlands and find that a large part of what is considered the effect of spatial externalities should actually be the effect of firm-specific characteristics. For Italy, Fazio and Piacentino (2010) investigate the spatial variability of fims labour productivity, while Aiello et al. (2014) analyse how firms' characteristics and regional factors affect TFP heterogeneity. Aiello et al. (2015) extend the analysis to sectoral membership. Mahlberg et al. (2013), with reference to Austria, explore the link between age and labour productivity. A related topic is innovation, which, in the framework of multilevel analyses, is investigated by Srholec (2015). He shows how national conditions affect the propensity of firms to cooperate on innovation at home or abroad.

The results of this paper are as follows. Having found high TFP heterogeneity across firms and regions, we confirm that firm-specific characteristics greatly affect individual productivity. Furthermore the regional effect results to be high when estimations disregard the country-effects: in such a case, location across EU7-EFIGE regions explains 15.1% of differences in TFP across firms. After controlling for country-effects, we find that 5.8% of TFP variance is due to be located in a region instead of another. The magnitude of firm and regional effects slightly differ when the regressions control for firms' sectoral membership. It has also been proved that the aforementioned results associated to the entire EU7-EFIGE sample hold when estimations regard France and Italy, while the regional effect is slightly higher in Spain. Finally, we show that the observable firm-specific variables meant to be important drivers of TFP (size, human capital, innovation, partnership and family-management) influence TFP with the expected sign. As far as the EU7-EFIGE sample is concerned, these individual factors, as a whole, capture 20% of the TFP variance ascribed to the first-level of our model.

The rest of the paper is organised into six sections. Section 2 briefly presents the EFIGE dataset. Section 3 reveals firms' heterogeneity in TFP at country, region, sector and individual level. Section 4 describes the multilevel models used throughout the empirical analysis. Sections 5 and 6 discuss the results, while the conclusions are in section 7.

2. The data source and the TFP

The empirical analysis is based on the EU-EFIGE/Bruegel-UniCredit dataset (EFIGE dataset in short), which is a by-product of the EU project "European Firms in a Global Economy: internal policies for external competitiveness". The dataset contains data from a survey and from balance-sheets. The survey, carried out in 2010, provides comparable cross-country data of manufacturing firms in seven European countries (Austria, France, Germany, Hungary, Italy, Spain and the United Kingdom) and covers quantitative as well qualitative information ranging from R&D and innovation, labor organization, financing and trade activities and pricing behavior.[5] While the survey refers to the 3-year-period 2007-2009, much information is averaged over the years under scrutiny, or relates only to 2008.[6]

For the purposes of this study, we use the TFP calculated for 2008 by the researchers involved in the EFIGE project. They have estimated the TFP by applying the Levinsohn and Petrin (2003) approach and considering sectoral production functions. Estimates also control for country and year fixed-effects over the 2001-2009 period. Firm TFP is then estimated from heterogeneous industry specific production functions. From the appendix table A1, it emerges that the estimated values of labour and capital elasticities are positive and highly significant whatever the sector.

Table 1 reports firms' distribution by country. The EFIGE project surveys around 15 thousand European firms, many of which are in Germany, France, Italy and Spain (about 3000 firms in each country), followed by the United Kingdom (slightly more than 2000 firms) and

[5] The sampling design has been structured following a three dimension stratification: industry (11 NACE-CLIO industry codes), region (at the NUTS-1 level of aggregation) and size class (10-19; 20-49; 50-250; more than 250 employees). Given their importance in aggregate competitiveness dynamics, but their relatively light weight in standard stratification of the population of firms, large firms have been oversampled. In computing the correlation over time (2001-2009) between some variables in EFIGE dataset (aggregated with proper weighs) and the national statistics provided by EUROSTAT, Altomonte and Aquilante (2012) show that the correlations are 0.82 for labour productivity, 0.71 for labour cost, 0.52 for revenues and 0.61 for workers. Correlations increase to 90% when considering the countries (France, Italy and Spain) with a good quality of balance sheet data. For details on EFIGE dataset see Altomonte and Aquilante (2012) and Barba Navaretti *et al.* (2011).

[6] As a by-product of the EFIGE project, the survey data has been integrated with firms' balance sheets of Amadeus database managed by Bureau van Dijk. The survey dataset is available in different versions, depending whether the user has an active licence with Bureau van Dijk. In this paper, we mainly refer to the version which is freely downloadable from the Bruegel website, plus the TFP array released by Bruegel after presenting a research proposal. We complement the study on TFP by using labour productivity and labour costs (footnote 18 and table A2). A potentially important data limitation of original "free" dataset is that it includes just randomised regional and industry identifiers. This is a sensitive data related issue that we address by running all regressions at Bruegel, in Brussels.

Austria and Hungary (less than 500 in each country). When matching the EFIGE survey with the Amadeus archive, the sample decreases by about 50% because of the many missing-values in Amadeus related to the variables needed to estimate the production function from which the TFP is retrieved.

In what follows we refer to the sample with TFP formed by 7435 European firms, the majority of which (more than 84% of the sample) are in France, Spain and Italy. 1605 of the firms are located in France, 2243 in Italy and 2410 in Spain. Surprisingly, the EFIGE survey comprises 2935 German firms which is reduced to just 579 in the archive containing TFP. The same holds in the case of UK (from 2067 to 394).

Table 1 Distribution of firms by country: EFIGE survey and the EFIGE-Amadeus sample.

Country	EFIGE Survey	%	EFIGE-AMADEUS	%
Austria	443	3.0	25	0.3
France	2973	20.1	1605	21.6
Germany	2935	19.9	579	7.8
Hungary	488	3.3	179	2.4
Italy	3021	20.5	2243	30.2
Spain	2832	19.2	2410	32.4
UK	2067	14.0	394	5.3
Total	14759	100.0	7435	100.0

Source: computation on data from EU-EFIGE-Bruegel-UniCredit dataset

3. Does heterogeneity in TFP exist across Europe?

National, regional and individual disparities in economic performance is a well known fact in the EU. Looking at data from EFIGE, one observes that the average TFP is 1.06 for the entire sample of firms in 2008, with marked differences across countries. Firms located in Hungary, Austria, Germany and France register a TFP which is above the average: for these countries, the TFP is equal to 1.8, 1.57, 1.49 and 1.17, respectively. At the extreme side, Spanish and Italian firms are below the overall average with a TFP of 0.97 and 0.9, respectively. In the UK, firms perform similarly to the EU average (table 2). An analogous heterogeneity exists when considering regions instead of nations. It emerges that in 59 out of the 130 regions covered by EFIGE, the TFP is higher than that of the overall sample, while the opposite holds for the remaining 71 regions. In 2008, differences in averaged regional TFP ranges from 0.55 to 1.85 with a dispersion around the EU7-EFIGE average of 0.23 expressed as standard deviation. Differences in regional TFP are displayed in figure 1, where data are expressed as deviations from the overall average. Two Spanish (Avila and Zamora) and one Italian (Molise) regions are at the bottom of the ranking, while the best performers are Hamburg (Germany), Burgenland (Austria) and Közép-Dunántúl (Hungary). Just to complement the description of data, figure 1 also displays the TFP at sectoral level: there are 5 sectors with a TFP less than the EU average, while the other 6 sectors register a TFP higher than the EU average.

Differences in aggregate TFP obviously reflect individual performance. Heterogeneity in TFP is extremely high at firm level. The minimum level of TFP is 0.008 (a firm located in Italy) and the maximum is 19.22 (in France). Table 2 shows that 10% of firms achieved levels of TFP less than 0.59 and that only 25% of the sample obtained scores equal to or below 0.68. Again, the median for the entire sample of firms is 0.88 and the average, as said above, is 1.06. Marked differences are revealed across firms in different countries. For instance, the percentiles of Italy are always less than those calculated in any other country. In the other countries, the percentiles are higher than those referring the distribution of all firms, expect for 1% percentile in Hungary and 1%, 10% 75%, 90%, 95% and 99% in the UK.[7] Figure 2 summarizes the differences by country. While the distributions differ from one country to another, all TFP density functions have a positive asymmetry. This seems to be consistent with the combination of neo-Schumpeterian and neoclassical theories, where TFP is intended as a proxy of technology produced by few leading innovative firms, which, however, the others follow to a limited extent because of their low absorptive capacity (Bhattacharjee *et al*. 2009).

What the data highlight is a considerable heterogeneity in individual performance, whatever the level of aggregation. The following sections propose a method to quantify and discuss to what extent firm heterogeneity in TFP is due to firm-specific factors and how much can be explained by other sources of variability. The next section will present the model, whilst the results will be discussed in sections 5 and 6.

[7] Hungarian data on TFP seem surprising, given that the GDP pro-capita in this country is far below the level of the other countries of the EFIGE sample (it was 40% lower than the 2012 EU-28 average). While the understanding of this country-specific evidence goes beyond the objective of the study, in the econometric section of the study we perform some robustness checks aimed at controlling for any potential bias due to outliers.

Table 2 TFP distribution in seven European countries in 2008. Summary statistics.

	Percentiles															
	1%	5%	10%	25%	50%	75%	90%	95%	99%	Minimun	Maximum	Mean	Std. Dev	Skewness	Kurtosis	Obs.
All Sample	0.25	0.44	0.59	0.68	0.88	1.2	1.65	2.1	4.1	0.008	19.22	1.06	0.85	8.16	119.2	7435
Austria	0.29	0.52	0.68	0.83	1.3	2.13	3.01	3.74	4.11	0.29	4.11	1.57	0.98	1.08	3.51	25
France	0.3	0.5	0.59	0.73	0.94	1.23	1.78	2.29	5.97	0.16	19.22	1.17	1.23	8.33	94.86	1605
Germany	0.27	0.54	0.69	0.91	1.21	1.6	2.13	3.25	7.33	0.1	16.75	1.49	1.3	5.47	47.69	579
Hungary	0.17	0.44	0.62	0.98	1.4	2.05	3.63	4.87	7.62	0.069	8.1	1.8	1.37	2.1	8.05	179
Italy	0.24	0.39	0.48	0.61	0.8	1.05	1.44	1.73	2.79	0.008	5.58	0.9	0.48	2.67	15.99	2243
Spain	0.29	0.46	0.53	0.65	0.85	1.12	1.52	1.84	2.87	0.038	6.45	0.97	0.53	3.45	25.61	2410
UK	0.2	0.43	0.55	0.71	0.92	1.18	1.56	1.96	3.45	0.15	7.24	1.03	0.6	4.19	35.1	394

Source: see table 1

Figure 1 TFP by region and sector in 2008 (deviation from the EU average)[8]

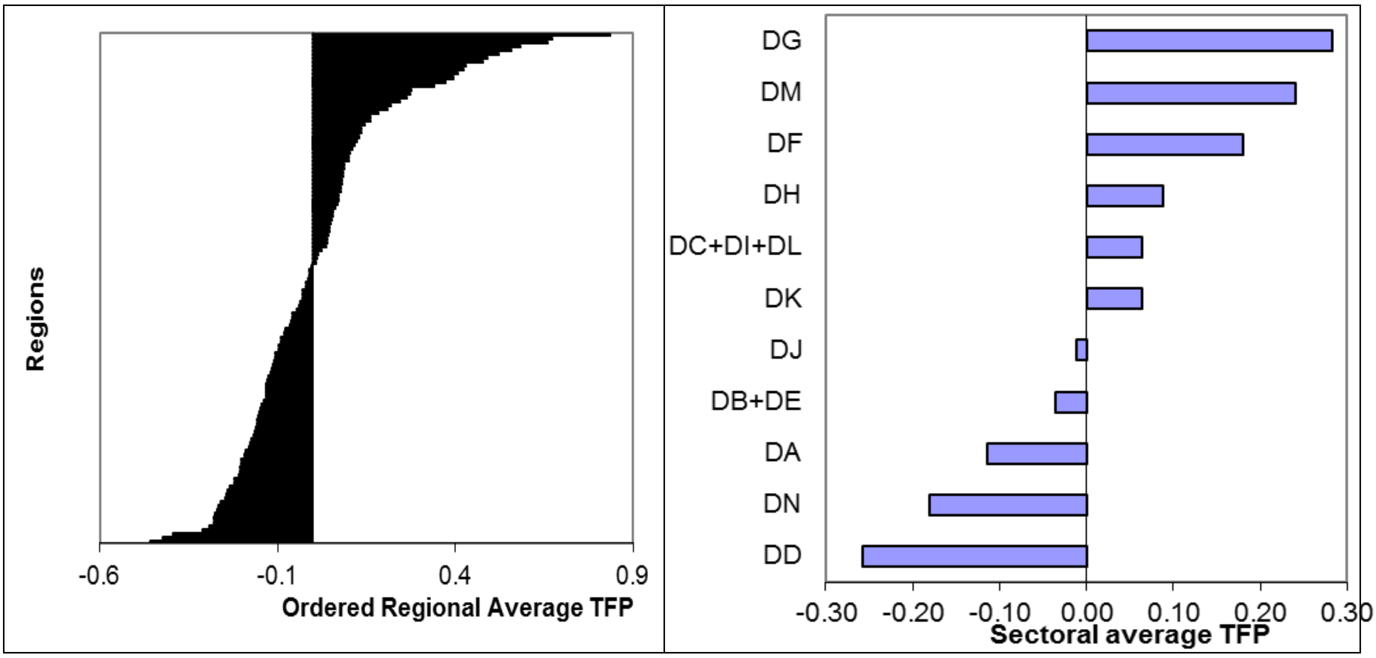
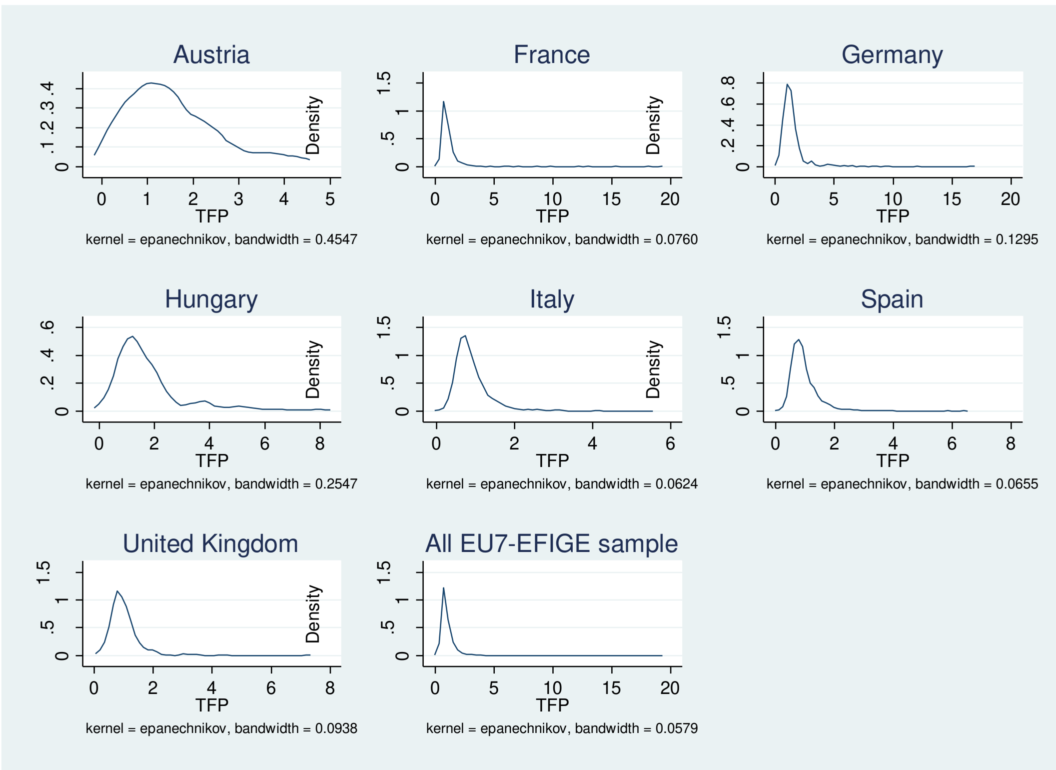


Figure 2 TFP distribution by country in 2008



[8] Sectors description follows the NACE-Rev1.1 classification. Labels are detailed in the appendix table A1.

4. Explaining TFP heterogeneity with multilevel models

In the previous section we have shown that heterogeneity exists and that TFP varies between firms, countries, regions and sectors. It is revealing to disentangle these different sources of variability by means of multilevel method. This approach allows us to incorporate unobserved heterogeneity into the model by taking into account the hierarchical structure of the data (Goldstein 2003).

It is reasonable to hypothesize that firms belonging to the same geographical area share the same external environment and thus are likely to be more similar to each other than firms operating in different territories. This similarity means that the assumption of independence of errors is violated. This issue is addressed by the multilevel approach which ensures efficient estimates since it controls for spatial dependence and corrects the measurement of standard errors, thereby reducing the risk of type I errors.[9] In fact, whereas standard regressions are designed to model an overall mean coefficient, the multilevel analyses consider, in addition, group level variance explicitly through the inclusion of random coefficients. An econometric specification of a multilevel model may be expressed as follows:

$$y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij} \qquad [1]$$

where the y_{it} is the TFP of firm i at time t, X comprises a set of variables measured at firm level, β_{0j} is the intercept, β_{1j} are the slope coefficients and e_{ij} is the random error term with zero mean and variance σ_e^2; j stays for regions (*j=1…r*) and i for firms (*i=1…N*$_j$). In eq. [1], the regression parameters β_j vary across level-2 units. The specification used here is a random intercept model, that is :

$$\beta_{0j} = \gamma_{00} + u_{0j} \qquad [2]$$

$$\beta_{1j} = \gamma_{10} \qquad [3]$$

In so doing, β_{0j} differs across groups (e.g., regions), while u_{0j} is the random error term defined at the group level with zero mean and assumed to be independent of e_{ij}. The random component u_{0j} captures variability in the intercept across clusters, while the fixed component γ_{00} is a weighted average of the intercept across all clusters. γ denotes the fixed level-two parameters.

The combining of micro (eq. 1) and macro models (eq. 2 and 3) produces a two-level mixed equation:

$$y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + (u_{0j} + e_{ij}) \qquad [4]$$

[9] It is well known that multilevel approach is not the only way to address the hypothesis of residuals independence. Spatial econometrics has made important advances in this respect, even though the interest is confined to single-level relationships (firms, regions), without treating the micro-macro interactions as multilevel does. Some methodological attempts to combine multilevel models and spatial econometrics are in Corrado and Fingleton (2012).

The deterministic part of the model, $\gamma_{00} + \gamma_{10} X_{ij}$ contains all the fixed coefficients, while the stochastic component is in brackets. The error term captures the residual variance, in the same way as OLS regression does, and the group-to-group variability of the random intercepts. It is clear that the error term displayed in eq. [4] is not independently distributed. Indeed, as data are nested at different levels of analysis, firms belonging to the same group tend to have correlated residuals, so violating the assumption of independence.

Eq. [4] also allows for the identification of the errors resulting from differences across firms or clusters. To this end, it is necessary to use an "empty" model, i.e. a model without any explanatory variables:

$$y_{ij} = \gamma_{00} + u_{0j} + e_{ij} \qquad [5]$$

From eq. [5] is possible to decompose the variance of y_{ij} into two independent components, i.e. the variance of e_{ij} (σ_e^2), the so-called within-group variance, and the variance of u_{0j} (σ_{u0}^2), also known as between-group variance. A useful way to interpret the relative magnitude of the variance components is to compute the Variance Partition Coefficients (VPCs) which are the proportion of the variance that lies at each level of the model hierarchy.[10] The VPC at regional level is calculated as the ratio of the regional variance to the total variance, that is:

$$VPC_{u0} = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_e^2} \qquad [6]$$

The firm VPC is written as the ratio of the firm variance to the total variance:

$$VPC_e = \frac{\sigma_e^2}{\sigma_{u0}^2 + \sigma_e^2} \qquad [7]$$

In the model we have described, data are hierarchically structured and, from a general point of view, it is worth noting that firms may belong to more than one group within a hierarchy and each group can be a source of random variation. For instance, firm performance may be affected by both the territorial conditions of the regions where they are located and by the specificities of sectors in which they operate. Firms from different sectors may be located in the same region and firms from different regions may operate in one given sector. In this sense, sectors are not nested in regions and regions are not nested in sectors, but, rather, regions and sectors are crossed one with another. There are two separate two-level hierarchies which cross one with another: a firm-within-regions hierarchy and a firm-within-sectors hierarchy. In such a condition, the data have a cross-classified structure. To sum up, in models for cross-classified data, a lower-level unit belongs uniquely to one

[10] For equation [5] VPC coincides with the intra-class correlation (ICC) that measures the expected degree of similarity between responses within a given cluster (e.g. region). This equivalence will not hold in more complex models, such as those including random coefficients (Leckie 2013).

higher-level unit of the first type (e.g. a region) and also uniquely to one higher-level unit of the second type (e.g. a sector), but the two types of unit are not nested in either way.

Moreover, firms may be also affected by the sector-region interaction. A general cross-classified model can be written as:

$$y_{i(sj)} = \gamma_{000} + u_s + u_j + u_{sj} + e_{i(sj)} \qquad [8]$$

where there are two indices at the second level, *s* and *j*, denoting simultaneous nesting in sector *s* and in region *j*. The dependent variable, $y_{i(sj)}$, refers to the *i-th* firm from the *(sj)-th* sector/region combination. In eq. [8], the variable $y_{i(sj)}$ is equal to the overall mean γ_{000} plus a random departure u_s due to sector *s*, a random departure u_j due to region *j*, an interaction term u_{sj} and an individual-level random departure $e_{i(sj)}$, with $e_{i(sj)} \sim N(0, \sigma_e)$, $u_s \sim N(0, \sigma_{u_s})$, $u_j \sim N(0, \sigma_{u_j})$ and $u_{sj} \sim N(0, \sigma_{u_{sj}})$.

Eq. [8] differs from eq. [5] for the u_s term that captures the variability in the intercept across sectors. The random intercept for sector u_s is shared across regions for a given sector, whereas the random intercept for region u_j is shared by sectors for a given region. The interaction term u_{sj} takes on a different value for each combination of sector and region. The random intercepts are independent of each other, across sectors, regions and combinations of sector and region, and are also uncorrelated with $e_{i(sj)}$.

Similarly to eq. [5], from eq. [8] it is possible to calculate the proportion of the response variance that lies at each level of the model hierarchy.

5. TFP heterogeneity and the empty multilevel model

This section refers to the estimations obtained when considering the empty multilevel model. An empty model allows us to evaluate how much of the variation in outcomes might be attributable only to unobserved factors operating at each level. In our case-study, the potential levels are four: firm, region, country and sector. However, there are 7 EU members in the sample, and this prevents us from considering country as a level of the model, as the multilevel approach ensures reliable estimations only when the group-size is at least 20. The same applies for the 11 sectors, albeit to a lesser extent.[11] Therefore, we restrict the data hierarchy to two levels (firms and regions). As a

[11] In the multilevel approach a key issue to be addressed concerns the sample size at any level of analysis. Indeed, the requirements of precise measurement of between-group variance impose a "sufficient" number of clusters. Although there are some, albeit very different from each other, rules of thumb, a clear indication does not exist in this respect

consequence, the country-effect has been controlled by using dummies, while the sector-effect has been addressed by recurring to dummies, as made for countries, and by admitting that sector is a specific level in a multilevel modeling (although in this case the results must be interpreted with caution).[12] In brief, throughout the paper the preferred model specification is that which treats regions as sources of randomness in the intercepts, while countries and sectors are modeled as fixed-effects. All the remaining estimations are considered as a robustness check, at best.

Table 3 displays the results obtained when running different regressions. In column 1, we consider the random-intercept equation in which the second level is formed by the 130 EU7-EFIGE regions only. In column 2, sectors replace regions. Column 3 refers to the estimations considering both regions and sectors as sources of randomness in the intercepts. Finally, column 4 refers to the cross-classified model which also incorporates the interaction region-sector. In order to control for the effect of potential outliers, all regressions consider the 7239 observations which lie in the first and the last percentile of TFP distribution and not all the sample as presented in table 1.

The first result to be discussed is the likelihood-ratio test, which compares the empty models with the standard OLS regression: under H_0 we have that $\sigma^2_{u0} = 0$, hence there is no random intercept in the model. If the null hypothesis is true, OLS can be used instead of a variance-components model. The test, which is highly significant, supports the use of multilevel methodology and indicates that the intercept should be considered as a group-by-group variant coefficient. The evidence in favor of the multilevel approach holds for each model considered in table 3.

As can be seen from column 1 of the table, region-specific factors capture 15% of the total TFP variance, while the remaining (85%) is explained by firms. If variability at the second-level is modeled through sectors alone, then the sectoral membership will explain 11.6% of TFP variability and the rest (88.4%) is due to firm-features (column 2). When using the cross-classified specification, we find that 12.2% of the unexplained variation in TFP lies at the regional level and 9.1% at the sectoral level, while the internal firm characteristics explain 78.7% of firms' TFP variance (column 3). Finally, the cross-classified model augmented by the interaction regions/sectors (column 4) suggests that this factor captures 5.3% of individual TFP variability. In

(Richter 2006). Some authors suggest that 20 is a sufficient number of groups (Heck and Thomas 2000; Rabe-Hasketh and Skondal 2008), others 30 (Hox, 2002) or 50 (Mass and Hox 2004). In addition, it is worth noting that in random-effects models the clusters must be sized with at least two observations. The alternative is a fixed-effects approach in which the number of groups is not important, although their dimension then becomes crucial as the estimated group-effect is unreliable for small-sized groups. These numbers condition our empirical setting: the preferred specification is a two-level random-intercept model where firms and regions are treated as source of randomness and countries and sectors are modelled with dummy variables.

[12] When considering sectors a source of randomness, the estimations have been made through the model allowing for random-intercepts for sectors and regions and augmenting this specification with the interaction region-sector (as the eq. [8] briefly highlights)

this specification, the explaining power at firm level declines to 74.6%, while 8.6% and 11.5% of TFP variance is related to sectors and regions, respectively. What we learn from table 3 is the robustness of the regional effect, which is high whatever the model used, ranging from 11.5% to 15.1%.

However, the role of country-effects is left out of table 3 and this issue needs to be tackled. With an insufficient number of countries (7), we decide to consider them as fixed-effects. This ensures consistency in estimations (*cfr* note 11). Results are displayed in table 4. On one hand, we observe that the results vary dramatically when the empty model is augmented with country-dummy variables. In such a case, the role of regions drops to 5.8% and the country-dummies are highly significant, except for Austria, which is similar to the controlling group (Germany). The estimated parameters of country-dummies confirm the considerable differences in productivity across European countries. Italy, Spain are at the lower bound, followed by UK and France. Germany, Austria and Hungary lead the group. On the other hand, it is possible to quantify the proportion of TFP variability at the second-level of the model (regions) which is due to country-effect: this proportion is high and equal to 63.3%. In other words, two-thirds of the variance assigned to the region-effect is a between-country effect.[13]

When modeling sectors as fixed effects through dummy-variables, the share of firms' TFP variability explained by regions is 13.4% (table 4 column 2), which is not much lower than the proportion (15.1%) estimated through the basic empty model. Again, when incorporating both country and sectoral dummies, we find that regions record 4.9% of heterogeneity in TFP (table 4 column 3).[14] The lesson learnt from tables 3 and 4 is that localization across EU7-EFIGE regions is important in explaining why TFP differs so much. In this respect, we find that the proportion of TFP variance we attribute to regions varies from 4.9% to 15.1%. The region-effect is a minimum (4.9%) in models embodying the country and sector effects, while the maximum (15.1%) is obtained when the issue of location is addressed considering regions only. From this evidence, it is easy to argue that countries dominate regions, which, however, explains around 5% of TFP

[13] The contribution of country-effect is calculated by comparing the total TFP variance (0.03) explained at regional level in the empty model (column 1 table 3) and the variance (0.011) obtained when this model is augmented by country-dummies (column 1 of table 4), that is: [(0.03-0.011)/0.03] (*cfr* note 22).

[14] In the remainder of table 4, the country-effect is modelled with dummies, whereas sectors act as random instead of fixed effects. In other words, these estimations replicate all the models used in table 3, with the inclusion of country-dummy variables. As can be seen, the results suggest that the proportion of TFP variance explained by the region-random effect is 4.4% in model 5, and 3.5% in model 6. Sectors contribute to explain about 11.5% of TFP variance. The evidence in columns 4-6, however, suffers from the small number of sector-groups, and should thus be treated with caution.

heterogeneity observed at EU7-EFIGE level.[15] Sector membership, on the contrary, exerts a limited impact on the proportion of heterogeneity due to regions.[17]

Our results demonstrate that firm TFP heterogeneity in the EU7-EFIGE sample is more sensitive to country than to regional location.[18] Given this and in order to evaluate the role of regions as a source of TFP variation, it appears to be worth complementing the analysis on the entire sample of EU7-EFIGE countries by focusing on each single country. The work proceeds by considering France, Italy and Spain given that these countries have a sufficient number of regions to ensure reliability in the results (20, 22 and 50, respectively). Another reason to concentrate on France, Italy and Spain is that the number of TFP-observations at firm level is fairly large, while in the other countries it is extremely low (*cfr* table 1). Table 5 reports the results: panel (a) refers to Italy, panel (b) to France and panel (c) to Spain.

As far as Italy is concerned, we find that the region-effect explains 5.3% of firm heterogeneity in TFP in 2008. This outcome is in line with two recent studies which use the multilevel modeling. In Aiello *et al.* (2014) the region-effect explains slightly less than 5% of firm TFP heterogeneity observed in Italy in 2006, whereas the spatial-regional-effect is 5% in Fazio and Piacentino (2010), a work which explains the dispersion of labour productivity across firms in Italian provinces (NUTS3) in the year 2005. According to our evidence, in France the region-effect is 3.6%. The results for Italy and France are much lower than those obtained for Spain, where regions contribute to explain 9.9% of differences in individual TFP. This might be due to the fact that Spain differs from Italy and France, being divided in many autonomous regions (Comunidades Autónomas) that receive state transfers for a very wide range of decentralized responsibilities and competencies. Beside this, we also consider the sectoral dimension. In each panel, we present the estimates when considering regions and sectors as random-effects (columns 2) and their interaction (columns 3). It can be pointed out that the role of sector membership is higher in Italy and France

[15] The results on the capability of regions to explain the TFP heterogeneity are robust to the potential bias due to outliers (*cfr* § 2). Indeed, the evidence holds when regressions for the EU7-EFIGE sample are estimated when excluding (a) Austria and Hungary (columns 1 and 2, table A3), (b) the 739 firm-observations falling in the first and last 5% TFP distribution (column 3, table A3) and (c) Austria and Hungary and the 739 potential outliers (column 4, table A3). As we can see, regions always explain less than 5% of TFP heterogeneity.

[17] The contribution of sector-effect is calculated by comparing the total variance (0.03) explained at regional level in the empty model (column 1 table 3) and the variance (0.025) obtained when this model is augmented by sector-dummies (column 2 of table 4), that is 16.7% [(0.03-0.025)/0.03] (*cfr* note 22).

[18] In order to check the robustness of location-effect at regional level, we complement the analysis on TFP by considering the labour productivity and the labour costs. Results are displayed in the appendix table A2. As far as the empty model is concerned, the location across the regions of EU7-EFIGE countries contributes to explain 25.4% of firm labour productivity (column 1). This proportion drops to 5.5% when the empty model is augmented with the country and the sectoral dummies (column 2). When attempting to explain labour costs heterogeneity, the role of regions is 4.8% in the empty model and just 0.8% in the more extended model. As in the analysis of TFP, these checks confirm that the country-effect is more important than the region-effect in explaining the heterogeneity in performance across European firms.

(16%-15%) than in Spain (more than 7%). The contrary holds for region-effects. Indeed, regions explain 7% of the variability in firm TFP in Spain, 4% in Italy and about 2.5% in France.

A final remark from table 5 regards the role of firm-specific factors as the dominant source of firm TFP heterogeneity. Whatever the empty model and the sample of firms used, the share of TFP variability due to unobserved firm-specific factors always exceeds 79%, and this rises to over 90% in the models controlling for region-random effects only.

Table 3 Explaining TFP firms' heterogeneity in the EU7-EFIGE sample. Results from multilevel regressions (2008)

	(1)	(2)	(3)	(4)
Constant	-0.0933***	-0.0810	-0.0736	-0.0758
	(-5.53)	(-1.70)	(-1.64)	(-1.73)
Random-Effects				
Variance				
Regions	0.030		0.025	0.024
Sectors		0.024	0.019	0.018
Regions & Sectors				0.011
Firms	0.169	0.182	0.161	0.153
Total	0.199	0.206	0.205	0.205
VPC				
Regions	15.1%		12.2%	11.5%
Sectors		11.6%	9.1%	8.6%
Regions & Sectors				5.3%
Firms	84.9%	88.4%	78.7%	74.6%
LR test	722.5	432.3	1063.5	1148.8
Log restricted-likelihood	-3977.4	-4122.5	-3806.9	-3764.2
Observations	7239	7239	7239	7239
N. of Groups				
Regions	130		130	130
Sectors		11	11	11

Source: see table 1

Table 4 Explaining TFP firms' heterogeneity in the EU7-Efige Countries in 2008. Results from multilevel regressions.						
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.135***	-0.0708***	0.142***	0.157**	0.138**	0.134**
	(3.86)	(-3.95)	(4.23)	(3.22)	(2.61)	(2.58)
Fixed effects						
Austria	0.0680		0.0864	0.0747	0.0856	0.0881
	(0.62)		(0.83)	(0.87)	(0.82)	(0.85)
France	-0.192***		-0.194***	-0.197***	-0.194***	-0.180***
	(-4.45)		(-4.91)	(-9.57)	(-4.91)	(-4.60)
Hungary	0.165**		0.174**	0.152***	0.173**	0.175**
	(2.66)		(3.03)	(4.11)	(3.02)	(3.08)
Italy	-0.378***		-0.361***	-0.345***	-0.362***	-0.356***
	(-8.50)		(-8.86)	(-17.50)	(-8.86)	(-8.81)
Spain	-0.307***		-0.271***	-0.258***	-0.272***	-0.276***
	(-7.76)		(-7.43)	(-13.09)	(-7.45)	(-7.62)
United Kingdom	-0.208***		-0.204***	-0.223***	-0.204***	-0.204***
	(-4.07)		(-4.34)	(-8.14)	(-4.33)	(-4.40)
S2		-0.111***	-0.114***			
		(-6.24)	(-6.44)			
S3		0.0622**	0.0591**			
		(2.98)	(2.83)			
S4		-0.0488**	-0.0510**			
		(-2.88)	(-3.02)			
S5		-0.172***	-0.176***			
		(-8.16)	(-8.34)			
S6		0.196***	0.192***			
		(7.74)	(7.63)			
S7		0.176***	0.174***			
		(6.32)	(6.26)			
S8		-0.248***	-0.251***			
		(-10.09)	(-10.24)			
S9		0.112	0.119			
		(0.96)	(1.02)			
S10		0.0196	0.0162			
		(1.23)	(1.02)			
S11		0.0366*	0.0349*			
		(2.18)	(2.08)			
Random-Effects						
Variance						
Regions	0.011	0.025	0.008		0.008	0.007
Sectors				0.022	0.019	0.018
Regions & Sectors						0.011
Firms	0.169	0.161	0.161	0.170	0.161	0.153
Total	0.180	0.186	0.169	0.192	0.188	0.188
VPC						
Regions	5.8%	13.4%	4.9%		4.4%	3.5%
Sectors				11.5%	9.9%	9.5%
Regions & Sectors						5.7%
Firms	94.2%	86.6%	95.1%	88.5%	85.6%	81.3%
LR test	332.2	628.9	258.9	416.1	676.5	763.4
Log restricted-likelihood	-3934.8	-3811.2	-3766.9	-3892.9	-3762.7	-3719.2
Observations	7239	7239	7239	7239	7239	7239
N. of Groups						
Regions	130	130	130		130	130
Sectors				11	11	11

Table 5 Explaining TFP firms' heterogeneity in Italy, France and Spain in 2008. Results from empty multilevel models.

	Italy (a)			France (b)			Spain (c)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.243***	-0.226***	-0.227***	-0.0534*	-0.0142	-0.0143	-0.177***	-0.172***	-0.173***
	(-9.11)	(-3.68)	(-3.73)	(-2.57)	(-0.25)	(-0.25)	(-8.18)	(-3.95)	(-3.97)
Random-Effects									
Variance									
Regions	0.010	0.008	0.008	0.006	0.005	0.005	0.017	0.013	0.012
Sectors		0.033	0.032		0.029	0.029		0.015	0.015
Regions & Sectors			0.001			0.001			0.007
Firms	0.172	0.159	0.158	0.172	0.156	0.155	0.154	0.144	0.139
Total	0.182	0.200	0.200	0.178	0.190	0.190	0.171	0.172	0.205
VPC									
Regions	5.3%	4.1%	4.1%	3.6%	2.5%	2.4%	9.9%	7.4%	5.7%
Sectors		16.4%	16.1%		15.2%	15.2%		8.8%	7.4%
Regions & Sectors			4.1%			0.6%			3.6%
Firms	94.7%	79.4%	79.2%	96.4%	82.3%	81.8%	90.1%	83.8%	67.8%
LR	104.4	253.9	255.1	45.3	176.9	177.3	202.3	324.9	343.6
Observations	2212	2212	2212	1568	1568	1568	2336	2336	2336
N. of Groups									
Regions	20		20	22		22	50		50
Sectors		11	11		11	11		11	11

6. Augmenting the multilevel model with firm-specific variables

This section presents the results obtained when the multilevel model is augmented through a set of firm-specific variables. Starting from a specification in which countries and sectors are treated as fixed effects, the aim of the section is twofold. On the one hand, it assesses whether, and to what extent, a set of observable firm-specific factors helps to explain the variability of firm productivity. Previous results indicate that the proportion of TFP variability explained by unobservable firm-specific effect is high. Given this, by augmenting the model with observed-firm specific variables considered to be good predictors of TFP, we expect to grasp part of this black-box of unobservable TFP. On the other, our main interest remains in understanding the role of regions after extending the analysis by modeling the role of individual variables.

Estimations are replicated for the entire sample of firms belonging to the EU7-EFIGE and separately for France, Italy and Spain. The equation to be estimated is the random intercept model (eq. [4]), with the inclusion of variables observed at firm-level:

$$y_{ij} = \beta_0 + \sum_{v=1}^{k} \beta_v X_{vij} + \sum_{q=1}^{2} \omega_q D_{qi} + \sum_{p=1}^{10} \lambda_p S_{pi} + \sum_{c=1}^{6} \eta_c C_{ci} + u_{0j} + e_{ij} \quad [9]$$

where y_{it} is the 2008-value of TFP (in logarithm) of the *i-th* firm operating in region *j, X* is a vector of firm-level variables. The first is the dummy *Process Innovator* that is unity if the firm has introduced a process innovation during the period surveyed and zero otherwise. The second variable is *Human Capital* taking the value of one if, at firm level, the share of workers with a BA degree is higher than the national average for the labor force overall. In explaining firm heterogeneity in TFP, we also control for the effect occurring when the firm is part of a group. Such membership acts as a stimulus to access more resources and knowledge that ultimately affect the individual firm's ability to innovate, thereby impacting on TFP (Beugelsdijk 2007). The variable *Group* is unity if the firm belongs to a group and zero otherwise. The data allow us to distinguish between foreign and national groups. We expect that firms belonging to a foreign group are more productive than other firms since they can capitalize on knowledge accumulated by parent companies abroad.[19] Another important factor explaining firm TFP regards the role of family in the management (see Schulze and Gedajlovich 2010). In order to take into account the possibility that TFP differs between family-managed firms and non-family managed firms, the model is augmented to include the dummy *Family* which is unity if, at firm level, the proportion of managers related to the controlling family

[19] This is why foreign-controlled enterprises benefit both from being part of a global group, and from the advantages of vertical and/or horizontal integration. They gain from factor price differentials, global economies of scale, outsourcing and the knowledge transfers from parent companies and flows among subsidiaries. This makes them more productive than firms which are not part of a foreign group (see, for example, Griffith (1999) for evidence on the UK, Benfratello and Sembenelli (2006) for Italy and Weche Gelübcke (2013) for Germany).

is higher than the national average. The impact of family management is not certain, as the evidence is mixed (Rutherford *et al*. 2008). Furthermore, one of the regularities relating to productivity is the positive link between productivity and exporting (Melitz 2003; ISGEP 2008; Altomonte *et al.* 2012).[20] Hence, we include a dummy taking the value of one if the firm is an exporter in 2008 or before 2008 (Altomonte *et al.* 2012). Regressions also include two dummy variables to control for size effect (D), one referring to medium-sized firms and the other to large-sized firms, whereas the control group comprises small firms. Finally, regressions have been always augmented by sectoral dummies (*S*) and, when the analysis refers to the entire sample of EU7-EFIGE dataset, by country-dummies (*C*). As mentioned above, countries and sectors are treated as fixed-effects instead of source of randomness in intercepts.

Finally, in order to take into account the role played by the characteristics of regional economic system, in some specifications of eq. [9] we also include two regional variables. They are the unemployment rate and the employment in manufacturing as share of total employment.[21] The first variable is meant to capture the effect of disequilibrium in regional factor-markets. In detail, a higher unemployment rate can be regarded as an indicator of market failures and this might reduce innovation capabilities (Bellman *et al* 2013). Therefore, we expect a negative effect of this variable on TFP. As sector matters for innovation and hence for productivity (Dosi and Nelson 2010; Malerba 2005), the use of employment in manufacturing is to control for any structural composition effect of regional economies.

Results are in table 6. The two columns refer to the whole sample of EU7-EFIGE, whereas columns 3-4 refer to Italy, 5-6 to France and the last two columns to Spain.

A useful aspect of the multilevel approach is the possibility of using the variance at the different levels of analysis to calculate the coefficient of determination and obtain a proportional reduction in the estimated total residual variance. This is done by comparing the "empty model" with an extended specification of the model (Rabe-Hesketh and Skrondal 2008).[22] As for the ability

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[20] Two hypotheses about the positive correlation between export activity and productivity have been extensively investigated. The first hypothesis is that the most productive firms self-select into foreign markets because they can overcome sunk costs associated with foreign sales (ISGEP 2008; Melitz 2003). The second hypothesis raises the possibility of "learning by exporting". Firms participating in international markets acquire knowledge and technology with positive feedback as regards knowledge and technology. Furthermore, firms which are active in world markets are exposed to more intensive competition than firms which only sell their products domestically.

[21] Data for Spain come from the Spanish National Institute of Statistics, while for the other countries the source is Eurostat Regional Statistics database.

[22] The coefficient of determination for the two-level model is given by:

$$R^2 = \frac{(\sigma^2_{\mu 0N} + \sigma^2_{eN}) - (\sigma^2_{\mu 0M} + \sigma^2_{eM})}{\sigma^2_{\mu 0N} + \sigma^2_{eN}}$$

where N stands for the null model and M for the model of interest.

The proportional reduction in each of the variance components can be calculated separately. The proportion of the level-2 variance explained by the covariates is:

of firm-level variables to explain the TFP variance of firms belonging to the EU7-EFIGE sample, we find that they absorb 20% of the variance estimated at the first-level of the hierarchy. As regards the individual countries, the variance explained by firm-level features ranges from a low 16% for France to a higher value, 27%-29% for Spain and Italy. As expected, after introducing firm-variables, the share of TFP variance explained by regions remains almost the same as before: 4.6% for the model referring to the entire sample of EFIGE firms, 4.6% for Italy, 2.7% for France and 7.7% for Spain (table 6).

Data in table 6 also highlight that EU7-EFIGE firms employing high-skilled workers more intensively than others perform better on average.[23] As in Griliches (2000) and Parisi *et al.* (2006) we find that human capital plays an important role for TFP in Italy and Spain, while we provide inconclusive evidence for French enterprises. In addition, the estimations indicate that the coefficient of the dummy *Process Innovation* is positive and significant, implying that EU7-EFIGE firms introducing process-innovation perform better than firms that do not innovate**.** The results concerning human capital and process innovation are coherent with the expectation that a firm's performance improves as a result of its propensity for innovation and the presence of skilled workers (see, e.g., Krueger and Lindahl 2001; Sveikauskas 2007). Basically, this is why qualified employees provide a firm with the capability not only to develop new processes, but also to absorb knowledge made by other firms (Cohen and Levinthal 1990). However, the estimated coefficient of process innovation is statistically significant in Italy, but not in France or Spain. This differs from the evidence provided by Griffith *et al.* (2006), where the impact of process innovation on productivity diverges in the case of France, while it is the same for Spain. As for the relationship between productivity and innovation, it is notable that gains in TFP are only associated with process innovation, whereas no effect is found when the innovation regards the introduction of a new product or other innovations, such as the organizational innovations (results available upon request). These findings contrast with the results of the studies surveyed by Hall (2011), who finds a

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$$R_2^2 = \frac{(\sigma_{\mu 0N}^2 - \sigma_{\mu 0M}^2)}{\sigma_{\mu 0N}^2}$$

and the proportion of the level-1 variance explained is:

$$R_1^2 = \frac{(\sigma_{eN}^2 - \sigma_{eM}^2)}{\sigma_{eN}^2}$$

[23] Estimations of eq. [9] may suffer from level-two endogeneity, that is the case where the random effects are correlated with level-one covariates. As shown by Snidjders and Berkhof (2007), the correlation between the lower level predictor variables and higher level error terms can be removed by including the group-level means of the lower level variables, a procedure known as the Mundlak (1978) correction. Estimations with Mundlak correction are displayed in appendix-table A3. As can been seen, the results are qualitatively the same as those discussed throughout the paper.

significant impact of product innovation on productivity and a somewhat more ambiguous impact of process innovation, being negative in Italy, not significant in Spain and positive in France.

Similarly to prior research, we find that TFP rises with firm-size. In addition, among firm-level characteristics size, is by far the most dominant explanatory variable. Medium-sized firms perform better than small firms, but less well than large enterprises. In short, for European manufacturing firms covered by the EFIGE project, this paper shows that economies of scale are at work. When considering the samples of French, Italian and Spanish firms the sign of the size-effect is confirmed, even though some differences in magnitude exist. In particular, the estimated productivity impact of firm size is larger in Italy and Spain, compared to France, but also to the sample as a whole. This is to say that the TFP gap between large and small-medium firms is relatively higher in Italy and Spain than in other countries. With regards to the role of group membership, we find that, all else being equal, firms belonging to a group are more productive than their counterparts and the impact is greater in the case of partnership with a foreign group. Being part of a foreign group ensures firms more TFP benefits. This always holds, although the impact is more marked in Italy and Spain than in France.[24]

Valuable insights come from the family-management effect. The coefficient of the *Family Management* variable is negative and statistically significant, indicating that family involvement in firm management negatively affects TFP. While this evidence is not comparable with other studies, it is fruitful to observe that the few papers focusing on EU firms find that family-controlled companies perform better than non-family firms (Barontino and Caprio, 2006; Maury, 2006; Pindado *et al.*, 2008).[25] When considering each single country, a negative and statistically significant impact of family-management on firm TFP has been found for Spanish firms, while the evidence is inconclusive for France and Italy.[26] In line with the current literature, our results are mixed, confirming that the relationship between family involvement and firm performance is complex and multifaceted (Barth *et al.*, 2005; Miller *et al.*, 2007).

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[24] For Italy, Benfratello and Sembenelli (2006) find that only firms owned by USA corporations tend to be more productive than national-owned firms.

[25] Performance measures are Tobin's Q and ROA in Barontino and Caprio (2006) and Mauray (2006) and the market value in Pindado *et al.* (2008). Barontino and Caprio find that performance is significantly higher in founder-controlled corporations and corporations controlled by descendants who sit on the board as non–executive directors. When a descendant takes the position of CEO, family-controlled companies are not statistically distinguishable from non-family firms.

[26] For Italy Cucculelli *et al.* (2014) show that family management has a negative impact on TFP but not for older firms: family-managed firms become more efficient as they mature. As for France and Spain, previous research focuses on profitability and the role of family ownership by considering the generation of family-management and the effect on firm. Sraer and Thesmar (2007) find that French family-managed firms, first or later generation, outperform non-family firms. For Spanish firms the relationship between ownership concentration and performance is significant only in first-generation family firms and it is positive at a low level of ownership concentration and negative at a high level (Arosa *et al.* 2010).

Turning to the role of internationalization, we find that being an exporter does not affect TFP. This evidence holds whatever the sample (see table 6) and even when the broader definition of an internationally active firm is considered (results available upon request).[27] Our finding contrasts with a number of papers showing that exporters self-select and over-perform (Wagner, 2007; ISGEP, 2008; Altomonte *et al.*, 2012), but is in line with the researchers arguing that the export *premium* may be the result of an omitted variables bias. This issue has been discussed, for instance, by Crozet (2010)[28] as regards the discussion on exports without considering the membership in a foreign group, and by Cassiman *et al.*, (2010) regarding the overestimation of the exports-effect on productivity when innovation is left out from the analysis.[29] Group membership and innovation are two variables included in our regressions. This might help to explain why our evidence on the impact of exporting is inconclusive.[30]

Furthermore, table 6 also displays the results obtained when using the unemployment rate and the manufacturing share at regional level. We find a negative and significant effect of the unemployment rate for the EU7-EFIGE sample as a whole and for Italy (table 6). On the contrary, employment in the manufacturing sector is significant only in the case of Spain, implying that TFP is high when firms operate in regions highly manufactured. The coefficient of manufacturing in EU7-EFIGE regression is not significant. For France, the estimated parameters of regional factors are not significant. What is also interesting from the augmented regressions is the impact on the goodness of fit of our hierarchical models. As far as the EU7-EFIGE sample is concerned, the estimates indicate that the unemployment rate and the manufacturing share induce an increase of the R^2 at level-two from 0.78 to 0.84, thereby, suggesting that these two regional variables explain 6% of what is treated as unobservable heterogeneity in Model 1. With regards Italy and Spain, the R^2 at

[27] Firms are defined "internationally active" when they have been involved in at least one international activity such as exports, imports of materials or services, active or passive outsourcing, production in another country via direct investment (Altomonte *et al.* 2012).

[28] Crozet *et al.* (2011) argue that the exporter productivity premium could be due to omitted variables, correlated to the probability to export as, for example, belonging to a foreign group. Barba Navaretti *et al.* (2011) show that firms belonging to a foreign group are more likely to be exporters and this finding may suggest a cost reduction effect stemming from belonging to a foreign group.

[29] Cassiman *et al.* (2010) suggest that one potential underlying mechanism for the selection of more productive firms in the export market could be the fact that successful innovation improves the firm's productivity and, hence, these more productive firms became exporters. As a result, the omission of an innovation variable from the analysis may lead to the overestimation of the productivity-export association. Using a panel of Spanish manufacturing firms for the period 1990-1998 they find support for their hypothesis. However, as far as French firms are concerned, Bellone *et al.* (2010) show that the introduction of innovation does not significantly alter the size of the export premium.

[30] For reference, we also estimate Model 1 of table 6 by running a standard OLS regression. In so doing, we have treated regions and sectors as fixed-effects and clustered standard errors at regional and sectoral level. Results are displayed in the appendix table A4. As expected, OLS estimations and the significance of firm-specific factors do not qualitatively differ from those reported in table 6, although hierarchical modeling has the advantage of discerning different sources of heterogeneity even in its most basic specification.

level-two increases from 0.4 to 0.62 and from 0.45 to 0.65 respectively, as the effect of including in the regression the two regional variables. .

Finally, at this point in the discussion, it becomes crucial to point out that the use of observable regional factors does not impact on the main results of the present paper. Two signals of this are evident and in line with expectations. On one hand, the decomposition of TFP variance confirms the dominant portion of heterogeneity explained by the first-level of our model. On the other side, augmenting equations with regional factors does not affect the evidence found by the more parsimonious Models 1, 3, 5 and 7. Indeed, results concerning firm-individual variables are confirmed in magnitude, sign and significance (table 6). This is summarized by the R^2 at level 1 which does not vary moving from Model 1 to Model 2 in the EU7-EFIGE sample. The same is true for Italy, France and Spain (table 6).

This discussion implies that after having firmly distinguished between the impact on TFP brought about by first and second level of data aggregation, further analysis should be carried out to address what still remains in the black-box of the unexplained TFP heterogeneity that we find at any level of our hierarchy.

Table 6 Explaining TFP heterogeneity of firms belonging to the EU7-Efige sample.
Evidence from multilevel models augmented by firm-specific characteristics and regional variables

Explanatory Variables	EU7-EGIFE		Italy		France		Spain	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.119***	0.00775	-0.292***	-0.119	-0.190***	-0.193	-0.161***	-0.235**
	(-3.71)	(0.10)	(-9.76)	(-1.00)	(-6.79)	(-1.36)	(-6.70)	(-2.34)
Fixed effects								
Level 1: Firms								
Medium	0.191***	0.191***	0.243***	0.243***	0.107***	0.107***	0.215***	0.215***
	(15.57)	(15.55)	(10.61)	(10.60)	(4.26)	(4.26)	(9.97)	(9.96)
Large	0.421***	0.420***	0.538***	0.538***	0.293***	0.293***	0.513***	0.513***
	(22.70)	(22.66)	(13.91)	(13.91)	(6.89)	(6.90)	(14.31)	(14.34)
Family management	-0.0617***	-0.0620***	-0.0482***	-0.0498***	-0.0283	-0.0287	-0.0597***	-0.0600***
	(-5.54)	(-5.56)	(-2.90)	(-3.00)	(-1.01)	(-1.03)	(-3.56)	(-3.57)
National group	0.0841***	0.0840***	0.109***	0.108***	0.0473*	0.0476*	0.0782***	0.0779***
	(6.47)	(6.46)	(4.58)	(4.56)	(1.90)	(1.91)	(3.31)	(3.30)
Foreign group	0.195***	0.196***	0.329***	0.328***	0.123***	0.124***	0.307***	0.308***
	(11.86)	(11.93)	(8.52)	(8.50)	(3.77)	(3.79)	(8.96)	(9.00)
Process Innovator	0.0370***	0.0370***	0.0412***	0.0414***	0.0325	0.0325	0.0462***	0.0459***
	(4.14)	(4.15)	(2.71)	(2.73)	(1.61)	(1.60)	(3.24)	(3.22)
Human capital	0.0461***	0.0474***	0.0511***	0.0526***	0.0277	0.0268	0.0578***	0.0575***
	(4.67)	(4.80)	(3.17)	(3.26)	(1.31)	(1.26)	(3.58)	(3.56)
Exporter	0.0152	0.0131	0.00467	0.00150	0.00668	0.00665	0.0250	0.0209
	(1.50)	(1.29)	(0.26)	(0.08)	(0.30)	(0.30)	(1.62)	(1.35)
Country dummies	YES	YES						
Sector dummies	YES	YES	YES	YES	YES	YES	YES	YES
Level 2: Regions								
Unemployment rate		-0.0148***		-0.0201***		0.0060		-0.0076
		(-3.95)		(-2.64)		(0.52)		(-1.17)
Manufacturing share		0.0007		-0.0023		-0.0024		0.008**
		(0.35)		(-0.65)		(-0.53)		(2.49)
Random-Effects								
Variance								
Regions	0.006	0.005	0.006	0.004	0.004	0.004	0.009	0.006
Firms	0.136	0.136	0.122	0.122	0.144	0.144	0.113	0.113
Total	0.142	0.141	0.128	0.126	0.148	0.148	0.122	0.119
VPC regions	4.6%	3.5%	4.6%	2.9%	2.7%	2.7%	7.7%	5.0%
R^2	0.28	0.29	0.30	0.31	0.17	0.17	0.28	0.30
R^2 *level 2*	0.78	0.84	0.40	0.62	0.38	0.34	0.45	0.65
R^2 *level 1*	0.20	0.20	0.29	0.29	0.16	0.16	0.27	0.27
LR test	231.5	156.1	65.9	31.0	29.4	24.8	142.9	77.68
Log restricted-likelihood	-3173.8	-3172.6	-866.3	-871.1	-751.1	-758.8	-839.7	-840.8
Number of observations	7239	7239	2212	2212	1568	1568	2336	2336

Source: see table 1

7. Conclusions

This paper analyzes the productivity gap across seven EU members and measures the impact of location on firms heterogeneity. To this end, it uses fully comparable cross-country micro-data and follows the multilevel approach. The preferred model is a random-intercept multilevel equation which considers firms as the first-level group in the hierarchy of data and regions as the second-level group. Hence, regions are treated as a source of randomness in the intercept, while countries and sectors enter into this specification as controlling fixed-effects.

The dataset, sourced from the EFIGE project, highlights the wide TFP gap across Europe. In 2008, Italy and Spain were lagging, while the UK and France were less so. On the other hand, Germany, Austria and Hungary are the leaders in the sample of the EU members covered by EFIGE. Huge disparities in TFP also exist at regional level. The variability in aggregate productivity reflects the remarkable heterogeneity at firm-individual level. Starting from these facts, the study has measured how much TFP heterogeneity is due to firm-specificities and how much depends on localization. This has been attempted by considering the entire EU7-EFIGE sample and by focusing on France, Italy and Spain (the choice to restrict the analysis to these three EU members is data-driven). The study yields two main results.

Firstly, heterogeneity in productivity is greatly affected by firm-specific factors. For instance, in the empty model, the proportion of TFP variability brought about by the first-level of our hierarchical structure of data is high, ranging from 90 % in the case of Spain and 96.4% for France. In Italy, it is equal to 94.7%. At EU7-EFIGE level, this share is 84.9%. While these results imply that the unobserved heterogeneity in firm-behaviour is the main source of heterogeneity in productivity, they should be looked at in greater depth. In this respect, the analysis incorporates the effect of a set of firm-specific variables relating to internationalization, size, innovation, human capital, group membership and family-involvement in management. The lessons we have learnt are twofold. On one hand, looking at the impact on TFP exerted by each factor, we find that economies of scale are at work whatever the sample of firms analysed. TFP always increases with human capital and partnership with a larger organization, while it diminishes when family is involved in management. It is positively linked to the introduction of process innovations only when referring to the sample of EU7-EGIFE firms and in the individual case of Italy. Finally, we find no conclusive evidence for the link between TFP and exporting activities. On the other hand, we evaluate the capacity of the above firm-level variables to explain the total TFP variance, as it is decomposed and attributed to the first-level of the hierarchy. As far as the EU7-EFIGE sample is concerned, we find that the enterprise-specific variables explain, as a whole, 20% of first-level TFP variance. This proportion is 16% for France and 27% for Spain and 29% for Italy, implying that much of TFP heterogeneity at individual basis is still unexplained. Something other than size, family-management, group membership, innovations, exports and human capital influences heterogeneity in productivity. This leaves room for further research with the aim of refining the measurement issues relating to other firm-level aspects, such as employee and management competence, organizational practices and resource and knowledge-related features. It would be interesting to analyse these issues in greater depth so as to develop research aimed at minimising the "sizable" and "unobservable" black-box of firm behaviour.

The second type of evidence regards the role of localization in different regions and countries. It emerges that TFP heterogeneity can, to a large extent, be explained by differences across countries. We have demonstrated that country-effect is more influential than region-effect across the EU7-EFIGE sample: it explains a high proportion (63%) of the firms' TFP variability that the multilevel approach assigns to regions, in other words to the second-level of our model. Regions explain 15% of TFP heterogeneity when regressions exclude countries, while this proportion drops around to 4-5% after controlling for sector and country-effects. This evidence is robust to outliers and to the composition of the EU7-EFIGE sample.

While policy considerations are beyond the scope of this study, two observations follow from the results. On one hand, the paper suggests that firm-based policies could be highly advantageous in terms of productivity gains, as they would act within the level that this study demonstrates to be the most important in explaining the TFP divide. Limiting the discussion to the innovation-*productivity* nexus, it seems that the policy making might be better oriented not only to increase firms R&D investments, as many programs already do, but much more ought to be done to stimulate organizational change. This would allow firms to translate R&D efforts into actual economic benefits by exploiting the technological complementaries between the firm-specific inputs (i.e., human capital, ownership, ICT adoption, managerial capabilities) that have to do with innovation and, thereby, productivity. On the other hand, this paper highlights the need for greater EU integration across countries. This is why the integration process aims at achieving greater harmonisation of national systems in terms of the rules influencing individual productivity. In the vein of this paper, it is considered that a more harmonized EU would be a source of overall benefits with regard the practising of business. To give just a few examples. Private individual performance would be less heterogeneous than it is actually observed if firms shared the same legal, fiscal and institutional systems. The same result would occur if discrepancies between national banking industries disappeared or bureaucracy worked similarly across countries. Translating this at national level means addressing the problem of low productivity in several areas of France, Italy and Spain. These regions suffer from supply-side structural problems and need selective and locally-based public support which, hopefully, will be more effective than the past EU regional policy.

Appendix

Table A1 Estimates of production function by sector. Results from Levinsohn and Petrin (2003) estimator (*)

NACE 2 Industry Code	Description	ln(l)	ln(k)
DA15	Food products, beverages and tobacco	0.538*** (0.02)	0.305*** (0.03)
DB17	Manufacture of textiles	0.604*** (0.03)	0.578*** (0.08)
DB18	Manufacture of wearing apparel; dressing and dyeing of fur	0.517*** (0.04)	0.532*** (0.08)
DC19	Leather and leather products	0.606*** (0.03)	0.402*** (0.07)
DD20	Wood and wood products	0.561*** (0.04)	0.328*** (0.05)
DE21	Manufacture of pulp, paper and paper products	0.527*** (0.05)	0.392*** (0.09)
DE22	Publishing, printing and reproduction of recorded media	0.471*** (0.04)	0.368*** (0.07)
DEF23	Coke, refined petroleum products and nuclear fuel	0.321 (0.32)	0.605** (0.26)
DG24	Chemicals, chemical productus an man-made fibres	0.534*** (0.03)	0.44*** (0.05)
DH25	Rubber and plastic products	0.525*** (0.03)	0.463*** (0.04)
DI26	Other non metallic mineral products	0.506*** (0.03)	0.495*** (0.06)
DJ27	Manufacture of basic metals	0.575*** (0.04)	0.416*** (0.05)
DJ28	Metal products, except machinery and equipment	0.541*** (0.03)	0.409*** (0.02)
DK29	Machine and equipment n.e.c.	0.526*** (0.02)	0.41*** (0.03)
DL30	Office machinery and computers	0.502*** (0.12)	0.452** (0.18)
DL31	Electrical machinery and apparatus n.e.c.	0.492*** (0.03)	0.44*** (0.05)
DL32	Radio, television and communication equipment and apparatus	0.467*** (0.05)	0.531*** (0.11)
DL33	Medical, precision and optical instruments, watches and clocks	0.596*** (0.06)	0.4*** (0.09)
DM34	Motor vehicles, trailers and semi-trailers	0.501*** (0.06)	0.425*** (0.08)
DM35	Other transport equipment	0.438*** (0.06)	0.573*** (0.12)
DN36	Other manufacturing n.e.c	0.519*** (0.03)	0.349*** (0.07)
DN37	Recycling	0.398*** (0.04)	0.497*** (0.09)

Note : the authors are grateful to Bruegel for providing this table.

(*) In specifying the production function, Bruegel researchers use a Cobb-Douglas and follow the standard practice of the literature based on Levinsohn and Petrin (2003) estimator. Indeed, they use the added value as proxy of output, deflated with industry-specific price indices. The labour is measured by the number of employees, while capital is proxied by the value of tangible fixed assets and expressed in real terms by using the GDP deflator. Refer to Altomonte and Aquilante (2012) for details.

Table A2 Labour productivity and Unit labour cost. Results from multilevel regressions

	Labour productivity (1)	Labour productivity (2)	Unit labour cost (3)	Unit labour cost (4)
Constant	3.775***	4.101***	-0.325***	-0.341***
	(142.94)	(99.20)	(-37.18)	(-18.64)
Fixed effects				
Austria		0.143		0.0122
		(1.18)		(0.16)
France		-0.178***		0.121***
		(-3.66)		(6.13)
Hungary		-1.230***		-0.0670*
		(-16.04)		(-1.72)
Italy		-0.142***		-0.0421**
		(-2.83)		(-2.07)
Spain		-0.377***		0.0143
		(-8.36)		(0.73)
United Kingdom		-0.196***		-0.0244
		(-3.41)		(-0.93)
S2		-0.0618***		-0.0861***
		(-2.83)		(-5.88)
S3		-0.0891***		-0.0101
		(-3.48)		(-0.60)
S4		-0.161***		0.0490***
		(-7.79)		(3.68)
S5		-0.212***		0.0544***
		(-8.26)		(3.13)
S6		0.213***		-0.0816***
		(6.94)		(-3.90)
S7		-0.00584		0.0316
		(-0.17)		(1.37)
S8		-0.236***		0.0429**
		(-7.71)		(2.17)
S9		0.558***		-0.291***
		(4.05)		(-3.04)
S10		-0.00467		0.00354
		(-0.24)		(0.28)
S11		0.0432**		0.0328**
		(2.12)		(2.41)
Random-Effects				
Variance				
Regions	0.079	0.013	0.006	0.001
Firms	0.232	0.223	0.127	0.126
Total	0.311	0.236	0.133	0.127
VPC				
Regions	25.4%	5.5%	4.4%	0.8%
R^2		0.24		0.04
R^2 *level 2*		0.84		0.83
R^2 *level 1*		0.04		0.01
LR test	804.4	169.1	195.2	9.6
Log restricted-likelihood	-4802.4	-4604.4	-3414.0	-3361.8
Observations	6734	6734	8584	8584
N. of Groups	130	130	130	130

Table A3 Robustness checks

Explanatory Variables	Without HUN and AUT	Without HUN and AUT	Without Outliers	Without Outliers, HUN & AUT	Mundlak Correction (b)
	(1)	(2)	(3)	(4)	(5)
Constant	0.191***	-0.0757**	-0.0932***	-0.0935***	-0.314**
	(4.87)	(-1.98)	(-3.34)	(-3.34)	(-2.31)
Fixed effects					
Level 1: Firms					
Medium		0.180***	0.168***	0.166***	0.187***
		(12.19)	(16.32)	(16.01)	(12.67)
Large		0.463***	0.324***	0.327***	0.465***
		(20.79)	(19.84)	(19.61)	(21.05)
Family management		-0.0509***	-0.0564***	-0.0550***	-0.0527***
		(-3.81)	(-6.05)	(-5.87)	(-3.92)
National group		0.0800***	0.0461***	0.0459***	0.0763***
		(5.18)	(4.20)	(4.17)	(4.91)
Foreign group		0.205***	0.129***	0.137***	0.204***
		(10.32)	(9.07)	(9.47)	(10.41)
Process Innovator		0.0371***	0.0262***	0.0263***	0.0402***
		(3.48)	(3.49)	(3.49)	(3.75)
Human capital		0.0428***	0.0462***	0.0450***	0.0448***
		(3.62)	(5.57)	(5.40)	(3.78)
Exporter		0.0130	0.0134	0.0131	0.00869
		(1.07)	(1.59)	(1.54)	(0.71)
Country dummies	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES
Mundlak correction					YES
Random-Effects					
Variance					
Regions	0.011	0.009	0.005	0.005	0.008
Firms	0.220	0.194	0.088	0.087	0.199
Total	0.231	0.203	0.093	0.092	0.207
VPC regions	4.8%	4.4%	4.4%	4.8%	3.8%
R	0.17	0.28	0.49	0.50	0.26
R^2 *level 2*	0.74	0.79	0.85	0.84	0.81
R^2 *level 1*	0.07	0.19	0.42	0.44	0.16
LR test	239.9	207.3	227.7	228.3	125.3
Log restricted-likelihood	-4860.2	-4417.7	-1483.5	-1428.3	-4638.4
Number of observations	7182	7182	6647	6503	7386
Number of groups	120	120	130	120	130

(a) Data of TFP below the 5th percentile and above the 95th percentile are considered outliers.
(b) Estimations with Mundlank (1978) correction (cfr. note 17).

Table A4 Explaining TFP heterogeneity of firms belonging to the EU7-Efige sample in 2008. OLS results

	ALL (1)	Italy (2)	France (3)	Spain (4)
Regional dummies	yes	yes	yes	yes
Sectoral dummies	yes	yes	yes	yes
Medium	0.1911***	0.2445***	0.1107***	0.2118***
	(0.013)	(0.022)	(0.023)	(0.024)
Large	0.4200***	0.5390***	0.2950***	0.5154***
	(0.022)	(0.049)	(0.051)	(0.040)
Family Management	-0.0612***	-0.0483**	-0.0313	-0.0576***
	(0.012)	(0.019)	(0.023)	(0.016)
National group	0.0834***	0.1069***	0.0451*	0.0786***
	(0.014)	(0.029)	(0.027)	(0.027)
Foreign group	0.1926***	0.3256***	0.1163***	0.3019***
	(0.020)	(0.043)	(0.035)	(0.046)
Process Innovator	0.0377***	0.0408**	0.0325*	0.0465***
	(0.009)	(0.017)	(0.019)	(0.016)
Human capital	0.0452***	0.0516***	0.0245	0.0575***
	(0.011)	(0.019)	(0.019)	(0.018)
Exporter	0.0116	-0.0010	0.0035	0.0226
	(0.010)	(0.019)	(0.023)	(0.015)
Constant	-0.0305	-0.2267***	0.0136	-0.1819***
	(0.159)	(0.029)	(0.048)	(0.037)
Observations	7,239	2,212	1,568	2,336
R-squared	0.314	0.344	0.222	0.366
F-test	22.77	32.24	22.69	36.32
p-value	0	0	0	0

Robust standard errors in parentheses. Clustering is at regional and sectoral level.
*** p<0.01, ** p<0.05, * p<0.1

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