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FIRM HETEROGENEITY IN PRODUCTIVITY ACROSS EUROPE. WHAT EXPLAINS WHAT?

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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 4.7% of TFP heterogeneity in Italy, while this proportion is lower (2.9%) in France and higher (7.6%) in Spain.

Keywords: TFP heterogeneity, firm-behavior, localization, European countries, multilevel model
JEL classification: C30, D22, L60, R15

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.

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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 from the Eurostat website).

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). 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 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 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, whatever their location. For instance, their size is different and they have specific approaches to production and different technological strategies (Teece et al. 1997). Again, many learning processes are firm-specific because they are driven by the individual skills of owners, workers and managers (Bloom and Van Reenen, 2010). Such heterogeneity in firm-specific

[1] The connections between micro and aggregate industry productivity have been surveyed by Foster et al. (2001) and Van Biesebrick (2003).

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 individual performance depends upon the spatially-constrained availability of environmental resources devoted to growth. In short, the higher the endowments of a given area, the greater the benefits for local firms (see Vernon Henderson et al. 2001; Krugman 1991; Rodriguez-Pose 2009; Ottaviano 2008).

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? 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 focusing on 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. While the choice to use TFP is also data-driven (cfr § 2), it is noteworthy to point out that a huge 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).

The empirical setting we propose is consistent with the type of issues to be addressed. Indeed, in order to explain the role of different factors in explaining firms' TFP heterogeneity, we consider the multilevel approach. This model - giving proper attention to nesting – allows the evaluation of whether, and to what extent, space matters in determining firm performance. In fact, multilevel regressions 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. This represents a methodological advantage with respect to single-equation models, which are too limited to handle hierarchical structures of data. Indeed, in a single-equation model, the statistical 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). Furthermore, multilevel models address the ecological and atomistic fallacies. The first of these 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. However, working with micro-data leads to the opposite issue related to the absence of any link between individual-level and group-level relationships. By simultaneously taking firm and regional levels into account, the approach followed in this paper addresses both ecological and atomistic issues (Raspe 2009). Finally, the multilevel approach offers the possibility of identifying and discerning different sources of disparity in individual productivity.[2]

The results are as follows. Having found high TFP heterogeneity across firms and regions, we confirm that firm-specific characteristics greatly affect individual TFP heterogeneity. Furthermore the regional effect results to be high when estimations disregard the country-effects: in such a case, location across EU7-EFIGE regions explains 15.2% of differences in TFP across firms. After controlling for country-effects, we find that 4.7% 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, Italy and 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, except exports. As far as the EU7-EFIGE sample is concerned, these individual factors, as a whole, capture 16% 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.

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[2] The multilevel approach has been applied to firm productivity only in the following published papers. Raspe and van Oort (2007) link the firm productivity to the knowledge-intensive spatial contexts in the Netherlands. 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. Mahlberg et al (2013) refer to Austria and explore the link between age and labour productivity.

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 was carried out in 2010, and provides representative and comparable samples of manufacturing firms in seven European countries (Austria, France, Germany, Hungary, Italy, Spain and United Kingdom) and covers quantitative as well qualitative information ranging from R&D and innovation, labour organisation, financing and organisational activities and pricing behaviour.[3] While the survey covers the 3-year-period 2007-2009, much information is averaged over the years under scrutiny, or relates only to 2008.[4]

For the purposes of this study, we refer to the TFP calculated for 2008 by the researchers involved in the project and released by Bruegel upon presentation of a research proposal. They have estimated the TFP by using 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.[5]

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 3,000 firms in each country), followed by United Kingdom (slightly more than 2,000 firms) and Austria and Hungary (less than 500 in each country). When matching the EFIGE survey with the Amadeus archive, the

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[3] 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).

[4] 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 use the version which is freely downloadable from the Bruegel website, plus the TFP array released by Bruegel after presenting a research proposal. For this reason, we do not have any link to the balance data of each firm with the consequence that we cannot complement our study on TFP with other outcome-variables, such as, for instance, labour productivity.

Another important data limitation refers to the fact that the EFIGE database includes just randomised regional and industry identifiers. At Bruegel, this is done to preserve anonymity of sensitive data. While the availability of randomised codes allows for regional and industry variation in the data, it places heavy constraints on the interpretation of results because users can only know that a given firm in a country is active in an 'industry 2' or/and in 'region 3', but they do not know what 'industry 2' or 'region 3' actually correspond to. Sectors are classified in 11 groups according to the NACE-Clio categories, while 159 regions are considered.

[5] In terms of the variables included in the estimation of the production function, Bruegel researchers follow the standard practice in this literature: they use the added value as proxy of output, deflated with industry-specific price indices retrieved from Eurostat datasets. The labour input 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 detailed information on TFP calculations.

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 7,435 European firms, the majority of which (more than 84% of the sample) operating in France, Spain and Italy. 1,605 of the firms are located in France, 2,243 in Italy and 2,410 in Spain. Surprisingly, the EFIGE survey comprises 2,935 German firms which is reduced to just 579 in the archive containing TFP. The same holds in the case of UK (from 2,067 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 other end of the scale, 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 94 out of the 159 regions covered by EFIGE, the TFP is higher than that of the overall sample, while the opposite holds for the remaining 65 regions. In 2008, differences in averaged regional TFP ranges from 0.069 to 2.93 with a dispersion around the EU7-EFIGE average of 0.34 expressed as standard deviation. Differences in regional TFP are displayed in figure 1, where data are expressed as deviation from the overall average. Just to complement the description of data, Panel (b) of figure 1 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 above or equal to 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% and 95% in the UK.[6] 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.

[6] 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-27 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)

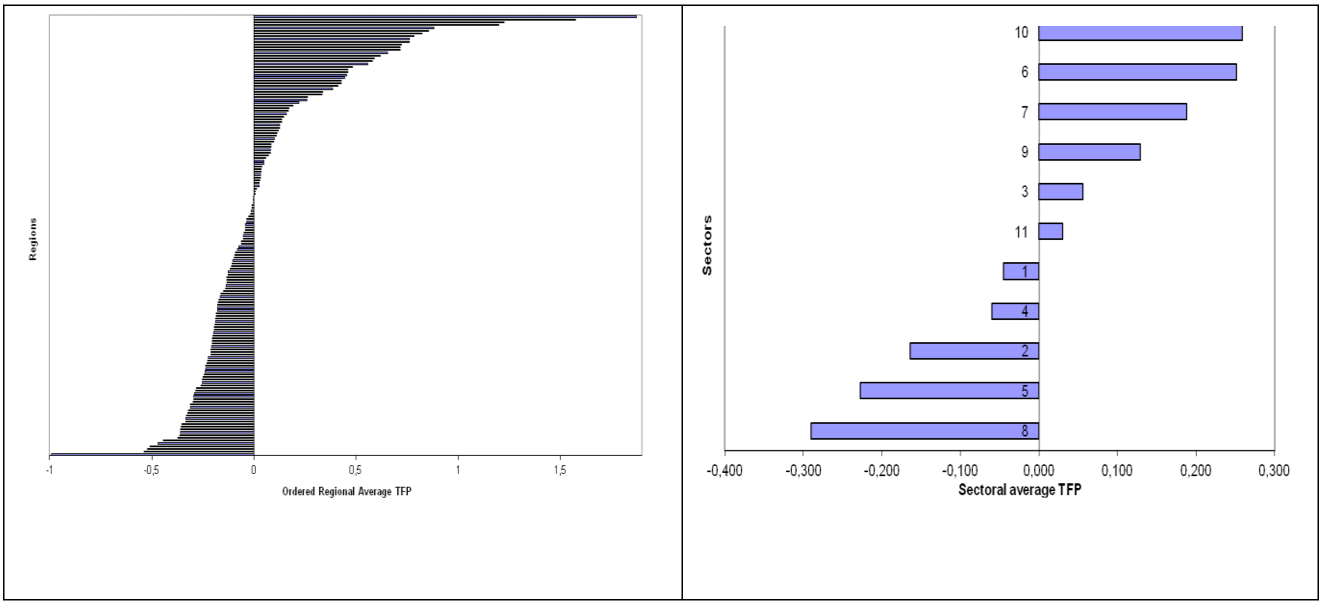
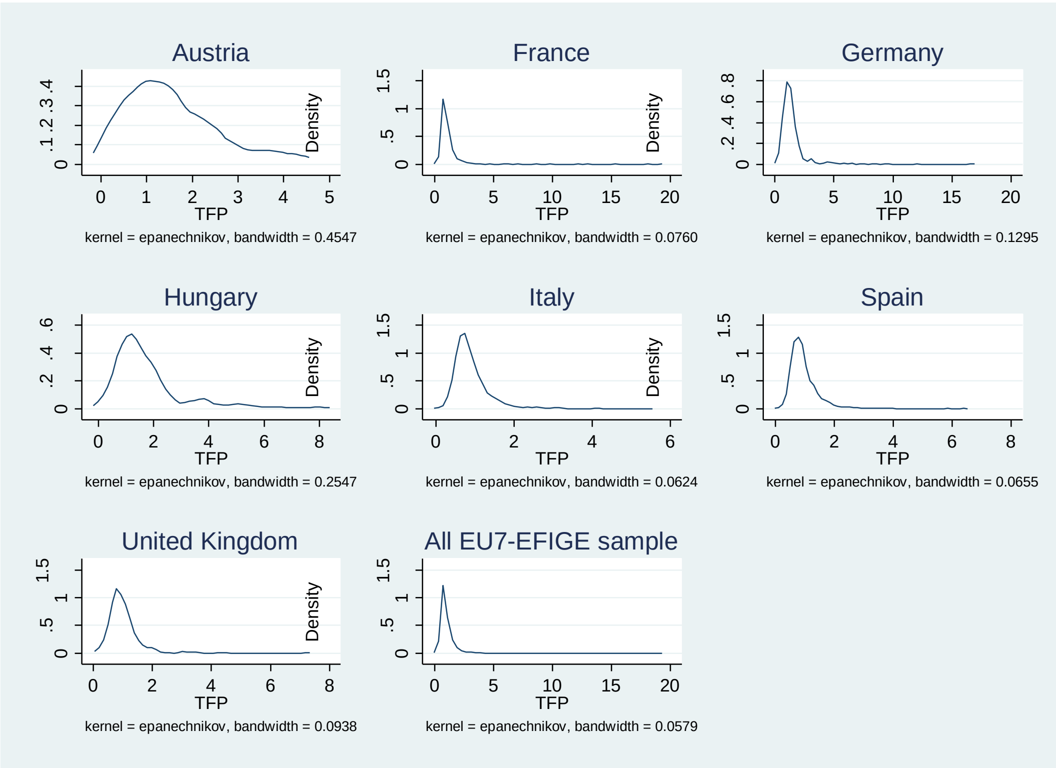


Figure 2 TFP distribution by country in 2008



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 the 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. In fact, whereas standard regressions are designed to model an overall mean coefficient, multilevel analyses considers, in addition, group level variance explicitly through the inclusion of random coefficients. In a multilevel framework with nested data, the left-hand side variable refers to firms and depends on a set X of variables measured at firm level:

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

Where 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 (i.e., 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:

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

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.[7] 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, the data are hierarchically structured. However, 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 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.

[7] 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).

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 model of a multilevel equation. 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. There are four potential levels: 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.[8] Therefore, we restrict the data hierarchy to two levels (firms and regions). As a

[8] 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 (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

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).9 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 159 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.

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 $u_{0j} = 0$, 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 15.2% of the total variance, while the remaining (84.8%) is explained by firms. If variability at the second-level is modeled through sectors alone, then the sectoral membership will explain 9% of TFP variability and the rest (91%) is due to firm-features (column 2). When using the cross-classified specification, we find that 13% of the unexplained variation in TFP lies at the regional level and 6.8% at the sectoral level, while the internal firm characteristics explain 80% 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 this specification, the explaining power at firm level declines to 76%, while 6.5% and 12% of TFP variance is related to

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estimated group-effect is unreliable for small-sized groups. In t understanding the econometric specification used in the analysis and in discussing the results, it is worth pointing out that the countries are 7, sectors are 11 and the number of regions in many countries (Austria, Germany, Hungary and United Kingdom) is less than 20. Moreover, as for group-size, it is important to note that some regions have few firms (e.g., 28 regions have less than five firm-observations). These numbers condition our empirical setting in two ways. Firstly, they force the use of a random effect multilevel model, instead of a fixed-effect multilevel model. Secondly, 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.

[9] 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)

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 12% to 15.2%.

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 and regions as random-effects. This ensures consistency in estimations (*cfr* note 8). 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 5.4% and the country-dummies are highly significant (Germany is used as controlling group). 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 66.7%. In other words, two-thirds of the variance assigned to the region-effect is a between-country effect.[10]

When modeling sectors as fixed effects through dummy-variables, the share of firms' TFP variability explained by regions is 13.9% (table 4 column 2), which is not much lower than the proportion (15.2%) estimated through the basic empty model. Again, when incorporating both country and sectoral dummies, we find that regions record 4.7% of heterogeneity in TFP (table 4 column 3).[11] The lesson learnt from table 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 4.7% to 15.2%. The region-effect is a minimum (4.7%) in models embodying the country and sector effects, while the maximum (15.2%) 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 about 5% of TFP heterogeneity observed at EU7-EFIGE level.[12] Sector membership, on the contrary, does not significantly alter the role of regions.[13]

[10] The contribution of country-effect is calculated by comparing the total TFP variance (0.042) explained at regional level in the empty model (column 1 table 3) and the variance (0.014) obtained when this model is augmented by country-dummies (column 1 of table 4), that is: [(0.042-0.014)/0.042] (*cfr*. note 14).

[11] 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 8% 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.

[12] 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 without 150-firm-observations meant to be potential outliers which lie in the first and the last percentile of TFP distribution (columns 1 and 8 of Appendix table A1). The same applies when excluding (a) Hungary (columns 2, 3 and 6, table A1), (b)

Our results demonstrate that firm TFP heterogeneity in the EU7-EFIGE sample is more sensitive to country than to regional location. 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 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 67, 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 5.5% 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 9.2% 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 (12%-13%) than in Spain (6%-5%). The contrary holds for region-effects. Indeed, regions explain 7% of the variability in firm TFP in Spain, 4.5% 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 80%, and this rises to over 90% in the models controlling for region-random effects only.

Austria and Hungary (columns 4 and 5, table A1), Austria and Hungary and outliers (column 9, table A1). The empty model in column 1 has been replicated by excluding the first and the last 5% of firms in TFP distribution (744 observations) and the evidence remains the same (results available upon request).

[13] The contribution of sector-effect is calculated by comparing the total variance (0.042) explained at regional level in the empty model (column 1 table 3) and the variance (0.037) obtained when this model is augmented by sector-dummies (column 2 of table 4), that is 12% [(0.042-0.0037)/0.042] (cfr. note 14).

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

	(1)	(2)	(3)	(4)
Constant	-0.0859***	-0.0857*	-0.0724	-0.0755*
	(-4.48)	(-1.74)	(-1.56)	(-1.66)
Random-Effects				
Variance				
Regions	0,042		0,037	0,034
Sectors		0,025	0,019	0,018
Regions & Sectors				0,015
Firms	0,236	0,254	0,226	0,215
Total	0,278	0,279	0,282	0,282
VPC				
Regions	15,2%		13,0%	12,0%
Sectors		9,0%	6,8%	6,5%
Regions & Sectors				5,3%
Firms	84,8%	91,0%	80,2%	76,2%
LR test	691,6	358,8	976,5	1067,5
Log restricted-likelihood	-5315,2	-5481,5	-5172,7	-5127,2
Observations	7435	7435	7435	7435
N. of Groups				
Regions	159		159	159
Sectors		11	11	11

Source: see table 1

Table 4 Explaining TFP firms' heterogeentiy in the EU7-Efige Countries in 2008. Results from multilevel regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.187***	-0.0649***	0.190***	0.202***	0.182***	0.174***
	(4.66)	(-3.11)	(4.85)	(3.98)	(3.19)	(3.10)
Fixed effects						
Austria	0.0633		0.0851	0.0743	0.0841	0.0869
	(0.52)		(0.73)	(0.75)	(0.72)	(0.75)
France	-0.238***		-0.239***	-0.238***	-0.239***	-0.228***
	(-4.83)		(-5.21)	(-9.98)	(-5.20)	(-4.99)
Hungary	0.152**		0.162***	0.152***	0.161***	0.165***
	(2.30)		(2.61)	(3.64)	(2.59)	(2.68)
Italy	-0.453***		-0.436***	-0.415***	-0.436***	-0.423***
	(-8.89)		(-9.18)	(-18.22)	(-9.17)	(-9.01)
Spain	-0.363***		-0.322***	-0.312***	-0.324***	-0.323***
	(-8.08)		(-7.66)	(-13.74)	(-7.68)	(-7.73)
United Kingdom	-0.278***		-0.275***	-0.288***	-0.275***	-0.267***
	(-4.83)		(-5.10)	(-9.03)	(-5.09)	(-5.00)
S2		-0.131***	-0.134***			
		(-6.28)	(-6.46)			
S3		0.0638***	0.0574**			
		(2.61)	(2.35)			
S4		-0.0564***	-0.0577***			
		(-2.84)	(-2.91)			
S5		-0.180***	-0.183***			
		(-7.29)	(-7.40)			
S6		0.184***	0.182***			
		(6.22)	(6.14)			
S7		0.154***	0.153***			
		(4.74)	(4.73)			
S8		-0.262***	-0.265***			
		(-9.14)	(-9.29)			
S9		0.109	0.119			
		(0.78)	(0.86)			
S10		0.0730***	0.0699***			
		(3.95)	(3.80)			
S11		0.0254	0.0238			
		(1.29)	(1.21)			
Random-Effects						
Variance						
Regions	0,014	0,037	0,011		0,011	0,009
Sectors				0,023	0,019	0,019
Regions & Sectors						0,015
Firms	0,236	0,226	0,226	0,237	0,226	0,215
Total	0,250	0,263	0,237	0,260	0,257	0,257
VPC						
Regions	5,4%	13,9%	4,7%		4,4%	3,5%
Sectors				8,8%	7,6%	7,2%
Regions & Sectors						5,8%
Firms	94,6%	86,1%	95,3%	91,2%	88,0%	83,6%
LR test	280,7	615,2	226,8	339,1	567,4	657,8
Log restricted-likelihood	-5268,0	-5176,7	-5128,6	-5238,8	-5124,6	-5079,4
Observations	7435	7435	7435	7435	7435	7435
N. of Groups						
Regions	159	159	159		159	159
Sectors				11	11	11

Source: see table 1

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	-0.266***	-0.248***	-0.249***	-0.0483*	-0.0267	-0.0274	-0.182***	-0.180***	-0.181***
	(-8.75)	(-3.89)	(-3.94)	(-1.81)	(-0.41)	(-0.42)	(-8.38)	(-4.26)	(-4.31)
Random-Effects									
Variance									
Regions	0,013	0,012	0,011	0,011	0,008	0,007	0,019	0,015	0,014
Sectors		0,033	0,033		0,037	0,037		0,014	0,013
Regions & Sectors			0,001			0,006			0,006
Firms	0,218	0,204	0,204	0,283	0,259	0,254	0,185	0,177	0,172
Total	0,231	0,249	0,249	0,294	0,304	0,304	0,204	0,205	0,205
VPC									
Regions	5,5%	4,6%	4,5%	3,6%	2,6%	2,3%	9,3%	7,2%	6,8%
Sectors		13,4%	13,1%		12,1%	12,0%		6,7%	6,5%
Regions & Sectors			4,5%			2,1%			2,8%
Firms	94,5%	82,0%	81,9%	96,4%	85,3%	83,6%	90,7%	86,2%	83,9%
LR	92,1	207,9	208,8	48,04	163,0	168,1	175,4	269,7	279,4
Observations	2243	2243	2243	1605	1605	1605	2410	2410	2410
N. of Groups									
Regions	20		20	22		22	67		67
Sectors		11	11		11	11		11	11

Source: see table 1

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 and regions and firms as random 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:

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

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.[14] Another important factor explaining firm TFP regards the role of family in the management (see Schulze and

[14] 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).

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 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).[15] 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, one referring to medium-sized firms (DM) and the other to large-sized firms (DL), 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. Results are in table 6. The first column refers to the whole sample of EU7-EFIGE, whereas columns 2-4 refer to Italy, France and 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).[16] As for the ability of firm-level variables to explain the TFP variance of firms belonging to the EU7-EFIGE sample, we find that the individual factors absorb 16% 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, 22%-23% for Spain and Italy. As expected, after

[15] 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.

[16] 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:

$$R^2_2 = \frac{(\sigma^2_{\mu 0N} - \sigma^2_{\mu 0M})}{\sigma^2_{\mu 0N}}$$

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

$$R^2_1 = \frac{(\sigma^2_{eN} - \sigma^2_{eM})}{\sigma^2_{eN}}$$

introducing firm-variables, the share of TFP variance explained by regions remains almost the same as before: 4.4% for the model referring to the entire sample of EFIGE firms, 4.7% for Italy, 2.9% for France and 7.6% 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.[17] Human capital plays an important role for TFP in Italy and Spain, while no significant impact has been found for French enterprises. With the exception of France, all the other findings are in line with the literature showing that human capital induces higher TFP (Griliches 2000; Parisi *et al*, 2006). 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 contrasts with 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), that show a 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

[17] 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 A1. As can been seen, the results do not qualitatively change.
Another way to address endogeneity would be the use of TFP determinants defined at regional level. In such a case, it would be expected that TFP regional factors acting as exogenous factors limit the endogeneity bias, because it is unlikely that firms' decisions would alter these factors, while the opposite holds. However, we cannot augment our regressions with regional variables because the EFIGE dataset provided by Bruegel does not allow for regional identification (cfr note 4).

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.[18]

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).[19] When considering the countries covered in this study individually, the 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.[20] 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).

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).[21] 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

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

[19] 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.

[20] 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).

[21] 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).

premium may be the result of an omitted variables bias. This issue has been addressed, for instance, by Crozet (2010)[22] 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.[23] 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.

[22] Crozet et al. (2110) 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.

[23] 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.

Table 6 Explaining TFP heterogeneity of firms belonging to the EU7-Efige sample. Evidence from multivel models augmented by firms-specific variables

	Explanatory Variables	EU7-EGIFE (1)	Italy (2)	France (3)	Spain (4)
	Constant	-0.118***	-0.376***	-0.263***	-0.237***
		(-3.05)	(-10.34)	(-6.52)	(-8.46)
Fixed effects					
	Level 1: Firms				
	Medium	0.170***	0.183***	0.112***	0.168***
		(13.49)	(9.42)	(3.63)	(9.60)
	Large	0.516***	0.621***	0.388***	0.609***
		(22.12)	(13.23)	(6.72)	(14.66)
	Family management	-0.0423***	-0.0286	-0.0152	-0.0398**
		(-3.14)	(-1.48)	(-0.41)	(-2.10)
	National group	0.0878***	0.105***	0.0636**	0.0889***
		(5.75)	(3.83)	(2.01)	(3.43)
	Foreign group	0.223***	0.363***	0.127***	0.316***
		(11.59)	(8.09)	(3.14)	(8.26)
	Process Innovator	0.0372***	0.0567***	0.0351	0.0253
		(3.50)	(3.21)	(1.35)	(1.58)
	Human capital	0.0418***	0.0525***	0.00197	0.0581***
		(3.55)	(2.80)	(0.07)	(3.23)
	Exporter	0.0110	-0.00816	0.0360	0.00949
		(0.91)	(-0.39)	(1.27)	(0.55)
	Country dummies	YES			
	Sector dummies	YES	YES	YES	YES
Random-Effects					
	Variance				
	Regions	0,009	0,008	0,007	0,012
	Firms	0,198	0,167	0,243	0,145
	Total	0,207	0,175	0,250	0,157
	VPC				
	Regions	4,4%	4,7%	2,9%	7,6%
	Firms	95,6%	95,3%	97,1%	92,4%
	R	0,26	0,24	0,15	0,23
	R^2 *level 2*	0,79	0,36	0,31	0,37
	R^2 *level 1*	0,16	0,23	0,14	0,22
	LR test	195,2	53,3	31,0	124,9
	Log restricted-likelihood	-4653,8	-1228,8	-1186,6	-1168,1
Number of observations		7435	2243	1605	2410

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-intercepts 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 intercepts, while countries and sectors enter into this specification as controlling fixed-effects factors.

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 analysis has tried to measure 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 analysis yields two main results.

Firstly, heterogeneity in productivity is greatly affected by firm-specific factors. In the more general model, the proportion of TFP variability brought about by the first-level of our hierarchical structure of data is high, ranging from 92.4% in the case of Spain and 97.1% for France. In Italy, it is equal to 95.3%. At EU7-EFIGE level, this share is 95.6%, net of sector and country-fixed effects. 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 we have carried out 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, 16% of first-level TFP variance. This proportion is also 16% for France and about 23% for Spain and 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 (67%) of the firms' TFP variability that the multilevel approach assigns to regions, in other words to the second-level of our model. Regions explain more than 15% of TFP heterogeneity when regressions exclude countries while this proportion drops to 4.4% after controlling for sector and country-effects. This evidence is robust to outliers and to the composition of the EU7-EFIGE sample. At individual country level, being located in different regions explains 4.7% of TFP heterogeneity in Italy, while the impact is lower (2.9%) in France and higher (7.6%) in Spain.

The main conclusion to be drawn from this paper highlights the need of 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 benefit with regard the practising of business. To give just a few examples. Private individual performance would be less heterogeneous than 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 cohesion/regional policy

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Appendix

Table A1 Robustess checks

Explanatory Variables	Without Outliers (a)	Without HUN	Without HUN	Without HUN and AUT	Without HUN and AUT	Without HUN	Without HUN and AUT	Without Outliers	Without Outliers, HUN & AUT	Mudlack Correction (b)	Without Outliers & Mudlack Correction (b)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	-0.085***	-0.116***	0.190***	-0.122***	0.191***	-0.115***	-0.115***	-0.137***	-0.137***	-0.360***	-0.309***
	(-5.24)	(-6.75)	(4.89)	(-7.16)	(4.92)	(-3.02)	(-3.01)	(-4.23)	(-4.19)	(-2.80)	(-2.88)
Fixed effects											
Level 1: Firms											
Medium						0.169***	0.170***	0.151***	0.151***	0.170***	0.152***
						(13.39)	(13.52)	(14.27)	(14.29)	(13.39)	(14.26)
Large						0.517***	0.518***	0.450***	0.453***	0.516***	0.450***
						(21.99)	(21.97)	(22.79)	(22.69)	(21.94)	(22.62)
Family management						-0.0386***	-0.0385***	-0.0572***	-0.0551***	-0.0391***	-0.0552***
						(-2.87)	(-2.87)	(-5.08)	(-4.90)	(-2.89)	(-4.88)
National group						0.0906***	0.0888***	0.0980***	0.0983***	0.0873***	0.0972***
						(5.96)	(5.84)	(7.60)	(7.64)	(5.69)	(7.51)
Foreign group						0.220***	0.220***	0.216***	0.219***	0.221***	0.214***
						(11.29)	(11.22)	(13.24)	(13.24)	(11.36)	(13.04)
Process Innovator						0.0346***	0.0343***	0.0365***	0.0358***	0.0371***	0.0371***
						(3.26)	(3.23)	(4.10)	(4.01)	(3.48)	(4.14)
Human capital						0.0405***	0.0412***	0.0425***	0.0420***	0.0422***	0.0427***
						(3.45)	(3.51)	(4.32)	(4.27)	(3.59)	(4.34)
Exporter						0.0108	0.0102	0.0157	0.0155	0.00667	0.0111
						(0.90)	(0.85)	(1.56)	(1.53)	(0.55)	(1.09)
Country dummies			YES		YES	YES	YES	YES	YES	YES	YES
Sector dummies			YES		YES	YES	YES	YES	YES	YES	YES
Mundlak correction										YES	YES
Random-Effects											
Variance											
Regions	0,030	0,030	0,011	0,029	0,011	0,009	0,009	0,006	0,007	0,008	0,005
Firms	0,169	0,230	0,220	0,229	0,220	0,193	0,192	0,136	0,133	0,198	0,136
Total	0,199	0,260	0,231	0,258	0,231	0,202	0,201	0,142	0,140	0,206	0,141
R	0,29	0,07	0,17	0,07	0,17	0,27	0,28	0,49	0,50	0,26	0,49
R^2 *level 2*	0,29	0,30	0,74	0,32	0,74	0,79	0,79	0,85	0,84	0,81	0,87
R^2 *level 1*	0,28	0,03	0,07	0,03	0,07	0,18	0,19	0,42	0,44	0,16	0,42
LR test	706	610	234	607	235	202	203	222	233	129	143
Log restricted-likelihood	-3993	-5075	-4911	-5045	-4885	-4449	-4425	-3201	-3047	-4652	-3202
Number of observations	7285	7256	7256	7231	7231	7256	7231	7285	7099	7435	7285

(a) Data of TFP below the first percentile and above the 99th percentile are considered outliers.

(b) Estimations with Mundlank (1978) correction (cfr. note 17).