

The Two Disjointed Faces of R&D and the Productivity Gap in Europe

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Abstract

This paper explores the determinants of productivity gaps within the European Union in computing, chemicals, basic metals and food manufacturing – four sectors that vary in terms of the intensity of sectoral R&D. Our analysis reveals that the main causes of these productivity gaps are intensity of unembodied or disembodied R&D activity and R&D embodied in purchased equipment and machinery, and their interplay. While disembodied and embodied R&D are both associated positively to closing productivity gaps, the interaction between the two does not have the same effect. There is no complementarity between these technology acquisition modes, despite both disembodied and embodied technology are crucial for productivity catch up. In a policy context, this suggests possible lack of coordination between R&D policy and technology transfer (that is, foreign direct investment, trade and industrial policy). We show, also, that the productivity gap between ‘peripheral’ (southern and eastern) and ‘north’ EU countries is widening.

Keywords: productivity; technology gap; multi-level analysis; European Union

Introduction

The World Bank once described the European Union (EU) as a ‘convergence machine’ (Gill and Raiser, 2012). However, especially since 2008, there has been a distinctive and accelerated polarisation in the production structures of ‘core’ EU countries (such as Germany and Austria) and southern ‘peripheral’ countries (Greece, Italy, Spain and Portugal) (Gräbner *et al.*, 2019a, 2019b; Landesmann, 2015; Landesmann *et al.*, 2015; Gräbner and Hafele, 2020), reflected, in part, by the growing divergence in labour productivity (Filippetti and Peyrache, 2013). Although the convergence machine seems still to be operating in some parts of Central and Eastern Europe, it is important to understand what is causing it to break down in other parts of the EU (Ridao-Cano and Bodewig, 2018).

There are at least three main strands of literature that focus on the convergence process. The first investigates ‘macroeconomic-cum-institutional’ issues and the institutional shortcomings of a European monetary union in the absence of a fiscal and political union (for example De Grauwe, 2012; Boyer, 2014). The second emphasizes differences in the structural reforms and supply-side policies among different EU macro-regions (south vs north vs east) (for example Ridao-Cano and Bodewig, 2018). The third investigates what we describe as ‘structuralist-cum-Schumpeterian’ issues and the differences among EU macro-regions in relation to their different capacity to generate technology. For example, Gräbner *et al.* (2019a, 2019b) focus on industrial structure polarization, manifested in

differences in technological capabilities, and the emergence of export-driven growth in the core regions and debt-driven growth in the periphery. Similarly, the technology gap approach to growth posits that differences in levels of development, ultimately, are rooted in different levels of technological development (Fagerberg and Verspagen, 2014).

The ‘structuralist-cum-Schumpeterian’ approach takes as a starting point the close link between changes in the production structure and the absorption of technology. As suggested by the literature review presented by Cimoli and Porcile (2016), this makes it the most relevant for understanding the determinants of the productivity gap. Also, absorption of technology takes place in firms through learning processes which are localized, tacit and path dependent. This makes it essential to recognize firms and their features as the key determinants of productivity where innovation and the diffusion of technology take place as closely linked processes (Cimoli and Porcile, 2016).

Our empirical model belongs to this theoretical stream. Specifically, we test a new technology gap model, based on two cumulative capacity-building mechanisms: acquisition and mastery of technology through Machinery and Equipment (M&E henceforth) – whether purchased locally or imported from abroad, and investment in R&D. We refer to these mechanisms as embodied and disembodied R&D respectively.

First, we conduct a firm-level analysis of the productivity growth in the EU and propose a single common EU-wide productivity ‘frontier’ to enable cross-country comparison. Second, we conduct an empirical analysis controlling for sector- and country-specific factors. This allows us to identify the relative prominence of different factors at different aggregation levels by discussing how contextual issues affect productivity and, more importantly, to account for possible effects of clustering of firms within sectors and countries. Third, we investigate the interplay between sectoral disembodied R&D and sectoral embodied R&D processes which extends our understanding of the Schumpeterian growth process.

Our results emphasize the significance of the technology gap variables. While, as expected, both embodied and disembodied R&D are positive factors (fostering catching-up), the interaction between them is not positive. We find a significant negative interaction between embodied and disembodied R&D in three of our four sectors (the exception being chemicals). This suggests lack of complementarity between these two modes of technology acquisition and mastery despite each being, on their own, essential preconditions for productivity gap reductions. Our results are robust to specifications accounting for unobserved firm heterogeneity (both fixed effects and random intercepts) and different sampling and country-per-industry clustered standard error weighting.

The paper is organized in five sections that are structured as follows: Section I provides a brief review of the broader literature on the determinants of productivity and technology gaps and explains our choice of empirical model; Section II describes the dataset and some stylised facts relevant to our analyses; Section III presents the econometric results; and finally, we offer some conclusions and implications for policy in Section V.

I. Literature Review

The debate on convergence/divergence in Europe focuses heavily on the macroeconomic and institutional differences involved. Although these differences are essential to understand short term trends, Celi *et al.* (2017) argue persuasively that they contribute little

to our understanding of the long-term determinants of divergence or convergence in Europe. In this respect, the literature on growth in Europe remains somewhat detached from the more general literature on economic growth. The latter body of work is dominated by macroeconomic issues and ignores micro factors and rarely considers the uneven distribution of technological capabilities as a potential determinant of differences among different European economies (for these exceptions, see the references in Table 1). Crafts and Hjortshøj O'Rourke (2014) and Gräbner and Hafele (2020) argue that the main features of economic growth (including in the EU) are divergence rather than convergence, absence of automatic catch-up and sustained labour productivity growth based on technological accumulation. Their argument is confirmed by productivity studies that emphasize significant and persistent productivity differences across countries (Bartelsman *et al.*, 2013). We adopt this perspective to provide a brief review of the most relevant contributions addressing the range of factors that can be described as structuralist and Schumpeterian. Our aim is to test the significance and relevance of the 'structuralist-cum-Schumpeterian' determinants of the productivity gaps; we focus on firm-level factors, market structure, technology and macro-factors. In what follows, we justify our choice of variables and highlight the novelty of our model.

Probably the most important stylized fact that has emerged from the recent literature on productivity is related to the significant and persistent differences identified among producers within very narrowly defined industries (Syverson, 2011). Such differences among producers are also the reflection of within- rather than between-sector reallocation of resources (Foster *et al.*, 2001). In other words, the literature points out the existence of patterns of broad productivity heterogeneity within single industries and relatively less heterogeneity between different sectors. The differences among firms include firm size,

Table 1: Summary of the Main Hypotheses based on the Literature Review

<i>Hypothesis</i>	<i>Selected relevant literature</i>
Firms' structural features (size, age, ownership, multi-nationality) are significant explanatory factors of productivity gaps	Foster <i>et al.</i> (2001); Jensen <i>et al.</i> (2001); Bellak (2004); Venables (2004); Syverson (2011), Bartelsman <i>et al.</i> (2013); Navaretti and Damijan <i>et al.</i> (2013); Ridao-Cano and Bodewig (2018)
Market structure differences have ambiguous effects on productivity gap reductions Structural differences between the EU 'core' and 'periphery' are significant explanatory factors of productivity gaps	Scherer (1967); Cheung and Garcia Pascual (2001); Aghion <i>et al.</i> (2005) Delgado-Rodríguez and Álvarez-Ayuso (2008); Filippetti and Peyrache (2015); Celi <i>et al.</i> (2017); Dosi <i>et al.</i> (2019); Fattorini <i>et al.</i> (2019), Gräbner <i>et al.</i> (2019b)
The technology gap in terms of embodied and disembodied R&D is significant determinant of productivity gap	Griliches (1979); Fagerberg (1987; 1994); Mowery and Oxley (1995); Eaton and Kortum (1999); Griffith <i>et al.</i> (2003; 2004); Fagerberg and Verspagen (2014); Dosi <i>et al.</i> (2015); Filippetti and Peyrache (2017); Gräbner and Hafele (2020)
(Mis)matches between endogenous (disembodied) and purchased (embodied) technology impact negatively (positively) on the productivity gap	Radosevic (1999); Jung and Lee (2010); Chung and Lee (2015); Filippetti and Peyrache (2015)

age, location, managerial abilities and innovation capability. The differences between different sectors include technological sophistication, access to value chains and so on. In this paper we look at both aggregation levels.

Bartelsman *et al.* (2013) find a positive covariance between productivity and firm size across countries, industries and over time, but also find considerable variation in the strength of the links. In EU countries, firm size distributions differ significantly. For example, microenterprises account for a considerably larger share of employment and value-added in both southern and eastern countries but are also much less productive (Ridao-Cano and Bodewig, 2018).

Age is used frequently to proxy for learning and accumulated capabilities. Thus, age may be correlated, also, with productivity; since firms learn by doing, we can expect older firms to have accumulated more technological capabilities and, therefore, to be more productive (Jensen *et al.*, 2001). On the other hand, ageing physical capital may influence negatively firm productivity.

The productivity gap may be narrower in countries with large shares of multi-plant and multinational firms, since multinationals are associated with high firm-level economies of scale combined with relatively lower plant-level economies of scale (Navaretti and Venables, 2004). In addition, there can be substantial differences in performance between foreign- and domestically owned firms (Navaretti and Venables, 2004; Damijan *et al.*, 2013). However, in most cases, performance gaps ‘disappear’ after controlling for firm and industry characteristics: compared to foreign ownership, structural effects and industry composition effects account for most of the disparities (see Bellak, 2004 for a review).

The market structure may affect productivity convergence through its effect on the incentives for firms to engage in R&D and innovation. The level of competition can have a positive or a negative effect on innovative behaviour and, thus, productivity gap reduction (Cheung and Garcia Pascual, 2001; Aghion *et al.*, 2005).

Delgado-Rodríguez and Álvarez-Ayuso (2008) analysed labour productivity growth and convergence in the EU-15, from 1980 to 2001, and found that technological progress tended to contribute to *divergence*. Filippetti and Peyrache (2017) show reducing the technology gap *via* an increase in endogenous technological capabilities, can be a significant source of growth, particularly for fast-converging EU countries. However, greater distance from the technological frontier does not *per se* guarantee faster labour productivity growth rates.

The EU cohesion policy was developed to address the technology gaps among member states. Regional entities receive substantial resources to build their R&D activities and technological capabilities. Filippetti and Peyrache (2015) show that productivity growth in laggard regions is driven mainly by capital accumulation and that the technology gap does contribute to driving labour productivity growth and is stable across regions. This suggests that the technology gaps in the EU are a source of untapped potential productivity growth, and that the cohesion policy seems to be affecting only physical investment (European Commission, 2017). However, it has been shown that poorly performing firms could benefit greatly from the EU cohesion fund, especially if resources are targeted at direct investment in R&D (Fattorini *et al.*, 2019).

One of the weaknesses of technology gap-based models is how they treat purchased (domestic and imported) technology and its interaction with domestic technology efforts.

The predominant focus is on the gaps in technology generation and technology absorption, with little attention paid to the interaction between purchased (including imported) technology versus internal technology efforts. However, previous evidence shows that there are considerable differences between economies that have been able successfully to exploit foreign technologies compared to those that have not (Mowery and Oxley, 1995). Access to external knowledge is especially crucial for narrowing technology gaps (Kim, 1997) and it is important, also, to consider the interaction between purchased embodied technology and disembodied (R&D) technology. The historical evidence suggests that successful convergence or catching up is characterized by a complementary relationship between purchased, especially imported technology and local technology efforts (Lee, 2013).

Part of the reason behind the small amount of research on this relationship is a lack of national data on firm-level technology transfer. However, Jung and Lee (2010) demonstrate that the sequencing of investment in R&D and import of knowledge from abroad matters for successful catch-up, but that the effects are different in different sectors. They show, also, that the form of the purchased technology matters. One of the major contributions of the present paper is that we take account of the sectoral level interaction between disembodied R&D and R&D embodied in purchased M&E, as distinct modes of technology acquisition and mastery.

Productivity levels and productivity growth depend on the level and growth of the knowledge stock, measured, conventionally, by R&D (Griliches, 1979). The standard view is that R&D differs from other forms of capital investment due to its intangible (disembodied) nature. Several papers provide evidence supporting the importance of foreign R&D (see Eaton and Kortum, 1999; Griffith *et al.*, 2003, 2004). Guellec and Van Pottelsberghe de la Potterie (2004) is probably the only paper that assesses the contribution of private, public and foreign R&D within a single framework. They show that there are high returns from foreign R&D but rather low returns from private R&D compared to public R&D. Their estimates of foreign R&D are of the same order of magnitude as in Coe and Helpman (1995), which suggests that ‘other countries’ R&D matters more than domestic R&D, provided that the country can absorb technology from abroad’ (Guellec and Van Pottelsberghe de la Potterie, 2004, p. 366).

Foreign knowledge and R&D can be embodied in M&E and in patent licences. Both types interact differently with local technology efforts (Jung and Lee, 2010). However, absorptive capability is always a precondition for benefiting from foreign technology (Cohen and Levinthal, 1989, 1990). We build on this critical insight by including variables for sectoral ‘external’ R&D embodied in purchased technology and, also, the more traditional sectoral ‘internal’ R&D and exploring how these sets of variables interact. Countries and local firms seeking to narrow their productivity gaps need to complement their R&D efforts with technology embodied in purchased M&E. If one mode of technology acquisition and mastery dominates, then in those countries and sectors that are operating behind the technology frontier these productivity gaps will persist.

The diversity among EU economies in terms of levels of direct investment in R&D activities has been well documented (Archibugi and Coco, 2005). However, investment in indirect R&D, that is, technology embodied in purchased M&E has been less well researched. There is some evidence showing that indirect R&D dominates in the less developed EU economies (Knell, 2008). If we extend the concept of R&D, it is possible that

some countries that are behind the technology frontier may *de facto* be more R&D intensive than the technology leaders since their technology efforts are directed, mostly, towards effective use and adoption of purchased M&E with high embodied R&D intensity. However, these efforts do not contribute to closing the productivity gap unless complemented by endogenous technology activities (Radošević, 1999; Jung and Lee, 2010; Filippetti and Peyrache, 2015).

EU efforts to facilitate technology upgrading in converging countries and regions include efforts to enhance the interactions between the converging and the more advanced countries' technology efforts and technology outputs, *via* integration in the EU and the broader international industrial and technology networks. The failure of this convergence machine role is partly a reflection of differences in regional capacities to promote innovation-based growth (Gräbner *et al.*, 2019b) and maintain innovation capabilities (Archibugi and Filippetti, 2011). It could be viewed, also, as a failure by the EU to facilitate interaction and coordination between internal technology efforts and external sources of technology and knowledge, at different levels.

In this paper, we consider three EU macro-regions as three different contexts that explain differences in productivity gap reductions. Our groupings are not purely geographically based; rather, they are based on technological and developmental similarities: 'North' EU includes Austria, Belgium, Germany, Finland France, Netherlands, and Sweden; 'South' EU includes Italy and Spain; and 'East' EU includes the following 'new' member states Bulgaria, Czech Republic, Hungary, Poland, Romania, and Slovenia.¹

In summary, we embrace a structuralist-cum-Schumpeterian perspective on growth to explore the firm, industry and country level determinants of productivity in the spirit of Dosi *et al.* (2015). Our model is novel in trying to capture a major, but often neglected stylised facts related to growth, that is, the interaction between different modes of technology acquisition and mastery. Another novelty of our approach is that we explore the productivity gap determinants at both the country, sectoral and micro, and, also, in a multi-level setting.

II. Empirical Analysis

Descriptive Statistics

We use Bureau van Dijk Amadeus data on four manufacturing 'macro-sectors': computing, chemicals, basic metals and food. This resulted in a sample of 38,991 firms during the period 2004 to 2013 and a total of 137,992 firm-year observations, covering 15 EU countries.² To minimize potentially adverse effects of extreme observations, we proceed as follows. Most of the variable follow a Power law. We have transformed them in natural logarithms. The new 'log-variables' assume now a symmetric distribution close to a 'Laplace'

¹The exclusion of Croatia, Cyprus, Denmark, Luxembourg, Malta, Ireland, Slovak Republic, United Kingdom is due to data availability/reliability, as we explain further in footnote 2.

²Austria, Belgium, Bulgaria, Czech Republic, Germany, Spain, Finland, France, Hungary, Italy, Netherlands, Poland, Romania, Sweden and Slovenia which account for around 78% of total EU GDP between 2004 and 2013. This sample includes countries at all levels of economic development spectrum (for example Germany and Netherlands high; Italy and Spain medium; Romania and Bulgaria low), making comparison of productivity gaps meaningful. The reduced sample is due to reporting of unreliable data by the other countries, to our interest in maintaining a streamlined version of Amadeus, and to consider the points expressed by Bajgar *et al.* (2020), Gal (2013) and Kalemli-Özcan *et al.* (2019).

distribution (Bottazzi and Secchi, 2003). This distribution shares some properties (for example, symmetry) with the more traditional Normal distribution. Hence the exclusion of the top 1 per cent and the bottom 1 per cent of log-variables allows for the elimination of genuine extreme values, that would not be detectable in the Power law version. Finally, all nominal variables are deflated using the relevant producer price index at the 2-digit country sector level. Appendix Tables A1 and A2 present the variables and their descriptive statistics. The log and deflated version of the variables is used in the regressions.

Disembodied R&D at the sectoral level is sourced from Eurostat Business Enterprise R&D (BERD) statistics (at the NACE2 level) and is defined as the ‘percentage of business production value spent on R&D’. *Embodied* R&D at the sectoral level was computed as follows. First, we used the World Input–Output Database (Timmer *et al.*, 2015) to collect the yearly value of the transactions occurring between one industry in a country to another industry in the same or another country, during the period 2004 and 2013 (input–output matrix). Second, we collected data, including the value of transactions, on the computing, chemicals, basic metal and food sectors for the EU-28 countries. These four sectors are among the top five in the EU for employment and share of value added, which means our results have both high macroeconomic and sectoral, relevance. Third, for each combination of receiving sector, country and year (for example ‘chemicals/Germany/2005’), we computed the relative weight of the transactions from all sectors (2-digit codes) in total transaction value (that is, the relative importance of the transaction values from different sectors in four ‘target’ sectors). Finally, we multiplied each relative weight (specific to each sector, country and year) by R&D intensity, as a percentage of gross value added (GVA), according to the OECD’s economic activity taxonomy which is based on R&D intensity (Galindo-Rueda and Verger, 2016, see Appendix Table A3). This procedure results in a R&D to GVA ratio, based on embodied technology from other EU sectors.

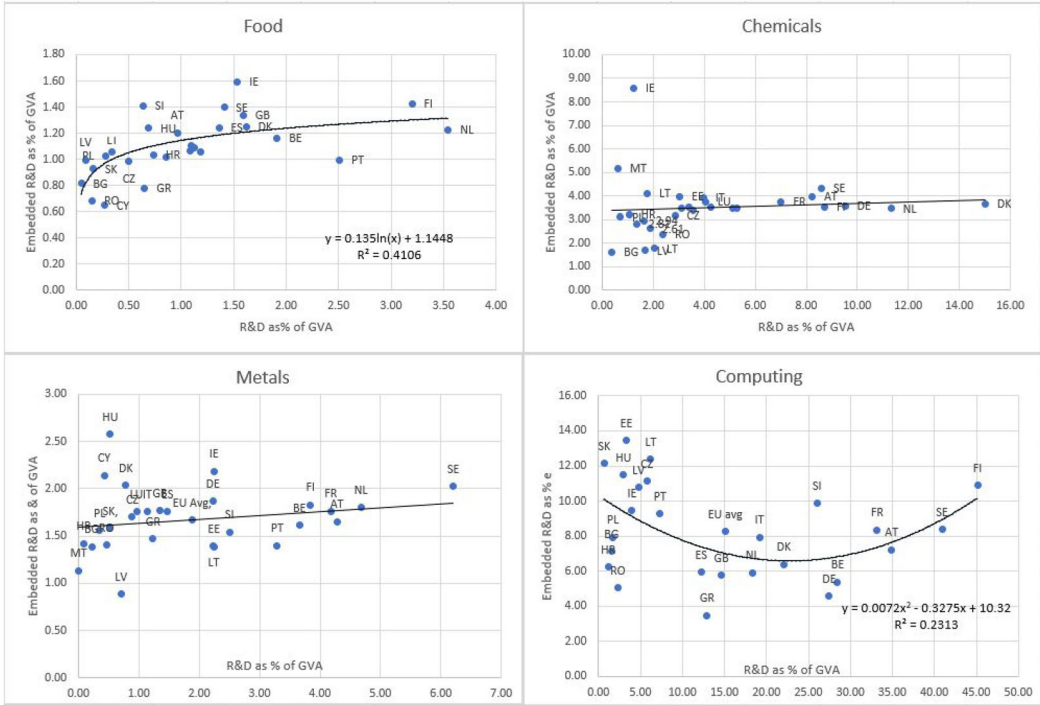
Figure 1 shows that in all four sectors, across countries, disembodied R&D intensity differs more than embodied R&D intensity. The less developed economies show larger differences in the sophistication of purchased technology and lower levels of disembodied R&D compared to the advanced economies.

Methodology and Empirical Model

We define the technology *frontier* as the leading EU country in terms of technical efficiency in the four-digit sector, in the period 2004 to 2013. We focus on firms in each of the four macro-sectors and explore productivity variability within and between four-digit sectors. The four sectors were selected based on their representativeness of the different levels of R&D intensity: food (NACE 10) low-tech, basic metals (NACE 24) medium/low-tech, chemicals (NACE 20) medium/high-tech and computing (NACE 26) high-tech industry.

Our empirical strategy is conducted in three steps. First, we follow Foster *et al.* (2001) and estimate ‘omegas’ as technical efficiency from a log of output as a function of the log of the inputs regression for each four-digit sector. Second, we follow Jung and Lee (2010) and compute an EU industry level frontier based on the best-performing country in a specific sector at the four-digit NACE level. The distance between the individual firm and the EU frontier constitutes the technological gap, which is our dependent variable. Third, we

Figure 1: Disembodied R&D and Embodied R&D Intensity in Four Sectors across the EU, 2004–13, with Country-Sector Averages. [Colour figure can be viewed at wileyonlinelibrary.com]



Source: Authors’ computations based on Eurostat BERD and WIOT. Note different vertical and horizontal scales.

estimate the determinants of this gap in a multilevel and a fixed-effects framework. We model the micro, meso and macro levels variables simultaneously, which addresses the sector and country level clustering effect (for example see Van Oort *et al.*, 2012; Goedhuysa and Srholecb, 2015). These three steps are described in more detail below.

Computation of the Omegas as Technological Efficiency

We adopt a log of output as a function of the log of inputs equation a la Levinsohn and Petrin (2003) and adjust for endogenous inputs following Akerberg *et al.*’s (2015) correction. We estimate each equation for a four-digit industry in terms of the production function coefficients:³

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where output y (log of value added) is explained by the inputs, divided by a ‘freely’ variable l (log of labour), a state variable k (log of capital) and another freely variable m (log of

³Estimating the equations at this disaggregated level addresses some common criticisms of the production function approach (see for example Felipe and McCombie, 2014).

material costs) with the intermediate input demand function expressed as $m_{it} = m_{it}(\omega_{it}, k_{it})$. Thus, material costs proxy for unobservable simultaneous changes to productivity (if material costs go up this is a sign of a positive productivity shock).

Finally, the error term is considered as additively separable in a technical efficiency (productivity) component ω_{it} and a pure i.i.d. residual ε_{it} . The first omega is our measure of firm level productivity (or Levinsohn and Petrin’s, 2003, technical efficiency’).

Computation of the Productivity Gap. We compute the productivity gap as the difference between the productivity of the firm and the highest sector-specific productivity level in the sample. More specifically we compute the 90th percentile of the natural logarithm of omega for every country, year and 4-digit sector and average the productivity of the top decile. We then can calculate the leading country for every year and every four-digit sector, that is, the sector- and time-specific European frontier. We then can calculate the gap as the natural logarithm of omega of the firm minus the European Max in a particular country/sector/year:

$$\text{Total Gap}_{\text{firm, country, sector, year}} = \text{Ln}(\text{Omega})_{\text{firm, country, sector, year}} - [\text{Max}^{\text{country}}_{\text{sector, year}}] \tag{2}$$

Figure 2 shows that the metal and chemical sectors recorded a progressive productivity gap increase over the period with the only exception of the last year. The computer sector generally shows a reducing productivity gap although, in 2008, the gap increased slightly, but then regained its reducing trend in 2009/2010. The productivity gap in the food sector initially reduced from 80% to 55% in the first year, but since then has increased slightly over time. However, at the end of the sample period, all four sectors have a similar productivity gap.

The Determinants of the Productivity Gap

We regress our dependent variable, Total GAP in equation 2, on a set of potential determinants, using a multilevel model (3) and a fixed-effects model (4):

$$\text{Total} - \text{gap}_{\text{isct}} = \beta_0 + \beta_1 X_{\text{isct}} + \beta_2 X_{\text{sct}} + D_t + \rho_{\text{isc}} + \rho_{\text{sct}} + \rho_{\text{ct}} + e_{\text{isct}} \tag{3}$$

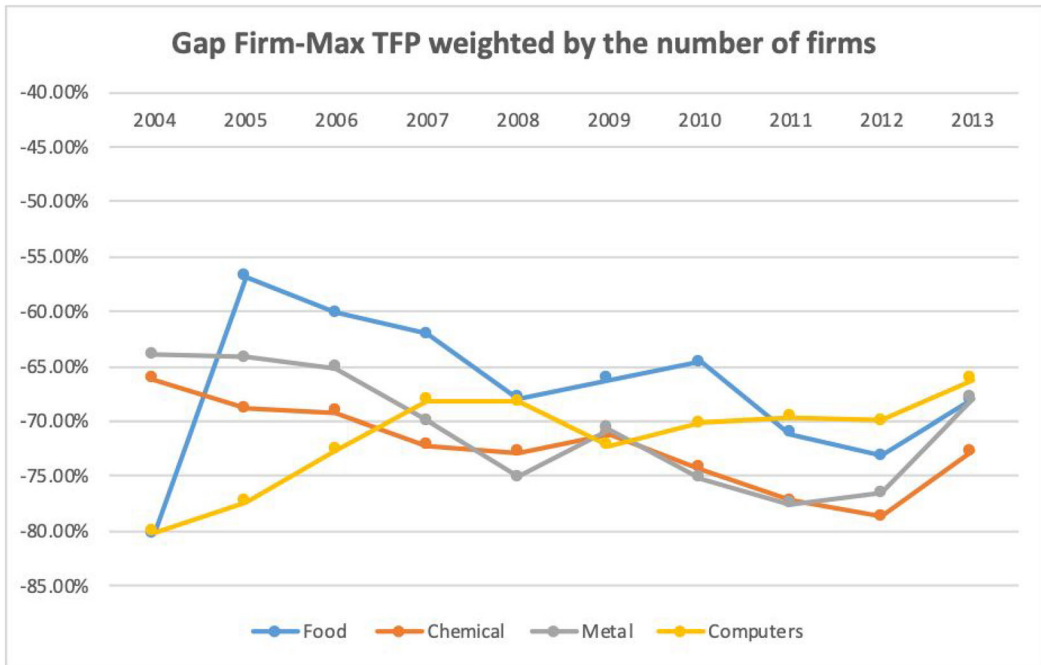
$$\text{Total} - \text{gap}_{\text{isct}} = \beta_0 + \beta_1 X_{\text{isct}} + \beta_2 X_{\text{sct}} + \rho_i + D_t + e_{\text{isct}} \tag{4}$$

X_{isct} denotes firm-level time-variant covariates, X_{sct} denotes sector-level covariates (within a country and a year), ρ_i denotes firms FE (or $\rho_{\text{isc}} + \rho_{\text{sct}} + \rho_{\text{ct}}$ – a set of random intercepts in a Multilevel specification), D_t denotes time dummies, and e_{isct} is the i.i.d. idiosyncratic error.

At firm level, we control for number of employees, firm age and fixed capital investment ‘spikes’. We define investment spikes or lumps as large (over 20 per cent) discrete changes in investment levels (Disney *et al.*, 2018).⁴ We also include the 4-digit within-country industry concentration and then, separately, 4-digit EU-level industry

⁴For this variable we eliminate outliers.

Figure 2: Average Gap Firm-Max Productivity Weighted by Shares of Countries in the Sample. [Colour figure can be viewed at wileyonlinelibrary.com]



Source: Authors’ calculation based on BvD Amadeus, see text, section II for a step-by-step gap computation.

concentration. Finally, we obtain both the level of disembodied R&D (as a percentage of production) and embodied technology (as a percentage of GVA) as critical explanatory variables. All the explanatory variables, except age and its square, are in natural logs and are lagged one year to address endogeneity concerns due to simultaneity.

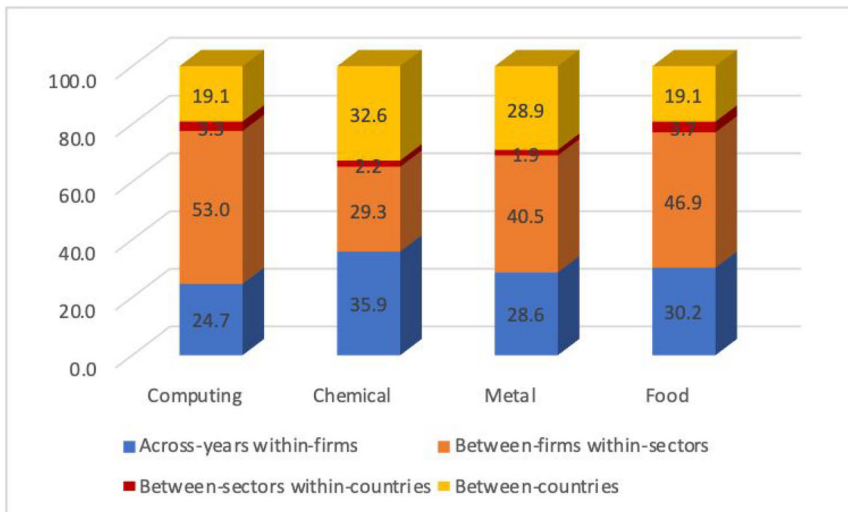
We use multilevel modelling to account for the fact that the structure of the dataset is hierarchical in which years represent level one, firms represent level two, industry (NACE 4-digit) represents level three and country represents level four. Failure to do this would lead to biased results (Rabe-Hesketh and Skrondal, 2012). A precondition for utilizing a hierarchical linear model is significant between-group variance for the dependent variable (Rabe-Hesketh and Skrondal, 2012). We also examined whether the choice of multilevel modelling with year-firm-sector-country effects was justified. We tested the significance of the between-group variances (random intercepts) by performing a likelihood ratio (LR) test to compare the multilevel model with a single-level model for each of the four sectors. We found that the random intercepts were significant which supported our choice of a multilevel model, as shown in detail in Table 2 and Figure 3. Table 2 highlights diagnostic statistics on the Multilevel as well as the fixed-effect models. In the top panel A, we see that the LR tests support the selection of the Multilevel model vis-à-vis the linear single-level one. In the bottom panel B, the Hausman test suggests the use of fixed-effect model against the Random effect; the F-test implies that all fixed effects are

Table 2: Diagnostic Statistics

	<i>NACE 26 Computers</i>	<i>NACE 20 Chemicals</i>	<i>NACE 24 Metal</i>	<i>NACE 10 Food</i>
Panel A: Multilevel diagnostics (non-weighted sample)				
LR test = chi2(3) (null hypothesis: there is no significance difference between the linear and ML model)	22654.95*** ($p < 0.000$).	27310.60*** ($p < 0.000$).	13975.23*** ($p < 0.000$).	85994.18*** ($p < 0.000$).
Panel B: Fixed Effect Diagnostics (non-weighted sample)				
Hausman test (null hypothesis: FE = RE) Prob>chi2	98.86*** 0.000	230.20*** 0.000	351.10*** 0.000	482.45*** 0.000
F-test (null hypothesis: all FE = 0) Prob > F	9.24*** 0.000	11.23*** 0.000	7.46*** 0.000	8.45*** 0.000
Cross-sectional dependence test (Null hypothesis error are weakly cross-sectional dependent)	15.453***	24.653***	14.399***	39.146***
<i>p</i> -value	0.000	0.000	0.000	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The LR tests compare the difference between the multilevel random intercept model and the single-level linear one to see which one could provide a better fit. The Hausman test allows to select the best model between Fixed Effect and Random Effect. The F-test allows us to verify whether the fixed effects intercepts are simultaneously equal to zero. The cross-sectional dependence test for panel data (Pesaran, 2015) checks for dependence in the N component.

Figure 3: Total Gap, Inter-class Correlations by Sector. [Colour figure can be viewed at wileyonlinelibrary.com]



Note: To calculate inter-class correlations we use a 4-level nested model, estimating it separately for each of the four sectors.

not simultaneously equal to zero; and the Pesaran, 2015 confirms the lack of cross-sectional dependence. Finally, Figure 3 depicts the inter-class correlations for each cluster group and sector, showing that the ‘between-firm within sector’ variance accounts for the highest proportion.

To preserve the representativeness of the population of firms across sectors and countries, we exploited the weighting of Eurostat firms’ demographic statistics. However, we cannot use weighting in the maximum-likelihood model due to the clustering of the random components of the error; instead, we use the fixed-effects weighted model in a robustness check regression (Table 5).

III. Results

We explore the determinants of the productivity gap between the firm and the EU technology frontier. Table 3 reports the multilevel results (unweighted); Tables 4 and 5 report the results of the fixed effects models, namely the unweighted and weighted samples, respectively.

Multilevel Results

Table 3 reports the results of the multilevel model. A positive coefficient can be interpreted as reduction in the gap. We interpret our results according to three groups of determining factors.

First, firm size contributes to closing the gap in the computer, food and chemical sectors, but not the metal sector. The number of subsidiaries (time invariant) is associated with a larger gap in the food, but not the other sectors. Firms in South-East Europe are farther from the technology frontier, regardless of sector. Foreign ownership (time invariant) seems to have no effect on closing the gap. Second, country-level concentration is detrimental (larger gap) in the computer sector but is beneficial (smaller gap) for chemicals and food. Third, the coefficients of disembodied and embodied R&D are positive and significant, that is, both reduce the technology gap. However, the coefficient of their interaction has the opposite sign, signalling the disjointed faces of R&D and productivity in Europe. In the next section we present the results for the fixed-effects model.

Fixed-Effects Model Results

The most prominent specific firm-level factors in the literature on productivity seem to be significant for explaining the productivity gap in the EU. Firm size, measured as number of employees, is correlated positively to closing the productivity gap; the coefficients are industry-specific, and are small and insignificant for the metal sector. This is consistent with the findings in Bartelsman *et al.* (2013). Firm age, used to proxy simultaneously for accumulated technological capability and old outdated capital, is mostly negatively correlated with closing the productivity gap except in the case of the computer sector where the coefficient is insignificant.

We would expect investments spikes or sudden episodes of investment by firms generally characterised by long periods of low investment activity (Doms and Dunne, 1998) to be positively related to productivity at firm level. It is important to control for the

Table 3: Multilevel Model (non-weighted sample)

	NACE 26 Computers	NACE 20 Chemicals	NACE 24 Metal	NACE 10 Food
Log(# Employees) _(t-1)	0.0183*** (0.00403)	0.00641* (0.00374)	-0.00429 (0.00477)	0.0391*** (0.00222)
Log(# recorded subsidiaries) _{t-invariant}	-0.00253 (0.0115)	-0.00808 (0.0100)	0.0116 (0.0136)	-0.0426*** (0.00757)
South-East Europe Dummy	-0.339*** (0.103)	-0.350*** (0.0732)	-0.506*** (0.0888)	-0.188** (0.0951)
Age _t	0.000357 (0.000908)	-0.000375 (0.000609)	0.000681 (0.000678)	-0.000294 (0.000342)
Age _t ²	0.0000207 (0.0000118)	0.00000342 (0.00000575)	-0.00000463 (0.00000571)	-0.00000268 (0.00000313)
Foreign Ownership Dummy	-0.00288 (0.0162)	0.0117 (0.0136)	-0.0267 (0.0188)	0.00283 (0.00969)
Log (Domestic Concentration 4-d) _(t-1)	-0.298*** (0.0499)	0.131** (0.0544)	0.0167 (0.0735)	0.0864** (0.0366)
Log (EU Concentration -d) _(t-1)	0.0357 (0.0607)	0.00900 (0.0441)	-0.133 (0.0815)	0.0325 (0.0402)
(Spike dummy) _(t-1)	0.00180 (0.00513)	0.000780 (0.00522)	-0.00356 (0.00709)	0.00364 (0.00347)
Log (disembodied R&D 2-d) _(t-1)	0.829*** (0.0680)	0.846*** (0.0962)	1.911*** (0.261)	9.704*** (0.272)
Log (embodied R&D 2-d) _(t-1)	0.882*** (0.0844)	0.639*** (0.0853)	0.262*** (0.0909)	2.270*** (0.0813)
Log (disembodied R&D 2-d) _(t-1)	-0.353*** (0.0343)	-0.588*** (0.0701)	-1.869*** (0.266)	-11.49*** (0.338)
# Log (embodied R&D 2-d) _(t-1)	Yes***	Yes***	Yes***	Yes***
Year FE	-2.605*** (0.187)	-1.645*** (0.134)	-0.785*** (0.119)	-2.700*** (0.1000)
Constant	19,531	23,734	15,485	79,242
Observations				

Clustered standard errors (sector-country) in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A positive coefficient entails a reduction of the gap. The technological variables are at the level of the 2-digit sector/time.

Table 4: Fixed Effects Model (non-weighted sample)

	NACE 26 Computers	NACE 20 Chemicals	NACE 24 Metal	NACE 10 Food
Log(# Employees) _(t-1)	0.0346*** (0.0110)	0.0312* (0.0168)	0.00391 (0.0207)	0.0425** (0.0188)
Age _t	0.0108 (0.00727)	-0.0138*** (0.00286)	-0.0130** (0.00444)	-0.0106** (0.00461)
Age _t ²	-0.00000841 (0.0000739)	0.0000871 (0.0000558)	0.00000562 (0.00005.94)	-0.00002.13 (0.0000527)
Log (Domestic Concentration 4-d) _(t-1)	-0.322 (0.397)	0.219 (0.145)	0.261 (0.171)	0.150 (0.190)
Log (EU Concentration 4-d) _(t-1)	0.0857 (0.0952)	0.0301 (0.0588)	-0.0167 (0.203)	0.0688 (0.106)
(Spike dummy) _(t-1)	-0.000557 (0.00543)	0.000368 (0.0105)	-0.000991 (0.00873)	0.00250 (0.0135)
Log (disembodied R&D 2-d) _(t-1)	0.835*** (0.226)	0.790 (0.756)	1.956*** (0.612)	10.05** (4.453)
Log (embodied R&D 2-d) _(t-1)	0.946** (0.420)	0.599 (0.757)	0.257** (0.111)	2.329*** (0.778)
# Log (embodied R&D 2-d) _(t-1)	-0.378** (0.170)	-0.559 (0.615)	-1.947*** (0.529)	-11.92** (5.068)
Constant	-3.036*** (0.652)	-1.599 (1.077)	-0.816*** (0.219)	-2.589*** (0.839)
Firm FE	Yes***	Yes***	Yes***	Yes***
Year FE	Yes***	Yes***	Yes***	Yes***
Observations	19,531	23,734	15,485	79,242
R-squared	0.831	0.828	0.756	0.808

Clustered standard (sector-country) errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A positive coefficient entails a reduction of the gap. The technological variables are at the level of the 2-digit sector/time.

Table 5: Fixed Effects Model (weighted sample)

	<i>NACE 26</i> <i>Computers</i>	<i>NACE 20</i> <i>Chemicals</i>	<i>NACE 24</i> <i>Metal</i>	<i>NACE 10</i> <i>Food</i>
Log(# Employees) _(t-1)	0.0311*** (0.00797)	0.0198* (0.00958)	-0.000418 (0.00726)	0.0246* (0.0139)
Age _t	0.00780* (0.00408)	-0.0134*** (0.00292)	-0.0121*** (0.00245)	-0.0133*** (0.00315)
Age _t ²	-2.00e-05 (3.82e-05)	6.56e-05* (3.65e-05)	-4.90e-06 (2.25e-05)	-4.56e-05** (2.05e-05)
Log (Domestic Concentration 4-d) _(t-1)	-0.0251 (0.186)	0.153* (0.0849)	0.207 (0.139)	0.0196 (0.0665)
Log (EU Concentration 4-d) _(t-1)	0.113** (0.0444)	0.0681** (0.0237)	-0.140 (0.108)	0.133** (0.0492)
(Spike dummy) _(t-1)	0.00144 (0.00435)	-0.00478 (0.00376)	-0.00128 (0.00594)	-0.00754 (0.00845)
Log (disembodied R&D 2-d) _(t-1)	0.892*** (0.289)	0.593 (0.606)	1.792*** (0.594)	9.398** (3.526)
Log (embodied R&D 2-d) _(t-1)	0.990** (0.431)	0.418 (0.575)	0.203** (0.0902)	2.319** (0.840)
Log (disembodied R&D 2-d) _(t-1)	-0.414** (0.176)	-0.421 (0.477)	-1.772*** (0.530)	-11.87*** (3.969)
# Log (embodied R&D 2-d) _(t-1)				
Constant	-3.107***	-1.235	-0.618***	-2.241***
Firms FE	Yes***	Yes***	Yes***	Yes***
Time FE	Yes***	Yes***	Yes***	Yes***
Observations	19,531	23,734	15,485	79,242
R-squared	0.837	0.829	0.713	0.831

Clustered standard errors (sector-country) in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, A positive coefficient entails a reduction of the gap. The technological variables are at the level of the 2-digit sector/time.

lumpiness of investment whose levels vary considerably across firms. However, this variable is not significant, which suggests that the quality or sophistication of physical capital, proxied by embodied R&D intensity and its interaction with disembodied R&D efforts, might be more important than the quantity of physical capital.

High country level concentration has a marginal or no effect on closing the productivity gap, but at the EU level, highly concentrated markets have a positive effect. The presence of a local domestic oligopoly (most EU countries are relatively small markets) may have a negative effect on productivity, but at the much larger EU market level, economies of scale have a more positive impact. These results are compatible with the notion that there is not a simple one-to-one relationship between industry structure, innovation and productivity growth (Aghion *et al.*, 2005).

An important and consistent finding from our analysis is that technology efforts are consistently, positively and significantly correlated to reducing the productivity gap. These efforts represent firms' investments in disembodied R&D (proxied by internal R&D expenditures at the 2-digit level) and R&D embodied in M&E. The more that 2-digit sector invests in R&D, the more they will be able to reduce their productivity gap. This confirms the broader literature on technology gaps. In all the models, except for the chemical sector, the coefficient of R&D is positive and significant. The coefficient

of embodied R&D is positive and significant, also, in the same three sectors, meaning that firms and countries that import more sophisticated M&E will achieve significantly smaller productivity gaps. However, the coefficients of the interaction between disembodied R&D and embodied R&D are significantly negative for the same three sectors (that is, not including chemicals).⁵ The coefficients for the interaction variable are high and are similar to the coefficients of disembodied and embodied R&D, but with the opposite signs. This suggests that a critical determinant of the productivity gaps in the EU is lack of complementarity between disembodied and embodied R&D.

We checked the robustness of our results employing a fixed effects model weighted by EU firm demographics (see Table 5).

The results are broadly consistent. Larger firm size has a positive effect on reducing the positive gap in all sectors except metals. Age tends to have a negative (but quadratic, inverted U-shaped) effect in three sectors not including the computer industry. At the country level, market concentration has only a marginal correlation with the productivity gap, but at the EU-level and excepting the metals sector, it has a positive effect. The sign, size and significance of the technology effort variables do not change, which confirms the dominance of these explanatory variables for three out of the four sectors analysed.

In the computer, metals and food sectors, this relationship is consistent with previous findings. Bogliacino and Pianta (2016), who point out that we cannot expect a single general relationship to describe the behaviour of the whole economy, propose a revised Pavitt taxonomy. The chemical industry is a complex and varied industry sector with some specific characteristics. For instance, its innovation activities tend to focus on processes and chemical industry equipment tends to have long life cycles. Also, Eurostat data indicate that the EU north economies account for six to seven times more research and development expenditures on GDP compared to the countries in the EU periphery (south/east). These facts help to explain why changes in chemical industry R&D and embedded R&D are not related significantly to a decreasing productivity gap. The interaction between these two modes of technology acquisition and mastery remains negative, but not statistically significant.

We conducted additional graphical and numerical analyses (results reported in Appendices 4 and 5) of the marginal effect of disembodied R&D on reducing the productivity gap *conditional* on embodied technology, and vice versa (marginal impact of embodied technology on closing the productivity gap *conditional* on disembodied R&D). The marginal effects are downward sloping, which is consistent with the negative sign of the interaction terms in the regressions in Table 5 (fixed effects weighted). This suggests that firms operating in subsectors with high levels of investment in both disembodied and embodied R&D are less likely to be associated with a decreasing productivity gap.

⁵We examined the relationship between productivity gap and R&D in all 20 chemical *subsectors* (NACE 4-digit codes 2000 2010 2011 2012 2013 2014 2015 2016 2017 2020 2030 2040 2041 2042 2050 2051 2052 2053 2059 2060) to check for different patterns. The pattern related to 2011 – manufacture of industrial gases, code 2014 - manufacture of other organic basic chemicals, code 2017 – manufacture of synthetic rubber in primary forms are similar to the pattern in non-chemicals sectors are a positive impact of disembodied and embodied R&D and negative interaction. However, these three sectors account for only 8 per cent of overall chemical manufacturing NACE2 SECTOR 20 which explains the negative results when we look at the whole sector.

Conclusion and Discussion

This paper explored the determinants of the productivity gaps in four EU manufacturing sectors with strong macroeconomic significance and varied R&D intensity. We used a multilevel structuralist-cum-Schumpeterian framework to study EU-wide productivity gap determinants. One of the novel contributions of our study is that we investigate the interaction between two modes of technology acquisition and mastery: embodied and disembodied R&D.

Our dataset enabled us to test the significance of the firm-level variables (size, age and investment lumpiness), firm structure (multi-plant firms and foreign ownership), market concentration at both the country and EU levels and technology efforts (disembodied R&D, embodied R&D and their interaction) while controlling for unobserved heterogeneity, macroeconomic shocks and macro-regional location (multi-Level model).

We find that the productivity gaps in the EU are related strongly to technology variables (R&D intensity and R&D embodied in purchased M&E in the sector) and how they interact. In three out of four sectors (excluding chemicals), disembodied and embodied R&D, considered separately, are both relevant for reducing closing the productivity gap, but their interaction is significant and negative. In the case of chemicals, the relationship is negative, but not statistically significant. Against expectations, this confirms the absence of complementarity between these two modes of technology acquisition. Instead, these two forms of R&D appear to be disjointed alternatives, suggesting mismatches between disembodied R&D investments and the level and nature of the R&D embodied in purchased M&E.

Identifying the cause of these mismatches would require further in-depth research by academics and policymakers. They might be due to inappropriate sequencing between the two types of investments, or the different significance of these forms of investments in different sectors. Alternatively, they might be due to lack of coordination between R&D and purchased technology, in the form of M&E, or purchased know-how in the form of patent licences.

Our results show that peripheral (south and east) member states are more likely to experience an increasing productivity gap compared to those in the north, it would thus seem that this mismatch especially penalises latecomer countries.

The results for our time dummies suggest that the cause of the EU's core-periphery polarisation is not the 2008 crisis. It seems that, instead, the financial crisis worked only to magnify and accelerate processes that seem to originate in the lack of complementarity between strong and weak national and sector-specific EU innovation systems (Celi *et al.*, 2017). Also, our results show that while some firm and meso level variables are important, the technology variables are equally, if not more important.

Firm size is often significantly positively correlated with narrowing productivity gaps, which suggests that economies of scale continue to matter in the new growth paradigm dominated by information and communication technology. However, size should be interpreted, also, in the context of varying market concentration levels. Size and market concentration both have a positive effect on the EU level productivity gap, but, in the case of individual countries, higher market concentration, on its own, has either no effect or increases the productivity gap.

One unexpected result is the either insignificant (productivity gap with foreign firm) or significantly negative relationship with multi-plant firm structure in the food sector (Navaretti and Venables, 2004). However, there is a large body of work on spill-overs from FDI in the EU that shows that these effects are not conclusive (Bruno and Cipollina, 2018). Also, research on economic catch up demonstrates that, in the absence of domestic technology efforts, FDI, on its own, is not sufficient (Mowery and Oxley, 1995; Radosevic, 1999; Jung and Lee, 2010). Our results confirm the robust stylised fact in the economics of development that interaction between R&D and purchased M&E, as distinct technology acquisition modes, is essential. What is perhaps surprising is that our study confirms this stylised fact in relation to a developed world region.

The conventional view of EU productivity is that peripheral countries are lagging in terms of structural reforms (Arpaia *et al.*, 2007; Vergeer *et al.*, 2015; Campos *et al.*, 2017; Römisch *et al.*, 2017) and that intra-Eurozone divergences might be caused by monetary union design defects (European Commission, 2010; Flassbeck and Lapavitsas, 2013; Wyplosz, 2014; Kollmann *et al.*, 2015; Caiani *et al.*, 2018). However, there is a recent World Bank study (Ridao-Cano and Bodewig, 2018) that attributes productivity gaps in many southern and central European countries to below-average opportunities or a combination of poor education outcomes, particularly strict regulation and weak support for firm innovation. This would suggest the need for macroeconomic, structural and institutional reforms within the Eurozone in particular, and the EU more generally. Our analysis complements the contribution by Celi *et al.* (2017) and extends it by suggesting that productivity gaps might be long-term in nature and rooted in technology gap factors.

Our analysis has some important implications for EU economic policy. First, our research suggests a lack of coordination between R&D policy and technology transfer, for example, Foreign Direct Investment (FDI), trade and industry policy. A general lesson is that technology catch-up may be more effective if investment in R&D is combined with and complements access to foreign technology. Second, the technology gap seems not to be driven by R&D policies *per se*, but by a decoupling between these and other policies such as FDI and global value chain policies. In other words, R&D-based policy, on its own, may no longer be sufficient to drive technology convergence and, also, that further increases in R&D intensity in central, eastern and southern EU states are likely to have progressively limited effects unless they are linked to appropriate GVC or FDI policies. Third, these policies must provide incentives for the diffusion of technological capabilities from Europe's core to its periphery and must entail investments in knowledge, rather than narrowly defined R&D investments, to support technological, organizational and institutional innovations in periphery areas. Recent EU initiatives focus on advanced manufacturing technologies where 'periphery' economies are unlikely to play a significant role, which could further deepen the existing policy rift.

The challenge will be to transform the EU's approach to upgrading its microeconomic assets and capabilities by focusing on cross-regional and international cooperation. A possible solution to regional imbalances in the EU would be to connect and upscale regional deployment of technology efforts. At the country level, this would require stronger links between innovation and FDI/GVC policy (Radosevic and Stancova, 2015). Our analysis highlights the need to link European regions with varying technology and cost levels, through GVC-oriented industry and innovation policies.

A limitation of our research is that we were unable to complement data on imports of embodied technology with data on imports of know-how and patent licences and information on non-R&D activities and other intangibles. Had this been possible, we would have been able to provide a more rounded picture of domestic knowledge generation activities and different forms of purchased knowledge. This would have enabled a better understanding of how these factors interact. Nevertheless, our results represent significant progress towards a better understanding of how the structural causes of the EU convergence machine breakdown are rooted in mismatches between different modes of acquisition and mastery of technology.

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Appendix

List and Description of Variables

<i>Variable</i>	<i>Variable description</i>	<i>Variable details</i>	<i>Source</i>
Productivity gap of the firm	Ln (Firm-Omega)-Ln (EU-frontier)	Three-step procedure: see Section II	Authors' computation using Amadeus BvD
Number of employees	Number of employees	Number of firm's employees	Amadeus BvD
No. of recorded subsidiaries	Number of recorded subsidiaries (last available year)	Number of the firm's subsidiaries	Amadeus BvD
Age	Age	Number of years the firm has been operating	Authors' computation using Date of Incorporation
Concentration Index within a 4-digit domestic sector	Concentration index	Market share of the top four firms (turnover) in each sector (based on 4-digit NACE rev.2) in each country	Authors' computation using Amadeus BvD
Concentration Index within a 4-digit European Union sector	Concentration index EU	Market share of the top four firms (turnover) in each sector (based on 4-digit NACE rev.2) across the whole EU	Authors' computation using Amadeus BvD
Disembodied R&D as % of Business Production	Disembodied R&D	Percentage of business production value spend on R&D.	BERD Eurostat (NACE2)

(Continued)

<i>Variable</i>	<i>Variable description</i>	<i>Variable details</i>	<i>Source</i>
Embodied R&D as % of Gross Value Added	Embodied R&D	R&D purchased from other technology-weighted sectors in the EU (including domestic) as a percentage of Gross Value Added	BERD Eurostat combined with WIOD (NACE2)
Dummy variables			
Lumpiness dummy	Spike dummy	'1' if the previous year investment capital ratio exceeds 20%, '0' otherwise	Authors' computation using Amadeus BvD
EU South East dummy	EU South-East dummy (fixed)	Dummy variable equal to '1' if the country is in eastern or southern Europe, '0' otherwise. 'North': Germany, France, Belgium, Netherlands, Austria, Ireland, the Scandinavian countries, plus the UK; 'South': Italy, Spain, Portugal and Greece; 'East': all 'new' member states except Croatia, Malta and Cyprus.	Authors' computation using Amadeus BvD
Foreign ownership	Foreign owner dummy (last available year)	Dummy variable equal to 1 if the firm has at least 10% foreign ownership, 0 otherwise	Authors' computation using Amadeus BvD

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Data S1. Supporting information