Unbundling technology adoption and *tfp* at the firm level: Do intangibles matter?

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Abstract

We use a panel of European firms to investigate the relationship between intangible assets and productivity. We distinguish between total factor productivity (*tfp*) and technology adoption, whereas standard estimations consider only a notion of productivity that conflates the two effects. Although we are unable to address simultaneity, we allow for the existence of multiple technologies within sectors through a mixture model approach. We find that intangible assets have non-negligible effects that both push firms toward better technologies (*technology adoption* effects) and allow for more efficient exploitation of a given technology (*tfp* effects).

Keywords: TFP, intangible assets, firm heterogeneity, firm selection, technology adoption, mixture models.
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1 Introduction

By including all those assets that lack a physical dimension (i.e., quality of management, customer loyalty, information infrastructure, trade secrets, research and development (hereinafter R&D), and, more generally, a company's intellectual capital), intangible assets form the "knowledge base" of a firm and are often found to play an important role in modern knowledge-intensive production (e.g., Delgado-Gomèz and Ramirèz-Alesòn (2004), Hall *et al.* (2005), Bontempi and Mairesse (2008), O'Mahony and Vecchi (2009)). However, whereas the existence of a positive relationship between intangible assets and firm performance is now widely accepted (see, e.g., Oliner *et al.* (2008)), empirical research on the channels through which the relationship takes place is rather scant. Notwithstanding a few contributions showing that investments in intangible assets foster productivity at the firm level (Bontempi and Mairesse, 2008; O'Mahony and Vecchi, 2009; Marrocu *et al.*, 2012), it remains unclear to what extent such productivity gains occur through total factor productivity (hereinafter *tfp* - intended, in a strict sense, as the ability to exploit "traditional" inputs) and through a process of technology upgrading that is induced by an increased ability to identify and adopt more productive technologies. In particular, extant productivity analysis is silent on whether intangible assets affect the process of technology adoption because standard productivity measures are only able to consider a notion of productivity that conflates technology and *tfp*.[1]

In this paper, we examine the relationship between intangible assets and productivity in a large sample of European manufacturing firms by adopting a *tfp* estimation strategy that enables us to distinguish between *technology* effects and *tfp* effects. We do so against the background of a world in which different production function coefficients identify different technologies. Several technologies are available in each sector-industry, with a number of firms using each technology. To aid in the definition of terms, let us anticipate the formal description and consider the following production function:

$$Y_{i,t} = A_{i,t} \prod_{n=1}^{N} (X_{n,i,t})^{\beta_{n,m}} \tag{1}$$

where $A_{i,t}$ is firm i's *tfp* (i.e., "Solow residual") at time t, $X_{n,i,t}$ denotes the amount of input n used by firm i at time t, $\beta_{n,m}$ is the associated production coefficient, and $Y_{i,t}$ denotes produced output. Index m is introduced to refer to a specific "technology", with $m = 1, \dots, M$ and M denoting the number of available technologies. According to Equation (1), the amount of output firm i is able to produce given the amount of inputs depends on two factors: the first ($A_{i,t}$) is firm-specific, whereas the other ($\beta_{n,m}$) is intrinsic to the adopted technology and is common to all the firms that use the same technology. A group of firms sharing a given technology may or may not share the same industry. Whereas firms' choices concerning these two factors are usually referred to as technological choices or productivity choices, we reserve the term "technology" to refer to $\beta_{n,m}$ and discuss

[1] To highlight this limitation, Bernard and Jones (1996) refer to such "mixed" measures of productivity as "total technology productivity".

tfp with regard to $A_{i,t}$.

Our analysis aims to examine whether the stock of intangible assets plays a role in productivity by separating out the effect that occurs through technology adoption (i.e., through $\beta_{n,m}$) from the effect that occurs through the *tfp* term $A_{i,t}$. We first employ mixture models to estimate the production function parameters in Equation (1), allowing for the existence of two technologies within each sector; we then use a first-order stochastic dominance criterion to identify the "high" and "low" technology. This method allows us to cluster our sample firms over the two technology groups and compute the *tfp* component in Equation (1) for each firm as the difference between the actual and predicted output, given the technology adoption. Finally, we estimate the effect of intangible assets on the probability of belonging to the high technology group (*technology adoption* effects) and on the ability to exploit the technology in use (*tfp* effects).

We find that intangible assets have positive and statistically significant effects on both technology adoption and *tfp*. For the firms in the low-technology group, the estimated increase in the probability of choosing the "high" technology associated with a 1% increase in the intangible-to-tangible assets ratio yields an expected gain in value added ranging from 0.89 to 1.56 on average. For the same increase in intangible assets, the value added for all firms is augmented by 1.17% due to the *tfp* effect.

The paper proceeds as follows. In Section 2, we briefly describe how our analysis contributes to the economic literature. In Section 3, we apply mixture models to production function estimation and obtain firms' technology clusters and *tfp* values. In Section 4, we separately measure the impact of intangible assets on technology adoption and *tfp*. Section 6 concludes. Appendix A describes the variables used in the analysis. Appendix B discusses some issues in production function estimation.[2]

2 Related literature

Our empirical results may be of interest in various veins of the economic literature.

The effect of a firm's innovation efforts on its productivity outcome is a central issue in the so-called "New New Trade Theory" (henceforth, NNTT) pioneered by Melitz (2003) and Bernard *et al.* (2003) and further developed by Bernard *et al.* (2007b), Melitz and Ottaviano (2008), and Chaney (2008).[3] This strand of literature

[2]Supplementary material is presented in an online Appendix.

[3]Several surveys of this literature have been published. See, in particular, Bernard *et al.* (2007a) and Greenaway and Kneller (2007).

assigns a key role to firms' productivity in the now well-documented (see, e.g., Wagner (2012) for a review of the empirical studies) process of firm selection.[4] However, whereas the original NNTT formulation features a one-way causality nexus running from productivity to any status associated with costly operational activities (e.g., exporting, foreign activities, innovation, R&D, etc.),[5] recent studies highlight the presence of endogenous innovation dynamics at the firm level (see Atkeson and Burstein (2010), Navas-Ruiz and Sala (2007), Costantini and Melitz (2008), and Aw *et al.* (2008)), allowing causality between innovation and productivity to run both ways. Through this perspective, our results are broadly consistent with the innovation dynamics of Klette and Kortum (2004), Luttmer (2007), König *et al.* (2012), and in particular with the endogenous productivity model of Doraszelski and Jaumandreu (2012), in which a firm's *tfp* is stochastically affected by its investment in knowledge.[6]

In contrast to other works in which intangible assets are considered an additional input in an otherwise standard production function (Bontempi and Mairesse, 2008; Oliner *et al.*, 2008; O'Mahony and Vecchi, 2009; Marrocu *et al.*, 2012), we focus on intangible assets' effects "from outside the production function". Together with mixture analysis, this approach enables us to separate the effects of technology adoption from the *tfp* effect. In this respect, our results and our methodology may contribute to a heterogeneous discussion related to technology adoption and diffusion. Parente and Prescott (1994) stress that the investment a firm must make to adopt a more advanced technology grows with the extent of the barriers to technology diffusion that are often placed in the path of entrepreneurs. Differences in these barriers, which vary across countries and time, account for the great disparities in income across countries. Since Parente and Prescott's pioneering paper, a number of other works have contributed to this debate. For instance, Barro and Sala-i Martin (1997) address the role

[4]In such a process, which is driven by a combination of import and export market competition, winners and losers emerge, with more productive firms earning handsome profits, mediocre firms earning lower profits, and the worst soon vanishing because they are unable to cover their production costs with revenues due to excessively low *tfp*.

[5]This circumstance is well documented by Bustos (2011), who relates Argentinean firms' technology upgrades to a reduction in Brazilian tariffs on entry to the export market.

[6]Whereas these studies use R&D expenditures as a measure of a firm's innovation efforts, we are forced to focus on intangible assets due to data availability constraints because the Amadeus database - which we use in this paper - does not provide sufficient firm-level data on R&D. Using intangible assets has both advantages and disadvantages. One advantage is that the costs borne to switch to superior technologies, while not included in R&D, should find a place in firms' balance sheets under "intangible fixed assets". A second advantage is related to the fact that our productivity analysis is based on a revenue-based measure (i.e., prices times sold quantities), similar to the vast majority of studies (notable exceptions are Foster *et al.* (2008) and Doraszelski and Jaumandreu (2012)), due to data unavailability on physical output. By including other costs that are explicitly oriented toward selling "larger quantities at higher prices" in addition to R&D, intangible assets are more consistent with this notion of productivity. One drawback is that on the balance sheet, intangible assets are a very general item that likely misstates a firm's true innovation efforts. However, there are cases in which firms' innovation efforts are not found in balance sheets at all, e.g., when innovation takes the form of in-house R&D or when a firm simply imitates other firms' techniques. In these cases, both intangible assets and R&D expenditures provide underestimated measures of innovation efforts. Finally, it is also worth noting that we focus on the stock of intangible assets and not on yearly investments in intangibles due to the limited time variability in our data. This choice finds theoretical support in the notion of "knowledge capital" (Griliches, 1979).

of imitation in technology diffusion, Howitt (2000) studies the role of R&D in the technology transfer between innovators, and Desmet and Parente (2010) investigate the relationship between market size and technological upgrading. Other studies (e.g., Acemoglu and Zilibotti (2001) and Desmet and Rossi-Hansberg (2013)) mainly focus on the relationship between economic development and technology diffusion. In an NNTT framework with heterogeneous firms, Bas (2012) models technology adoption as an investment in new and more advanced skill-biased production technology. Another strand of literature studies the dynamic process of technology adoption at the firm level, where competition between potential adopters is modeled in a framework of strategic interaction with technology upgrading as a key variable in firms' strategies (see, among others, Fudenberg and Tirole (1985), Riordan (1992), and Cabral and Dezsö (2008)).

Other studies related to our paper are those that examine "absorptive capacity", which refers to a firm's ability to identify, assimilate, and exploit knowledge for subsequent technological advancements (see, in particular, Cohen and Levinthal (1989)). Whereas this strand of the literature usually stresses the learning channel, absorptive capacity also depends (see World Bank, 2008) on country-level characteristics - e.g., governance, quality of regulation, legal environment, political and macroeconomic stability, and government actions that help overcome market failures, such as R&D and building infrastructure - many of which we control for in our analysis.

Incidentally, we contribute to the literature on theory of the firm and technological change. In particular, our empirical findings on the link between a firm's performance and being listed relate to the research of Ferreira *et al.* (2012), while the estimated role of labor laws relates to Michie and Sheehan (2003) and Bassanini *et al.* (2009). In addition, our result showing that larger firms are relatively more productive may be regarded as additional evidence in favor of the Schumpeterian hypothesis (see, among many others, Pavitt *et al.* (1987) and Cohen and Klepper (1996a, 1996b)).

Finally, it is worth noting that the first part of our analysis also adds to the theoretical literature on production function estimation by suggesting an estimation strategy that, although we are unable to control for important issues such as the simultaneity bias (cfr. Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg *et al.* (2006), Wooldridge (2009), and Doraszelski and Jaumandreu (2012)), provides the opportunity to estimate, even within the same sector, sets of technology-specific production function parameters without any type of ex-ante assumption on the degree of technological sharing across firms, countries, or regions. Because the number of available technologies is endogenously determined by the mixture estimation algorithm, the geographical distribution of technologies is in fact observed ex-post.

3 Production function(s) estimation

In studying the relationship between intangible assets and productivity, we wish to unbundle technology adoption effects and *tfp* effects according to Equation (1). To do so, we should, in principle, estimate as many sets of production function coefficients as the number of available technologies. In practice, however, this is not possible because the number of technologies is unknown. Therefore, *mixture models* may be used (Mc Lachlan and Peel, 2000). In contrast to standard methodologies (see the surveys by Del Gatto *et al.* (2011) and Van Beveren (2012)), mixture analysis allows us to control for the presence of within-sector technological differences. Sample firms may be clustered across technologies and, consistent with Equation (1), group-specific input coefficients may be estimated without any ex-ante assumption on the technology in use. The probability of belonging to a given technology cluster is produced by the estimation algorithm. In Appendix B, we highlight the advantages and drawbacks of this approach.

To describe the algorithm, let us start by writing the (implicit) probability distribution function of Equation (1) as a weighted average of the M specific segment (i.e., technology) densities $f_m(Y_{i,t}|\mu_m, \sigma_m)$, each with proper mean (μ_m) and variance (σ_m^2):

$$f(Y_{i,t}|\mu, \sigma) = \sum_{m=1}^{M} \varphi_m f_m(Y_{i,t}|\mu_m, \sigma_m^2). \tag{2}$$

Weights φ_m measure the ex-ante probability of belonging to group m.

Assuming a normal density for $f_m(Y_{i,t}|\mu_m, \sigma_m^2)$,[7] the production function coefficients can be obtained by maximizing the following log-likelihood function:

$$\ln \mathcal{L} = \sum_i \sum_{t=1,\dots T} \ln \sum_{m=1,\dots,M} \varphi_m (2\pi\sigma_m^2)^{-\frac{1}{2}} \exp\left\{ \frac{-(Y_{i,t} - (\alpha_m + \beta_{K,m} K_{i,t} + \beta_{L,m} L_{i,t}))^2}{2\sigma_m^2} \right\} \tag{3}$$

where the mean of f_m has been replaced by a linear predictor - i.e., $\mu_m = \alpha_m + \beta_{K,m} K_{i,t} + \beta_{L,m} L_{i,t}$ - in which the coefficients are found by the maximization process and the number of firms may vary across years because

[7] One may also assume another density belonging to the exponential family (see Wedel and De Sarbo, 1995).

the panel is unbalanced.

Since the ex-ante probabilities φ_m are unknown, a problem of missing data arises in the maximization of Equation (3). The problem is solved through the EM (expectation-maximization) algorithm of Dempster *et al.* (1977), which starts with random values of φ_m to compute the posterior probability that firm i belongs to group m at time t:

$$p_{i,m,t} \equiv pr(i_t \in m) = \frac{\varphi_m f_m(Y_{i,t}|K_{i,t}, L_{i,t}; \hat{\sigma}_m^2, \hat{\beta}_{K,m}, \hat{\beta}_{L,m}, \hat{\alpha}_m)}{\sum_{m=1}^{M} \varphi_m f_m(Y_{i,t}|K_{i,t}, L_{i,t}; \hat{\sigma}_m^2, \hat{\beta}_{K,m}, \hat{\beta}_{L,m}, \hat{\alpha}_m)}. \tag{4}$$

This set of probabilities is then used to update the regression coefficients by changing the weights φ_m according to

$$\varphi_m = \frac{\sum_i \sum_t p_{i,m,t}}{\sum_m \sum_i \sum_t p_{i,m,t}} \tag{5}$$

with the following constraints:

$$\varphi_m \geq 0 \qquad \forall m = 1, \dots M \qquad \text{and} \qquad \sum_{m=1}^{M} \varphi_m = 1. \tag{6}$$

Because De Sarbo and Cron (1988) show that maximizing Equation (3) is equivalent to performing a weighted least squares (WLS) regression with weights provided by the segments' probabilities, we iteratively alternate the WLS production function estimation and the computation of probabilities until a log-likelihood convergence criterion is reached. We repeat the process many times to avoid running into local optima.

In each sector, we assume that two technologies are available (i.e., $M = 2$). Without introducing a loss of generality in terms of results, this approach greatly simplifies the exposition, making the identification of the "high" technology through stochastic dominance analysis straightforward.[8]

The estimation takes advantage of detailed information on value added, tangible fixed assets, and the number of employees, which is available in the Amadeus database provided by "Bureau van Dijk". Descriptive statistics are reported in Table 1.

insert Table 1 about here

[8] In Section B of the online Appendix, we show that a model selection analysis performed under alternative values of M always rejects the case of $M = 1$. The suggested number of within-sector technologies ranges from 2 to 4. Moreover, when the *tfp* effects are re-estimated with those technology groups, the role of intangible assets is only slightly affected.

Estimated values of $\beta_{K,m}$ and $\beta_{L,m}$ obtained for the two technologies $m = 1$ and $m = 2$ are reported in Table 2. The coefficients, as well as the unreported constant, are highly significant in all sectors for both clusters.

insert Table 2 about here

For each firm i in period t (i.e., each observation), the procedure provides us with the probability of belonging to Cluster 1 ($p_{i,1,t}$) and the probability of belonging to Cluster 2 ($p_{i,2,t}$). Because these probabilities add up to one, we are able to assign firms to Technology Group 1 in year t if $p_{i,1,t} > p_{i,2,t}$, and vice versa for Technology Group 2. It is worth noting that 6.09% of our sample firms do not remain assigned to the same group in all of the years under consideration but change groups across years.[9] None of these firms changes groups more than once.[10]

4 Modeling technology adoption and *tfp* effects

Having assigned each firm to a technology cluster, we model the effects that intangible fixed assets exert on the following: *i*) firms' technology adoption, by improving the firm's ability to identify and adopt the more productive technology; and *ii*) *tfp*, by allowing for a more efficient exploitation of a given technology.

Modeling technology adoption. To analyze the role of intangible assets in the process of technology adoption, we must first know which of the two identified clusters uses the more productive technology. To this end, we use the estimated production function coefficients together with the actual values of capital and labor to compute each firm's predicted output as $ln\hat{Y}_{i,m,t} = \alpha_m + \hat{\beta}_{K,m} lnK_{i,t} + \hat{\beta}_{L,m} lnL_{i,t}$. We then apply a first-order stochastic dominance criterion to compare the cumulative distribution function of the predicted output within the two technology groups. Distributions by group and sector are reported in Figure 1. The figure makes clear that Technology Group 2 first-order stochastically dominates Group 1 in all sectors. We thus do not need more sophisticated tests to begin referring to the technology used by Cluster 2 as the high technology (hereinafter,

[9] Specifically, the percentage of firms switching from Cluster 1 (2) to 2 (1) in each year is 4.20 (2.28) in 2004, 3.12 (2.18) in 2005, 2.88 (2.06) in 2006, 3.05 (2.09) in 2007, 3.02 (3.83) in 2008, and 3.08 (10.33) in 2009.

[10] As an alternative to our approach, a Cobb-Douglas production function with three production factors - labor, physical capital and intangible assets - might be estimated (see Marrocu *et al.* (2012) for an empirical study based on this "three-input approach"). In addition to producing a substantially similar clustering to ours (as we have verified in an unreported estimation), such an approach addresses the productivity effects of intangible assets from a very different perspective. With intangible assets entering the production function directly, it is impossible to analyze whether they have an impact on the technology used by the firm, which is our main purpose.

Technology $\mathcal{H}$) and to the other technology as the low technology (hereinafter, Technology $\mathcal{L}$).[11]

insert Figure 1 about here

We thus define the following two sets of firms:

$$\Theta_{\mathcal{H}} \equiv \{i_t : p_{i,2,t} > p_{i,1,t}\} \qquad \text{and} \qquad \Theta_{\mathcal{L}} \equiv \{i_t : p_{i,1,t} > p_{i,2,t}\} \tag{7}$$

The regional distribution of the ratio $\Theta_{\mathcal{H}}/\Theta_{\mathcal{L}}$ (i.e., the ratio of the number of observations in the two technology groups) is reported in Figure 2.

insert Figure 2 about here

We then model the relationship between intangible assets and technology adoption through the following regression equation:

$$\begin{aligned} Group\ \mathcal{H}_{i,t} = \delta_0 + \delta_1 Firm\ Intangibles_{i,t} + \delta_F F_{i,t} + \delta_R R_{r,t} + \delta_D C_{c,t} + \\ + \delta_S Sector_s + \delta_C Country_c + \delta_Y Year_t + u_i + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where $Group\ \mathcal{H}_{i,t}$ indicates whether firm i at time t belongs to the high-technology group, i.e.,

$$Group\ \mathcal{H}_{i,t} = \begin{cases} 1 & \text{if} \quad i_t \in \Theta_{\mathcal{H}} \\ 0 & \text{if} \quad i_t \in \Theta_{\mathcal{L}} \end{cases} ; \tag{9}$$

$Firm\ Intangibles$ measures the stock of a firm's intangible assets as the intangible-to-tangible assets ratio; $F_{i,t}$, $R_{r,t}$ and $C_{c,t}$ indicate the firm-, region-, and country-level control variables described below, respectively; u_i are unobservable firm-specific effects; $\varepsilon_{i,t}$ is the residual. Subscript i refers to firms, r to regions, s to sectors

[11]This approach makes the advantage of assuming $M = 2$ to be evident. It is also worth noting that in two out of nine sectors, Technology $\mathcal{L}$ displays higher estimated returns to scale ($\beta_K + \beta_L$), compared with Technology $\mathcal{H}$ (see Table 2). As a consequence, basing the identification of the superior technology on returns to scale would yield inconsistent results. Moreover, the high-technology group is larger, as the overall productivity distribution is right-tailed, and it displays higher labor coefficients (consistent with cross-country evidence reported by Caselli and Coleman (2006), among others), likely due to a skill bias in the estimates.

(with $Sector_s$ denoting sectoral dummies), c to countries (with $Country_c$ denoting country dummies), and t to time (with $Year_t$ denoting year dummies). δ_1 is the parameter of interest. $Firm\ Intangibles$ is expressed in logarithmic terms to appropriately model possible non-linearities (see Appendix A for a detailed description of this variable).

Modeling *tfp*. Having computed each firm's predicted output on the basis of the estimated group-specific production function coefficients, we are able to calculate the *tfp* of each firm at time t as $lnA_{i,t} = lnY_{i,t} - ln\hat{Y}_{i,m,t} = lnY_{i,t} - \alpha_m - \hat{\beta}_{K,m}lnK_{i,t} - \hat{\beta}_{L,m}lnL_{i,t}$. The regional *tfp* distribution is reported in Figure 3.

insert Figure 3 about here

The relationship between intangible assets and *tfp* is thus modeled as follows:

$$tfp_{i,t} = \gamma_0 + \gamma_1 Firm\ Intangibles_{i,t} + \gamma_F F_{i,t} + \gamma_R R_{r,t} + \gamma_D C_{c,t} + \\ + \gamma_S Sector_s + \gamma_C Country_c + \gamma_Y Year_t + u_i + \eta_{i,t} \tag{10}$$

where the right hand side is specified exactly as in the technology adoption regression (Equation (8)) and γ_1 is the parameter of interest.

It is worth noting that the empirical equivalent of the (firm-specific) *tfp* term $A_{i,t}$ in Equation (1) is *de facto* influenced by firm i's belonging to a specific technology group. The *tfp* of all of the firms in a given group is in fact expressed with respect to the average firm (i.e., the firm whose observed output exactly matches the output predicted on the basis of its group-specific input coefficients $\beta_{n,m}$) in the group. By definition, the *tfp* of this firm amounts to zero. Therefore, the estimated coefficients in Equation (10) provide information on firms' move in the (sector- and technology-specific) *tfp* distribution.

Control variables. Vector $F_{i,t}$ includes the following set of firm-level variables: firms' age ($Firm\ Age$), firms' dimension, proxied by the level of sales ($Sales$), and a dummy variable indicating whether a firm is listed on a stock market ($Listed\ Firm$). Age and size should both have a positive influence on high technology adoption and *tfp*. On the one hand, higher firm age should imply a greater cumulative knowledge of the technological alternatives available in the industry; on the other hand, a larger size should increase a company's capability to exploit sizeable developmental laboratories and equipment (Pavitt *et al.*, 1987; Cohen and Klepper, 1996a, 1996b). Moreover, if firm size is positively related to market power, a firm's incentives may be increased to employ more productive technologies because of preemption motives (Gilbert and Newbery, 1982). In contrast, the effect of being listed is expected to be negative. Under private ownership (i.e., the firm is not listed), insider shareholders, such as a manager-entrepreneur, may time the market by choosing an early exit after receiving bad signals about production; therefore, managers are more tolerant of early failures and are more inclined to invest in new and more profitable - even if riskier - projects (Ferreira *et al.*, 2012). In addition, listed companies are relatively more vulnerable to the adoption of sub-optimal business strategies by activist short-termist shareholders (Kochnar and David, 1996; Sherman *et al.*, 1998; Hoskisson *et al.*, 2002).

At the regional level, vector $R_{r,t}$ includes the R&D levels of the region (*Regional R&D*) and the neighboring regions (*Neighbouring Regions R&D*). With these variables, we aim to measure R&D spillovers within and between regions. An abundance of studies on this issue suggest a positive relationship between R&D spillovers and both technology dynamics and firms' *tfp* (e.g., Cohen and Levinthal (1989), Griliches (1992), Ciccone (2002), and Autant-Bernard and Mairesse (2007)). $R_{r,t}$ also includes a control for a region's accessibility (*Region Accessibility*). This variable measures the total population reachable from the region, weighted by the ease of access to the other regions. The rationale for its inclusion is that accessibility might be regarded as a measure of market potential. On the one hand, greater market potential may stimulate more efficient firms by providing them with an opportunity for larger gains from successful productions; on the other hand, greater accessibility may also entail more space for less productive firms. The expected sign of this variable thus depends on which dimension takes over.

At a country level, vector $C_{c,t}$ includes a measure of the labor costs (*Labour Cost*) and a set of three institutional variables. The rationale for including labor costs lies in the expected greater intensity of selection effects, associated with higher production costs. By cutting firms' profits, higher labor costs should be associated with stronger firm selection and a higher probability of a larger share of firms in the $\mathcal{H}$ Technology Group and/or in the right tail of the *tfp* distribution. This result would suggest a positive sign in the regressions. For institutional variables, we consider a measure of employment protection (*Country EPL*), an index of minority shareholder rights (*Shareholder Rights*) and the minimum percentage of independent board directors required by law (*Independent Directors*). The effect of employment protection legislation is difficult to predict ex-ante. Stringent labor laws may stimulate the adoption of more efficient knowledge-intensive production methods because such laws protect employees from contract renegotiation by employers and therefore create incentives for workers to apply their efforts to learning processes (Michie and Sheehan, 2003; Acharya *et al.*, 2010). However, strong employment protection may favor employees' resistance to the use of innovative technologies if such new production technologies imply job losses or increase the labor burden (Zwick, 2002). Stronger minority shareholder rights should have a negative effect on our dependent variables to the extent that minority shareholders use increased voice opportunities for private gain-seeking, causing sub-optimal business strategies (Belloc, 2013). Finally, the presence of independent directors is expected to exert a positive influence on both Technology $\mathcal{H}$ adoption and *tfp*. The involvement of outside directors on a board should reduce agency costs and consequently improve strategic business decisions (Kaplan and Minton, 1994).

A detailed description of the variables is reported in Appendix A, while descriptive statistics are presented in Table 3.

insert Table 3 about here

5 Results

Equations (8) and (10) are estimated through a panel fixed-effect logit regression and a standard Generalized Least Square (GLS) panel regression, respectively. The results of the two estimations are reported in Table 4.

insert Table 4 about here

The regression coefficients for *Firm Intangibles* are positive and strongly significant in both equations, suggesting that a higher stock of intangible assets both pushes firms toward better technologies and allows for more efficient exploitation of a given technology. Therefore, intangible assets not only increase a firm's ability to exploit the technology in use (consistent with the findings of Bontempi and Mairesse (2008), O'Mahony and Vecchi (2009) and Marrocu *et al.* (2012)), i.e., the *tfp* effect, intangible assets are also relevant to firms' technological choices. In particular, the estimation of Equation (8) shows that a 1% increase in the intangible-to-tangible assets ratio of low-technology firms determines an increase in the probability of belonging to the high-technology group that translates into an average 1.56% expected gain in value added. Moreover, for the same increase in the *Firm Intangibles* variable, the value added of all firms is increased by 1.17% due to the effect estimated in the *tfp* regression.[12] Note that the technology adoption effect takes the form of an increased probability of adopting a more productive technology; therefore, in a world of two technologies (as in our framework), only low-technology firms may take advantage of technology adoption effects, whereas both types of firms benefit from the *tfp* effect.

Other results emerge from the control variables' estimated coefficients.

At the firm level, we observe that *Firm Age* has a positive effect on technology adoption and an insignificant effect on *tfp*, whereas *Sales* has a positive and *Listed Firm* has a negative effect on both technology adoption and *tfp*. The two latter results are consistent with the Schumpeterian argument that larger firms are more productive and Ferreira *et al.*'s (2012) theory that public ownership increases the incentives to choose conventional projects, respectively.

At the regional level, we find that *Regional R&D* has a positive and statistically significant effect (at the 1% level) in both regressions, while *Neighbouring Regions R&D* does not exert a statistically significant influence. *Region Accessibility* shows only a negligible impact on *tfp* and an insignificant effect on technology adoption.

At the country level, *tfp* and the probability of adopting Technology $\mathcal{H}$ are positively affected by *Labour Cost*. This result may suggest the presence of a self-selection process in which less productive firms withdraw from the market due to insufficient revenue when labor costs are higher, all else being equal. Technology adoption and *tfp* are also positively influenced by *Independent Directors* (consistent with the results of Kaplan and Minton (1994)) and negatively affected by *Shareholder Rights* (this result is consistent with the argument that stronger minority shareholder intervention power in general meetings causes coordination failures in strategic business decisions, consequently reducing firms' ability to develop innovative products). Finally, stronger employment protection laws do not influence technology adoption but do exert a positive effect on *tfp*. The latter result corroborates previous findings by Acharya *et al.* (2010), who present cross-country evidence showing that

[12] Marginal effects on value added are calculated as follows. For the *tfp* effects, we can apply the estimated *Firm Intangibles* coefficient as such, given the production function defined in Equation (1). For the technology adoption effects, we obtain the marginal effect for a 1% increase in *Firm Intangibles* on the probability of adopting Technology $\mathcal{H}$. Therefore, for this increased probability, we calculate the expected gain in value added as the difference between the value added that low-technology firms would show with high-technology capital and labor coefficients and their actual value added, keeping all else equal. Admittedly, this quantification holds true only under the hypothesis that technological progress is not "localized", as advocated by Atkinson and Stiglitz (1969) and echoed by Basu and Weil (1998), Jones (2005), Acemoglu and Zilibotti (2001), and Caselli and Coleman (2006), among others.

stringent dismissal laws provide firms a commitment device to not punish short-run failures and thereby spur employees' efforts to pursue value-enhancing practices in the production process. However, we are aware that the detected positive correlation between employment protection and *tfp* contrasts with some recent studies (see Bassanini *et al.* (2009) and Cingano *et al.* (2010)), suggesting the need for further research on this issue.[13]

We assess the robustness of our technology adoption and *tfp* analysis through a set of modified versions of the baseline regressions. The results are shown in Table 5 (technology adoption analysis) and Table 6 (*tfp* analysis). In both tables, Model 1 includes only firm-level variables, while firm-level and regional variables are included in Model 2. Model 3 is specified as in the benchmark analysis, but it is estimated by excluding firms that have a foreign parent (or controlling shareholder) or foreign subsidiaries to purge the estimates of potential benefits from the innovation efforts exerted by international subsidiaries or parent companies.[14] In Model 4 and Model 5, we address the possible reverse causality between intangible assets and contemporaneous values of the dependent variable: in Model 4, the full set of controls is included, and $Firm\ Intangibles$ is one-year lagged; in Model 5, the full set of controls is included, and $Firm\ Intangibles$ is instrumented by its one-year lagged values (a two-stage instrumental variable procedure is used). In Model 6, the full set of controls is employed, and $Firm\ Intangibles$ is expressed in absolute levels (i.e., not in log) and included in a polynomial form of order 2 to check for the presence of non-linearities. Finally, Model 7 is specified as the benchmark model, but the technology adoption equation and the *tfp* equation (presented in the last columns of Table 5 and Table 6, respectively) are estimated simultaneously; in this case, the dependent variable of the technology adoption equation is the probability $p_{i,2,t}$ of belonging to $\Theta_{\mathcal{H}}$.[15]

insert Table 5 about here

insert Table 6 about here

The estimates are stable across different model specifications. In particular, the level of a firm's intangible

[13]In unreported estimations, we verify that our main findings also remain statistically significant in sector-specific regressions. From this result, we can conclude that sector-size effects, if present, do not drive our results.

[14]Following the Amadeus database definitions, we identify a foreign parent as a company that is at least 51% controlled by a firm located in another country, and we identify a foreign subsidiary as a company that is at least 51% owned by a firm located in another country.

[15]We observe a loss in the number of observations from specifications 1 to 7 in both the technology adoption and *tfp* effects regression analyses. This result does not indicate country-specific selection in the data but rather is due to the fact that data for some of the country-level variables are not available for the entire period from 2003 to 2009.

assets is shown to have a positive and statistically significant effect on both *Group* $\mathcal{H}$ and *tfp* in all the robustness-check regressions. Moreover, we observe that the square of $Firm\ Intangibles$ has a small, negative, and statistically significant parameter in Model 6; this result indicates that the magnitude of the intangible assets' (positive) effect decreases as the intangible-to-tangible assets ratio increases. The estimated parameters of the control variables also remain virtually unchanged.

We use Model 7, which includes the same set of control variables as our benchmark model and is run on the same set of observations, to re-obtain the expected gains in value added associated with a 1% increase in $Firm\ Intangibles$. The expected gain occurring through technology adoption amounts to 0.89%, on average, for the subset of firms whose probability $p_{i,2,t}$ rises above 0.5. This result complements the baseline 1.56% expected gain obtained from the benchmark analysis. Interestingly, the increase in value added associated with the *tfp* effect is unchanged.

6 Conclusions

Intangible assets play an important role in modern, knowledge-intensive production (Bontempi and Mairesse, 2008; Corrado *et al.*, 2008; Oliner *et al.*, 2008; O'Mahony and Vecchi, 2009; Marrocu *et al.*, 2012). However, despite growing interest among economists, it has so far been unclear whether intangible assets may allow for a more efficient exploitation of a firm's "traditional" inputs (i.e., tangible fixed capital and labor), whether they help a firm identify and adopt more productive technologies, or both. This gap in the previous studies stems from the fact that standard estimates of tfp are obtained under the assumption that firms use a single given technology, thereby precluding the possibility of analyzing firms' technological choices.

In this paper, we propose an empirical strategy that allows for multiple technologies within the same sector and enables us to separate the technology adoption effects from the *tfp* effects. We find that intangible assets have a positive and statistically significant effect on both a firm's probability of choosing relatively more productive technologies and *tfp*. In particular, a 1% increase in the intangible-to-tangible assets ratio leads to an expected gain in value added ranging from 0.89 to 1.56 for low technology firms due to the technology effect and an expected gain of 1.17% for all firms due to *tfp*.

We use a production functions estimation strategy based on mixture models. Although this approach neglects some recently highlighted issues in the literature on productivity estimation, such as the "simultaneity bias", it may represent a useful tool when technological heterogeneity across firms or countries is at the core of the analysis.

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A Variables description

Added Value. Log of added value. Added value is defined as profit for the period + depreciation + taxation + interest paid + cost of employees. It is a firm-level variable covering the period from 2003 to 2009, which we deflated using the OECD-Stan sector-country-specific deflators (source: Amadeus - 2012).

Labour Input. Log of total number of employees included in the companys payroll. It is a firm-level variable covering the period from 2003 to 2009 (source: Amadeus - 2012).

Capital Input. Log of tangible assets. Tangible assets include buildings, machinery and all other tangible assets. It is a firm-level variable covering the period from 2003 to 2009, which we deflated using the OECD-Stan sector-country-specific deflators (source: Amadeus - 2012).

Firm Intangibles. Log of intangible-to-tangible assets ratio. Intangible assets include formation expenses, research expenses, goodwill, and development expenses. Tangible assets include buildings, machinery and all tangible assets. It is a firm-level variable covering the period from 2003 to 2009 (source: Amadeus - 2012).

Firm Age. Age of the firm (years). It is a firm-level variable covering the period from 2003 to 2009 (source: Amadeus - 2012).

Listed Firm. Dummy variable (1 = the firm is listed on the stock market, 0 = otherwise). It is a firm-level variable covering the period from 2003 to 2009 (source: Amadeus - 2012).

Sales. Log of net sales. It is a firm-level variable covering the period from 2003 to 2009, which we deflated using the OECD-Stan sector-country-specific deflators (source: Amadeus - 2012).

Regional R&D. Total intramural R&D expenditures. It is a region-level variable covering the period from 2003 to 2009 and is expressed by the Purchasing Power Standard per inhabitant at constant 2000 prices. "Total" refers to the fact that the variable covers the following: *i*) the business enterprise sector, *ii*) the government sector, *iii*) the higher education sector, and *iv*) the private non-profit sector (source: Eurostat).

Region Accessibility. Multi-modal potential accessibility, std. It is a region-level variable covering 2001 and 2006 (source: Espon database). The accessibility of region j is defined as $Acc_j = \sum_r Pop_r exp(-\beta \bar{c}_{jr})$, where $\bar{c}_{jr}$ refers to the aggregation over transport modes (i.e., air, rail, road) of the cost (c_{jrm}) of reaching region r from region j using transportation mode m - i.e., $\bar{c}_{jr} = -(1/\lambda) ln \sum_m exp(-\lambda c_{jrm})$, where Pop_r is population in region r and λ is a parameter indicating the sensitivity to travel cost. The interpretation is that the accessibility of region j increases with the number of "accessible" regions and with their size (expressed in terms of population).

Neighbouring Regions R&D. This is a region-level variable covering the period from 2003 to 2009. It is derived as a local clusters indicator of the class known as "*Gi** statistics" (Anselin, 1995). These statistics are the ratio of the sum of a variable over the neighbors to the total sum of the variable within the sample. The variable we use is R&D expenses, and the spatial framework is the EU27 region plus Norway and Switzerland, at the NUTS 2 level. The numerator is computed over a defined neighborhood that depends on the weight-distance matrix. In our case, the number of allowed neighbors is set at $k = 4$ (we obtain similar results with k=3,5,...,10) (source: authors' own calculation on Eurostat data).

Labour Cost. Hourly labor costs, manufacturing. It is a country-level variable covering the period from 2003 to 2008 (source: Eurostat).

Country EPL. Unweighted average of sub-indicators for regular contracts (EPR) and temporary contracts (EPT). EPR covers notification procedures and delays involved before notice can start. It sets the length of the notice period at 9 months / 4 years / 20 years of tenure and the period for severance pay at 9 months / 4 years / 20 years of tenure. EPR also defines a justified or unfair dismissal, the length of the trial period, the compensation allowed following an unfair dismissal, and the possibility of reinstatement following an unfair dismissal. EPT covers valid cases for the use of fixed-term contracts, the maximum number of successive fixed-term contracts, the maximum cumulative duration of successive fixed-term contracts, the types of work for which temporary work agency employment is allowed, restrictions on the number of renewals of temporary work agency contracts, and the maximum cumulative duration of successive temporary work agency contracts. The summary indicator is based on a scale from 0 (least restrictions) to 6 (most restrictions). It is a country-level variable covering the period from 2003 to 2008 (source: OECD Indicators of Employment Protection).

Shareholder Rights. Unweighted sum of 3 sub-indicators. Sub-indicator 1 equals 1 if the sale of more than 50% of the companys assets requires the approval of the general meeting, it equals 0.5 if the sale of more than 80% of the assets requires approval, and it equals 0 otherwise. Sub-indicator 2 equals 1 if the shareholders who hold 1% or less of the capital may put an item on the agenda, it equals 0.75 if there is a hurdle of more than 1% but not more than 3%, it equals 0.5 if there is a hurdle of more than 3% but not more than 5%, it equals 0.25 if there is a hurdle of more than 5% but not more than 10%, and it equals 0 otherwise. Sub-indicator 3 equals 1 if every shareholder may file a claim against a resolution by the general meeting, it equals 0.5 if there is a threshold of 10% voting rights, and it equals 0 if this type of shareholder action does not exist. It is a country-level variable covering the period from 2003 to 2005 (source: Siems *et al.* (2009)).

Independent Directors. Equals the minimum percentage of independent members on the board of directors as required by law. It is a country-level variable covering the period from 2003 to 2005 (source: Siems *et al.* (2009)).

Table 7 provides a synthetic description of the variables used in the analysis.

insert Table 7 about here

B Issues in production function estimation

Production function estimation at the firm level raises a number of issues. There is a large body of literature in this field, and several methods have been proposed, with the choice depending on the economic focus (see, e.g., Del Gatto *et al.* (2011) and Van Beveren (2012) for overviews of the available methodologies) of the analysis.

As discussed in Section 3, to estimate a specific production function for each available technology is not possible because the number of available technologies is unknown. We tackle the issue by resorting to *mixture models* (Mc Lachlan and Peel, 2000). This choice has pros and cons.

B.1 Technology bias

The main advantage is that our mixture analysis may help us identify clusters of firms that are characterized by similar production function parameters without any ex-ante assumptions regarding the technology used by each firm.[16] The probability of belonging to a given cluster is produced by the estimation, which enables us to estimate group-specific sets of input coefficients that are fully consistent with the idea of technology expressed

[16]The only assumption is that the production function is always of the Cobb-Douglas form.

by Equation (1).[17] This approach represents an important departure from standard *tfp* measures, which may reveal incomplete information when the focus of the analysis is technology rather than productivity in general. Standard estimates may only refer to a sectoral (rather than a technology-specific) benchmark to express the *tfp* of each firm. In this case, cross-firm technological differences flow entirely into the residual *tfp* term.[18]

To better describe how our approach differs from standard *tfp* estimates, let us assume a one-input production function. It is common practice in productivity analysis to estimate the production function in logarithms and retrieve the term $A_{i,t}$ (i.e. Solow residual) as follows:

$$lnY_{i,t} - \hat{\beta} lnX_{i,t} = ln\hat{A}_{i,t} \tag{11}$$

where the input coefficient (β) is estimated without allowing for the presence of different technologies within the same sector. In this case, the *tfp* term includes a bias that may be easily identified using Equation (1) to substitute for the output in Equation (11) and by adopting an asterisk to refer to the "true" values of $A_{i,t}$ and β_m:

$$lnA^*_{i,t} + (\beta^*_m - \hat{\beta}) lnX_{i,t} = ln\hat{A}_{i,t}. \tag{12}$$

As a result, *tfp* estimates obtained without controlling for (within-sector) technological differences conflate technology and "pure" *tfp* effects. The *tfp* of firms that use relatively more productive technologies is overstated (due to underestimation of their input coefficient - i.e., $\beta^*_m > \hat{\beta}$), and the *tfp* of firms that adopt relatively less productive technologies is understated (due to overestimation of their input coefficient - i.e., $\hat{\beta} > \beta^*_m$).[19]

Our mixture-analysis approach produces firm-level *tfp* estimates (i.e., $\hat{\beta_m}$) that, because they are expressed in relative terms with respect to the average firm in the same technology group, are virtually purged of the "technology bias" (provided that the "true" value of M is correctly identified - i.e., $\beta^*_m = \hat{\beta}_m$).

Whereas we limit our benchmark analysis to the case $M = 2$ for the reasons explained above, estimates

[17] This process entails using a *tfp* distribution in which each firm's *tfp* is expressed in relative terms with respect to the average firm in the technology group. The *tfp* of the average firm (i.e., the firm whose observed output exactly matches the output predicted on the basis of its group-specific coefficients $\beta_{n,m}$) amounts to one (i.e., the exponential of zero), and the *tfp* of all of the other firms in the same technology group is expressed with respect to this benchmark.

[18] In general, *tfp* is a relative notion that only makes sense if it is expressed with respect to a benchmark. Whereas the frontier approach (i.e., "efficiency analysis") relies on the identification of a "best practice" firm, non-frontier methods (e.g., Olley and Pakes, 1996) express each firm's productivity in relative terms with respect to the "average" firm. In both cases, because the benchmark is identified on a sectoral basis, the resulting *tfp* term is a "composition of" technology and *tfp* (in a strict sense).

[19] With Equation (1) in mind, the input coefficient in Equation (12) can be seen as a weighted average of the M technology-specific betas, with weights given by the ratio of the number of firms in the m-technology group to the total number of firms in the sector: $\hat{\beta}_n = \sum_{m=1}^{M} \hat{\beta}_{n,m} \frac{\Theta_m}{\sum_{m=1}^{M} \Theta_m}$.

obtained under alternative values of M are reported in Section B of the online Appendix, where we employ model selection criteria to identify the number of technologies in each sector.

B.2 Simultaneity bias

The opportunity to obtain technology-specific input coefficients and *tfp* estimates comes at the price of not being able to consider other important issues highlighted by the literature on production function estimation. Among these issues, recent works have focused on the "simultaneity bias". The source of the simultaneity bias is the fact that information on actual productivity, although unknown to the econometrician, is to some extent known to the firm when the decision concerning the amount of inputs is made. Therefore, our estimated production function parameters obtained through WLS are biased by the potential correlation between the regressors and the error term associated with the presence of simultaneity.

Olley and Pakes (1996) suggest a proxy-variable strategy to control for simultaneity. Key studies examining this approach, which is commonly referred to as "semi-parametric", also include those of Levinsohn and Petrin (2003), Ackerberg *et al.* (2006), and Wooldridge (2009). The basic idea consists of identifying a (proxy) variable that reacts to the changes in the *tfp* observed by a firm and is thus a function of these changes. Insofar as this function is invertible, its inverse may be calculated and plugged into the production function estimating equation. Olley and Pakes (1996) suggest resorting to investment as a proxy, whereas Levinsohn and Petrin (2003) use intermediates. In a recent paper, Doraszelski and Jaumandreu (2012) develop an extension of Olley and Pakes (1996) in which a firm's *tfp* is stochastically affected by its investment in knowledge (considered in terms of R&D) because firms' productivity is assumed to evolve according to a Markov process, which is "shifted" (either positively or negatively) by R&D expenditures. The R&D choice gives rise to an additional policy function (besides the policy function for investment in physical capital) that, under the crucial assumption that the error in t is uncorrelated with the innovation choice in $t-1$, may be exploited in the production function estimation to purge the estimates from the part of the error correlated with the input choice. Loosely speaking, this approach allows for the estimation of firms' *tfp* while controlling for simultaneity and the effect of innovation choices at the same time. The two controls are somewhat separable, but it is their combination that might matter for our purposes because the combination would provide us with the opportunity to collapse the production function estimation and the analysis of intangible assets into a single step. However, because the innovation choice endogenous, the only way to study its impact on productivity in the Doraszelski-Jaumandreu framework consists of contrasting the estimated *tfp* obtained when controlling for R&D with one obtained without such control. Moreover, because the method is not designed to consider the presence of within-sector technological differences, it cannot fit within our main objective.

The implementation of a simultaneity-free mixture regression (based on the GMM approach of Doraszelski and Jaumandreu (2012) and Wooldridge (2009)) raises a number of identification and computational problems that are beyond the scope of the present paper. For instance, the endogenous relationship of innovation with technology and *tfp* should be specified separately because firms' input choices may be correlated with both technology parameters and *tfp*.

In the online Appendix, we speculate on the effect of not controlling for the simultaneity bias on our estimated coefficients and *tfp*.

Table 1: Amadeus dataset, sectoral statistics after data cleaning.

SECTOR - COUNTRY	**CODE**	**OBS.**	**FIRMS**	**VA/L**	**K/L**
Chemical products (including pharmaceuticals)	CH	13578	3366	76.85	58.39
Rubber and plastic products	RP	10274	2714	54.51	39.03
Other non-metallic products	ONM	7711	2021	58.14	58.94
Basic metals	BM	2867	812	45.62	37.94
Metal products (except machinery and equipment)	ME	8371	2293	46.59	23.05
Electronic, electrical and optical products	EL	13380	3701	63.56	20.83
Machinery and equipment	MA	16248	4477	55.92	21.96
Motor vehicles and trailers	MV	3604	1025	50.33	28.61
Other transport equipment	OTR	1308	384	51.51	23.66
Austria	AT	935	359	74.25	36.30
Belgium	BE	3811	852	76.67	41.25
Czech Republic	CZ	6841	1447	22.66	25.01
Germany	DE	11391	4073	67.05	32.11
Spain	ES	9008	1673	56.22	49.06
Finland	FI	1973	453	63.21	34.63
France	FR	14384	3456	66.08	27.59
United Kingdom	GB	7038	2057	63.89	35.93
Hungary	HU	1026	479	24.10	29.40
Italy	IT	15134	3943	62.43	40.42
Netherlands	NL	687	186	67.86	44.37
Norway	NO	201	197	59.94	28.69
Portugal	PT	369	254	45.62	43.83
Sweden	SE	2594	881	65.20	32.75
Slovenia	SI	419	106	30.46	30.95
Slovak Republic	SK	1530	377	27.17	25.71
TOTAL	-	77341	20793	59.22	35.16

VA=Value Added (th Euro, deflated), K=Tangible Fixed Assets (th Euro, deflated), L= n. of employees.

Table 2: Mixture regression, 2 technology clusters ($M = 2$).

SECTOR	Cluster 1							Cluster 2						
	β_K	β_L	n.obs.	β_K/β_L	$\beta_K+\beta_L$	VA/L	K/L	β_K	β_L	n.obs.	β_K/β_L	$\beta_K+\beta_L$	VA/L	K/L
CH	0,353*** (0,039)	0,454*** (0,039)	553	0.78	0.80	16.2	47.9	0,183*** (0,005)	0,775*** (0,006)	13301	0.23	0.96	79.4	58.8
RP	0,477*** (0,020)	0,426*** (0,020)	1422	1.12	0.91	19.5	28.4	0,153*** (0,006)	0,797*** (0,006)	9106	0.19	0.95	60.1	40.7
ONM	0,550*** (0,026)	0,290*** (0,025)	944	1.90	0.84	21.1	45.0	0,260*** (0,007)	0,700*** (0,008)	6960	0.37	0.96	63.1	60.9
BM	0,537*** (0,037)	0,322*** (0,039)	671	1.69	0.86	12.6	32.6	0,249*** (0,013)	0,640*** (0,012)	2297	0.39	0.89	55.3	39.6
ME	0,479*** (0,019)	0,243*** (0,021)	2098	2.00	0.72	15.7	20.2	0,160*** (0,006)	0,706*** (0,006)	6525	0.23	0.87	56.6	24.0
EL	0,453 (0,348)	0,348*** (0,018)	2132	1.29	0.80	21.2	16.0	0,040*** (0,007)	0,909*** (0,008)	11652	0.04	0.95	71.3	21.7
MA	0,433*** (0,018)	0,312*** (0,017)	2182	1.39	0.74	19.1	17.5	0,071*** (0,004)	0,880*** (0,005)	14535	0.08	0.95	61.5	22.7
MV	0,493*** (0,025)	0,513*** (0,027)	980	0.96	1.00	19.9	24.8	0,169*** (0,013)	0,751*** (0,013)	2723	0.23	0.92	61.3	29.9
OTR	0,364** (0,095)	0,574*** (0,092)	232	0.63	0.93	13.2	20.2	0,106** (0,018)	0,795*** (0,018)	1120	0.14	0.91	59.5	24.3

***,**,* significant values at 99, 95, 90%; Bootstrapped standard errors (100 replications) in parenthesis.

Table 3: Descriptive statistics on key variables by sector (average values).

Sector	**Firm-level variables**							
	Intangibles (%)		Age (years)		Listed (%)		Sales (th Euros)	
	Group H	Group L	Group H	Group L	Group H	Group L	Group H	Group L
CH	57.02	47.2	30	19	2.09	5.62	163145	37065
RP	16.84	9.16	26	15.7	1.37	0.72	76074	22778
ONM	13.07	38.36	28.4	17.6	1.32	0.88	68025	29521
BM	8.4	3.49	31.3	14.3	1.54	0.46	131111	36693
ME	14.08	7.91	30	13.3	1.18	0.98	45487	14424
EL	71.78	30.34	26	14.7	3.54	2.63	163747	52399
MA	46.62	30.13	28.4	15	1.85	0.66	67311	23861
MV	17.59	8.81	24.2	13.1	1.45	1.79	912009	86408
OTR	50.00	18.56	27.70	15.9	3.71	0.45	223752	37516

Sector	**Regional variables**					
	Accessibility (*)		Neighb. R&D (*)		R&D (PPS per inh)	
	Group H	Group L	Group H	Group L	Group H	Group L
CH	3.90E+08	2.00E+08	4.17E-03	2.99E-03	357.76	274.18
RP	3.80E+08	1.60E+08	4.34E-03	2.90E-03	337.09	200.16
ONM	3.40E+08	1.40E+08	3.72E-03	3.05E-03	305.77	196.98
BM	5.00E+08	1.50E+08	4.81E-03	2.80E-03	399.09	204.36
ME	4.40E+08	1.40E+08	4.89E-03	3.34E-03	423.06	212.91
EL	4.40E+08	1.90E+08	4.66E-03	3.27E-03	385.66	225.08
MA	4.60E+08	1.90E+08	4.78E-03	3.27E-03	364.88	235.84
MV	3.90E+08	1.60E+08	4.80E-03	3.24E-03	367.01	208.98
OTR	3.60E+08	1.40E+08	4.54E-03	3.01E-03	430.72	244.19

Sector	**Country-level variables**							
	Labour Cost (PPS)		EPL (*)		Sh. Rights (*)		Ind. Directors (*)	
	Group H	Group L	Group H	Group L	Group H	Group L	Group H	Group L
CH	23.82	15.96	2.23	2.05	1.68	1.8	17.88	12.01
RP	24.11	14.27	2.21	2.12	1.66	1.83	17.25	9.02
ONM	22.78	13.74	2.25	2.14	1.55	1.8	16.19	6.36
BM	28.38	15.26	2.43	2.07	1.97	2	12.02	2.33
ME	28.22	13.71	2.54	2	1.99	1.97	11.84	3.23
EL	24.35	14.4	2.09	1.91	1.73	1.78	18.88	10.89
MA	24.79	14.1	2.11	2.02	1.55	1.76	16.99	7.53
MV	26.05	14.63	2.20	1.96	2.12	2.01	16.76	6.94
OTR	25.76	15.17	2.02	1.97	2.2	2.05	21.54	6.6

*Unit: see Appendix A.

Table 4: Baseline regression results.

	Technology adoption effects (Eq. 8)	*tfp* **effects (Eq. 10)**
Dependent variable:	*Group* $\mathcal{H}$	tfp
Firm Intangibles (log)	0.120***	0.012***
	(0.031)	(0.001)
Firm Age	0.022***	0.000
	(0.004)	(0.000)
Listed Firm	-1.520**	-0.114***
	(0.624)	(0.025)
Sales (log)	0.762***	0.077***
	(0.070)	(0.002)
Regional R&D	0.001***	0.000***
	(0.000)	(0.000)
Region Accessibility	0.000	0.000**
	(0.000)	(0.000)
Neighbouring Regions R&D	17.032	0.242
	(43.342)	(1.686)
Labour Cost	0.941***	0.041***
	(0.325)	(0.010)
Country EPL	-1.275	0.422***
	(1.419)	(0.055)
Shareholder Rights	-4.295***	-0.367***
	(1.356)	(0.038)
Independent Directors	0.080***	0.011***
	(0.029)	(0.001)
Constant	-17.015*	-2.124***
	(8.893)	(0.271)
Firm effects	yes	yes
Country effects	yes	yes
Sector effects	yes	yes
Year effects	yes	yes
n. obs.	16190	16190
n. firms	8974	8974
n. firms changing technology group	907	907
Estimation method	FE panel logit	FE panel GLS

***,**,* significant values at 99, 95, 90%; Standard errors in parenthesis.

Table 5: Technology adoption effects. Robustness checks.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Firm Intangibles (log)	0.074*** (0.015)	0.090*** (0.018)	0.116** (0.045)	-	-	-	0.006*** (0.001)
Firm Intangibles $t-1$ (log)	-	-	-	0.141*** (0.036)	-	-	-
Firm Intangibles (log, instr.)	-	-	-	-	0.139*** (0.036)	-	-
Firm Intangibles (levels)	-	-	-	-	-	0.130** (0.064)	-
Firm Intangibles (sqrd levels)	-	-	-	-	-	-0.003** (0.001)	-
Firm Age	0.015*** (0.002)	0.012*** (0.003)	0.018*** (0.006)	0.020*** (0.005)	0.020*** (0.005)	0.018*** (0.004)	0.001*** (0.000)
Listed Firm	-1.798*** (0.306)	-1.843*** (0.400)	-1.043 (-0.853)	-1.466** (0.741)	-1.466** (0.741)	-1.405** (0.610)	-0.055** (0.027)
Sales (log)	1.063*** (0.042)	1.144*** (0.049)	0.899*** (0.104)	0.803*** (0.078)	0.803*** (0.078)	0.760*** (0.065)	0.035*** (0.002)
Regional R&D	-	0.001*** (0.000)	0.001** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Region Accessibility	-	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)
Neighbouring Regions R&D	-	-20.437 (29.484)	29.278 (65.865)	-18.637 (48.901)	-18.637 (48.901)	17.498 (39.525)	3.937*** (1.499)
Labour Cost	-		0.896* (0.460)	0.978*** (0.323)	0.978*** (0.323)	1.184*** (0.225)	0.028*** (0.000)
Country EPL	-	-	-1.468 (1.874)	-0.962 (1.448)	-0.962 (1.448)	-1.348 (1.317)	0.087*** (0.009)
Shareholder Rights	-	-	-4.900** (2.293)	-4.408*** (1.414)	-4.408*** (1.414)	-4.131*** (1.068)	-0.223*** (0.009)
Independent Directors	-	-	0.136** (0.059)	0.105*** (0.030)	0.105*** (0.030)	0.085*** (0.028)	0.004*** (0.000)
Constant	-13.701*** (0.581)	-14.784*** (0.685)	-17.474 -12.741	-18.665** (9.059)	-18.669** (9.059)	-23.505*** (6.861)	-
First-stage R2 Wald χ^2 [Prob> χ^2]					0.967 987382.39 [0.000]		
Firm effects	yes	yes	yes	yes	yes	yes	yes
Country effects	yes	yes	yes	yes	yes	yes	not
Sector effects	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	not
Number of obs.	59727	38656	6865 (a)	15137	15137	18168	16190

Dependent variable: *Group* $\mathcal{H}_{i,t}$ (Model 1 - Model 6); $p_{i,2,t}$ (Model 7)
Estimation method: FE panel logit (1 to 6); SUR panel (7).
(a) Sub-sample excluding firms having a foreign parent (or controlling shareholder) or foreign subsidiaries.

***,**,* significant values at 99, 95, 90%; Standard errors in parenthesis.

Table 6: *tfp* effects. Robustness checks.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Firm Intangibles (log)	0.011*** (0.001)	0.013*** (0.001)	0.011*** (0.002)	-	-	-	0.012*** (0.001)
Firm Intangibles $t-1$ (log)	-	-	-	0.013*** (0.001)	-	-	-
Firm Intangibles (log, instr.)	-	-	-	-	0.015*** (0.006)	-	-
Firm Intangibles (levels)	-	-	-	-	-	0.016*** (0.002)	-
Firm Intangibles (sqrd levels)	-	-	-	-	-	-0.000*** (0.000)	-
Firm Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.028*** (0.008)	0.000 (0.000)	0.000** (0.000)
Listed Firm	-0.126*** (0.016)	-0.124*** (0.020)	-0.140*** (0.032)	-0.121*** (0.026)	-0.178 (0.171)	-0.105*** (0.025)	-0.088*** (0.018)
Sales (log)	0.103*** (0.002)	0.099*** (0.002)	0.076*** (0.004)	0.079*** (0.003)	0.266*** (0.010)	0.077*** (0.002)	0.070*** (0.002)
Regional R&D	-	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Region Accessibility	-	0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (1.10e-11)
Neighbouring Regions R&D	-	1.209 (1.342)	-1.430 (2.823)	-0.310 (1.770)	-33.264 (139.941)	-0.029 (1.608)	4.345*** (0.995)
Labour Cost	-		0.040*** (0.015)	0.045*** (0.009)	0.039*** (0.010)	0.069*** (0.007)	0.010*** (0.001)
Country EPL	-	-	0.444*** (0.075)	0.457*** (0.055)	0.286*** (0.059)	0.416*** (0.052)	0.024*** (0.006)
Shareholder Rights	-	-	-0.316*** (0.070)	-0.376*** (0.038)	-0.381*** (0.040)	-0.375*** (0.034)	-0.013** (0.006)
Independent Directors	-	-	0.009*** (0.002)	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.005*** (0.000)
Constant	-1.310*** (0.029)	-1.263*** (0.032)	-2.234*** (0.412)	-2.296*** (0.274)	-2.255*** (0.277)	-2.867*** (0.223)	-
First-stage R2 F-stat [Prob>F] H0 of weak IV (Cragg-Donald)					0.966 2.1e+05 [0.000] rejected		
Firm effects	yes	yes	yes	yes	yes	yes	yes
Country effects	yes	yes	yes	yes	yes	yes	not
Sector effects	yes	yes	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes	yes	not
Number of obs.	59727	38656	6865 (a)	15137	13470	18168	16190

Dependent variable: firm-level tfp
Estimation method: FE panel GLS (Model 1 to Model 6); SUR panel (Model 7).
(a) Sub-sample excluding firms having a foreign parent (or controlling shareholder) or foreign subsidiaries.

***,**,* significant values at 99, 95, 90%; Standard errors in parenthesis.

Table 7: Data sources and definitions.

VARIABLE	**STAT. UNIT**	**SOURCE**	**TIME SPAN**	**DESCRIPTION**
Added value	Firm	Amadeus	2003-2009	Log of added value (EUR, deflated)
Labour input	Firm	Amadeus	2003-2009	Log of total number of employees.
Capital input	Firm	Amadeus	2003-2009	Log of tangible assets (EUR, deflated)
Firm intangibles	Firm	Amadeus	2003-2009	Intangible to tangible assets ratio.
Firm age	Firm	Amadeus	2003-2009	Age of the firm (years).
Listed firm	Firm	Amadeus	2003-2009	Dummy variable (1 = the firm is listed in the stock market, 0 = otherwise).
Sales	Firm	Amadeus	2003-2009	Log of net sales (EUR, deflated)
Regional R&D	Region	Eurostat	2003-2009	Total intramural R&D expenditure (PPS)
Region accessibility	Region	Espon	2001, 2006	Multi-modal potential accessibility, std.
Neighbouring regions R&D	Region	Eurostat	2003-2009	Local clusters indicator of R&D expenses of the neighbouring regions.
Labour cost	Country	Eurostat	2003-2008	Hourly labour costs, manufacturing (PPS).
Country EPL	Country	OECD	2003-2008	Index of employment protection legislation.
Shareholder rights	Country	Siems et al. (2009).	2003-2005	Index of minority shareholder power to intervene in the general meeting.
Independent directors	Country	Siems et al. (2009).	2003-2005	Extent at which independent directors must be present in the board by law.

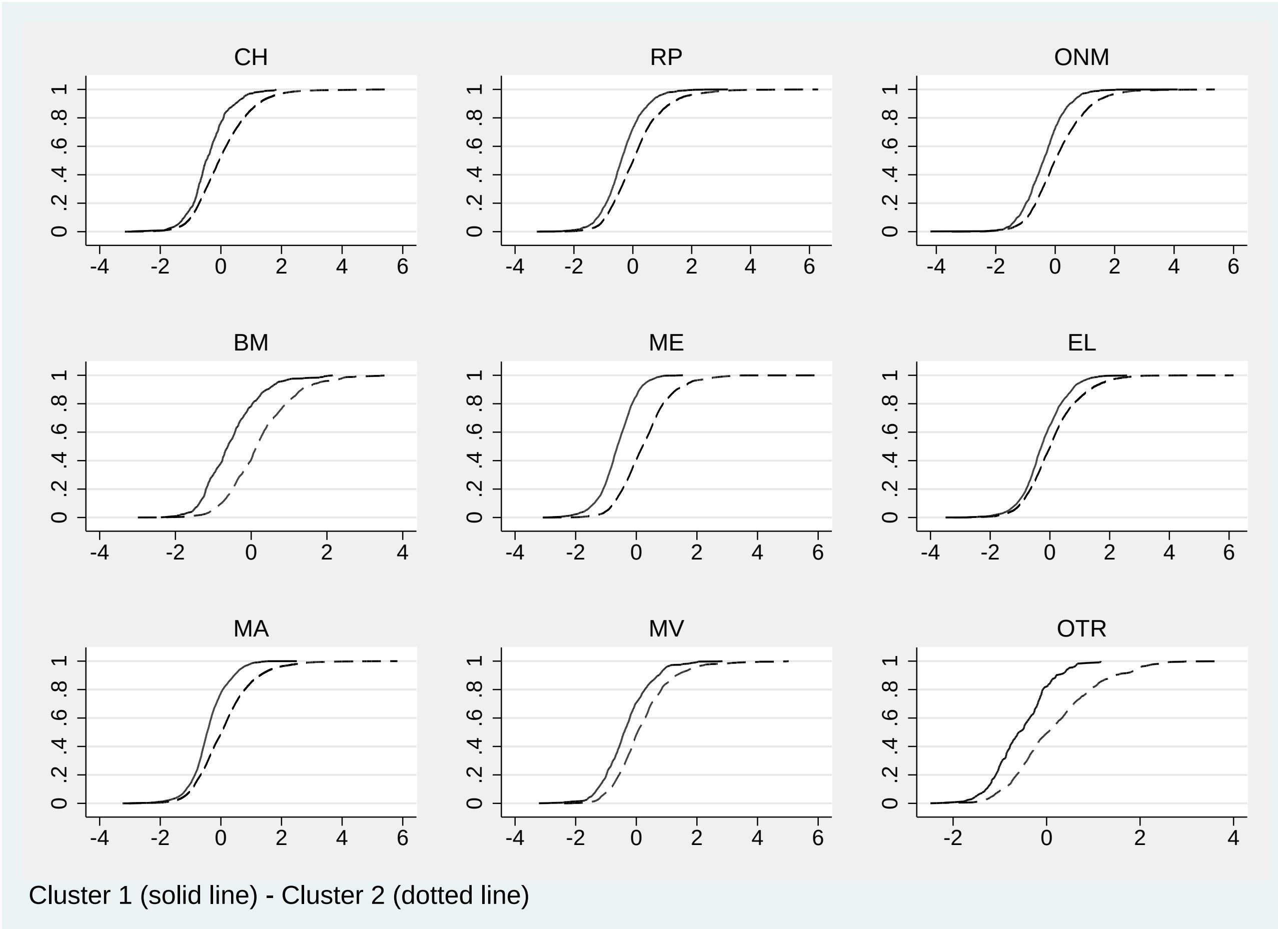

Figure 1: Predicted output, cumulative distribution functions by sector

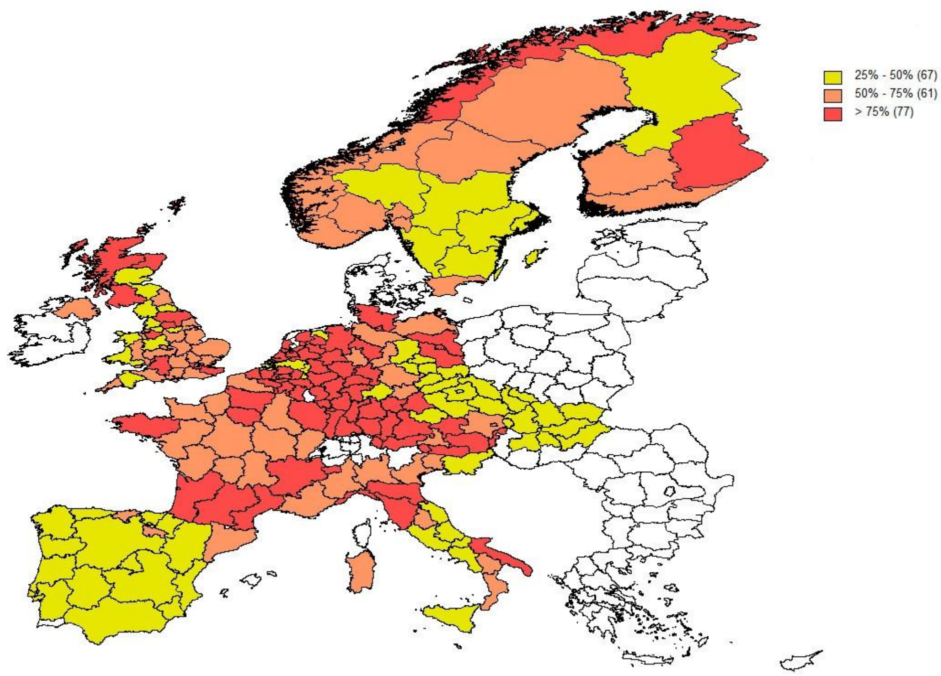

Figure 2: High to low technology firms ratio ($\Theta_{\mathcal{H}}/\Theta_{\mathcal{L}}$), NUTS 2 regions.

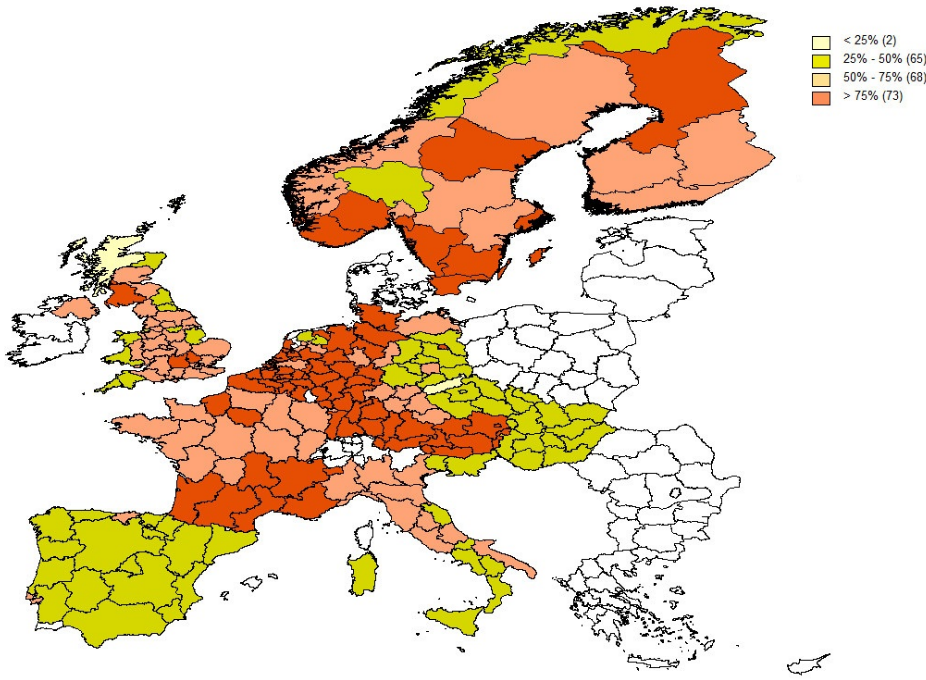

Figure 3: Firms' *tfp* distribution, NUTS 2 regions, average values.

Unbundling technology adoption and *tfp* at the firm level: Do intangibles matter?

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Online Appendix

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A Clustering over sub-periods

Our benchmark production function coefficients are estimated in a pooled regression under the assumption that observations are independent across firms and time. Such a framework allows for free technology change but does not control for the existence of firm-specific effects.

To take advantage of the panel nature of our data, we split the sample into two sub-periods (2003-2005 and 2006-2009) and re-estimate the production function parameters introducing firms' fixed effects to account for time dependency at the firm-level in the mixture regression.[20] This assumption is theoretically consistent with the idea that technology changes typically do not occur in the short run and is empirically consistent with the low number of transitions and the absence of "double changes" that we find in our benchmark analysis with i.i.d. observations.

We obtain the following results.

First, we show in Table 8 that coefficients' estimates are virtually unchanged with respect to coefficients reported in Table 2. We observe a slight reduction of the capital coefficients from the first to the second sub-period. This reduction is in general small.

Second, the results of the technology adoption and *tfp* regressions (see Table 11) obtained under the present specification are substantially similar to those obtained in the benchmark estimation (cfr. Table 4). In Table 11, the first column lists the variables, the second and the third columns list the estimated parameters from the technology adoption and *tfp* regressions respectively. The model specification is that of Model 5 in Tables 5 and 6, with the full set of controls included and the intangible assets variable instrumented by its one-year lagged values.[21]

[20] This follows the same logic of the longitudinal clustering of McNicholas and Murphy (2010).

[21] In back of the envelope calculations, we also checked whether our ex-ante probabilities, and thus our clustering, might be explained by omitted drivers, so-called concomitant variables (Dayton and Macready, 1988). In a first robustness check, we consider a vector of concomitant variables including intangible fixed assets and firm's age. In a second check, we instead include labor costs (under the reasonable assumption that capital costs are constant across European countries). Though with some differences across sectors, we find that the relative size of the clusters is very similar to the benchmark size reported in Table 2. This result suggests that our initial random assignment does not affect the final clustering. Results of these checks are available upon request.

B Identification of the "true" number of technologies: flexible number of clusters

We assumed the existence of two technology-clusters (i.e., $M = 2$) in our analysis. This assumption makes the identification of the "high" technology in the technology adoption analysis straightforward.

In this Section we re-estimate the production function under alternative values of M and follow a sound statistical criterion in search of the "true" number of clusters (i.e., technologies) in each sector.[22]

We use a log-likelihood ratio (LR) bootstrapped test (Mc Lachlan, 1987)[23], which uses bootstrapped replications of the model to test (as a chi-square) the difference about the log-likelihoods of two solutions (e.g., $M = 2$ *versus* $M = 3$).

Table 9 shows the LR-test results with respect to the alternative hypothesis that the number of segments is greater than a given M, with decisive values highlighted. We observe that the LR-test always rejects the hypothesis of $M = 1$ and suggests the presence of two technology clusters (i.e., $M = 2$) in only one out of nine sectors, three clusters (i.e., $M = 3$) in five sectors, and four clusters (i.e., $M = 4$) in three sectors. For each sector, Table 10 reports the technology-specific coefficients estimated through a mixture regression in which the number of technology clusters is set to the value suggested by the LR-test. Notwithstanding some variability across clusters, the values remains economically meaningful. We then re-obtain each firm's *tfp* using the new inputs' coefficients and re-run the *tfp* analysis of Section 4. Results are presented in the last column of Table 11. The estimated coefficients of our main explanatory variables are broadly similar, in sign and statistical significance, to those obtained in our basic estimation (see Table 6).

We can conclude that the analysis of the relation between intangible assets and *tfp* is not significantly affected by our assumption of $M = 2$.

[22] In order to our mixture analysis approach produce *tfp* estimates that are virtually purged of the "technology bias" highlighted in Section B.1, the number of available technologies has to be correctly identified. Only in that case, in fact $\hat{\beta}_m$ equals β^*_m.

[23] Alternatives, such as the MAIC - Modified Akaike Information Criterion (Hawkins *et al.*, 2001) and the classical BIC - Bayesian Information Criterion (Fraley and Raftery, 2002), yield equivalent results.

C Country selection

The clustering obtained in the mixture model analysis may be driven by country size or other unobservable country-level differences (that lead to a selection bias in the sample of firms). In this Section, we address the robustness of our results with respect to this possibility.

First, we calculate the composition of each country in terms of share of firms belonging to $\Theta_{\mathcal{H}}$ and $\Theta_{\mathcal{L}}$. $\Theta_{\mathcal{H}}$ and $\Theta_{\mathcal{L}}$ being defined at a sectoral level, we report each country's composition averaged across sectors. See Table 12. Although it is reasonable to expect that firms adopting a high technology are relatively more numerous in continental or scandinavian economies whereas firms adopting a low technology are more common in eastern Europe, we observe that $\Theta_{\mathcal{H}}$ and $\Theta_{\mathcal{L}}$ do not merely reproduce single countries or groups of countries. Indeed, technology-$\mathcal{H}$ and technology-$\mathcal{L}$ firms coexist within each country. As expected, countries such as Belgium, Germany and Sweden are characterized by a very high share of technology-$\mathcal{H}$ firms, and countries such as Slovak Republic, Czech Republic and Slovenia by a high share of technology-$\mathcal{L}$ firms. Nevertheless, no country is composed entirely by only one type (i.e., one cluster) of firms. This appears clearly in Figure 2, where the ratio of the number of observations in the two technology groups is reported at a regional level.

Second, we re-run the mixture model for *tfp* estimation on country-specific samples of firms for given countries, in order to examine whether multiple clusters of firms emerge also within country-specific populations. We select two countries that in the Amadeus database have populations of firms with very different coverage (France, for which we have 14384 observations, and Norway, for which we have 201 observations) and a third country (Slovak Republic, with 1530 observations available) as a representative less advanced eastern European country. The results are presented in Table 13, where the within country technology clusters (obtained through the within country mixture model regression) are presented along with the within country technology composition (obtained through the cross-country mixture model regression). We find sub-populations of firms - for France, Norway, and Slovak Republic, separately - characterized by one cluster in some sectors and by two clusters in some other sectors. We find one single cluster for all of the three considered countries only in the metal products industry. Hence, even if an unobservable country-specific selection bias may be present (according to which, for example, only large firms or more "efficient" firms are included in the sample, with the consequence that within country heterogeneity may be reduced), multiple technology clusters still emerge within countries. Although this is not a proof on the number of clusters of any country-sector sub-population, firms from country-sector sub-populations in most cases are shown to cluster into the two groups $\Theta_{\mathcal{H}}$ and $\Theta_{\mathcal{L}}$. This unveils that, while the one-technology assumption may be justified for some country-sector sub-populations, it should be always relaxed when cross-country firm-level data are used.[24]

D Simultaneity bias

In this Section we re-estimate the production function coefficients following the semi-parametric approach suggested by Olley and Pakes (1996) to show to which extent not controlling for simultaneity affects our baseline estimates. Several methods have been suggested by the literature to cope with the presence of simultaneity (cfr. Levinsohn and Petrin (2003), Ackerberg *et al.* (2006), Wooldridge (2009), and Doraszelski and Jaumandreu (2012). As shown by Ornaghi and Van Beveren (2012), different estimation routines may lead to very different estimated coefficients. We choose the Olley-Pakes approach because it is currently the most widely used. However, since Olley and Pakes assume that labour is a fully variable input, we introduce the correction suggested by Ackerberg *et al.* (2006) (and adopt the acronym OPACF to refer to the resulting estimation procedure). For more details on the estimation routine, the reader is redirected to Section 5.2.1 of Del Gatto *et al.* (2011).[25]

As a first comparison, we report in Table 14 the coefficients estimated through the OPACF method, and compare them with those obtained through a simple OLS estimation. The latter estimation is equivalent to a one-group mixture regression.

We observe that, as expected, OLS estimates are always in the middle, compared to the mixture-based coefficients obtained in the two-groups case (see Table 2). This is a consequence of the fact that $\hat{\beta}_n = \sum_{m=1}^{M} \hat{\beta}_{n,m} \frac{\Theta_m}{\sum_{m=1}^{M} \Theta_m}$ (see footnote 19).

No clear pattern emerges from the comparison of the OPACF and the OLS coefficients, neither in terms of returns to scale, nor in terms of capital-to-labour coefficients ratio. This might be interpreted as evidence of the fact that the simultaneity bias does not affect our results in a given direction.

[24]Note that firms may cluster in different technology groups in the within country estimation while they cluster in a single group in the cross-country mixture estimation, and vice-versa. This is due to the fact that, as explained in Section 3, the segment-specific parameters μ_m and σ_m^2, on which the groups are determined, vary with the available information set.

[25]As discussed in Section B.2, in principle we might also take advantage of the Doraszelski and Jaumandreu (2012) approach to endogenize the innovation choice, while taking into account simultaneity. Unfortunately, this would require data on R&D that are not available in our dataset. We might replace R&D with investment in intangible assets, obtained as difference between intangible assets levels in two consecutive years, but this would change the data generating process with respect to Doraszelski and Jaumandreu (2012).

As a further check, we re-compute firms' *tfp* using OPACF within the two groups identified by the mixture analysis. This strategy presents some drawbacks. First, using the mixture regressions as a first step aimed at identifying the groups is not correct, because the identification of the two technology groups is endogenous to the estimation. In other words, firms that fall in one group might fall in the other group in an ideal "simultaneity free" mixture regression. Second, the Olley-Pakes procedure requires information on firms' investments, and this dramatically reflects onto the number of observations, which shrinks by 2/3. This notwithstanding, we re-compute firms' *tfp* by technology groups, using the Olley-Pakes coefficients reported in Table 14. Interestingly, the correlation with the mixture-based *tfp* is around 0.7 for both technologies.

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Table 8: Robustness, mixture regression with clustering over sub-periods.

		Sub-period 2003-2005						Sub-period 2006-2009					
		Cluster 1			Cluster 2			Cluster 1			Cluster 2		
SECTOR		β_K	β_L	**const**	β_K	β_L	**const**	β_K	β_L	**const**	β_K	β_L	**const**
CH	**coeffs**	0.361***	0.509***	-0.469***	0.184***	0.777***	0.088***	0.247***	0.639***	-0.357***	0.169***	0.772***	0.196***
	st.err.	(0.029)	(0.031)	(0.021)	(0.008)	(0.008)	(0.006)	(0.017)	(0.017)	(0.011)	(0.008)	(0.008)	(0.006)
	n.obs		**991**			**5568**			**2298**			**4997**	
RP	**coeffs**	0.502***	0.451***	-0.575***	0.172***	0.781***	0.116***	0.367***	0.531***	-0.444***	0.153***	0.793***	0.238***
	st.err.	(0.026)	(0.025)	(0.023)	(0.007)	(0.008)	(0.005)	(0.020)	(0.018)	(0.015)	(0.008)	(0.008)	(0.005)
	n.obs		**778**			**4028**			**1690**			**4032**	
ONM	**coeffs**	0.586***	0.357***	-0.573***	0.307***	0.652***	0.130***	0.498***	0.392***	-0.467***	0.252***	0.708***	0.175***
	st.err.	(0.027)	(0.026)	(0.024)	(0.009)	(0.009)	(0.006)	(0.024)	(0.029)	(0.024)	(0.010)	(0.011)	(0.007)
	n.obs		**593**			**3208**			**946**			**3157**	
BM	**coeffs**	0.526***	0.423***	-0.904***	0.235***	0.661***	0.323***	0.439***	0.438***	-0.826***	0.269***	0.613***	0.189***
	st.err.	(0.052)	(0.057)	(0.027)	(0.016)	(0.016)	(0.008)	(0.041)	(0.044)	(0.031)	(0.015)	(0.016)	(0.008)
	n.obs		**231**			**892**			**424**			**1421**	
ME	**coeffs**	0.502***	0.314***	0.313***	0.157***	0.712***	0.255***	0.355***	0.497***	-0.871***	0.154***	0.704***	0.341***
	st.err.	(0.028)	(0.032)	(0.004)	(0.009)	(0.008)	(0.005)	(0.021)	(0.028)	(0.020)	(0.007)	(0.007)	(0.005)
	n.obs		**698**			**2726**			**1350**			**3849**	
EL	**coeffs**	0.485***	0.404***	-0.620***	0.096***	0.841***	0.138***	0.373***	0.460***	-0.436***	0.101***	0.833***	0.288***
	st.err.	(0.024)	(0.021)	(0.018)	(0.010)	(0.011)	(0.007)	(0.017)	(0.015)	(0.012)	(0.009)	(0.009)	(0.006)
	n.obs		**1334**			**4883**			**2559**			**5008**	
MA	**coeffs**	0.466***	0.349***	-0.751***	0.097***	0.864***	0.097***	0.378***	0.445***	-0.519***	0.082***	0.856***	0.208***
	st.err.	(0.027)	(0.026)	(0.022)	(0.006)	(0.006)	(0.004)	(0.018)	(0.020)	(0.014)	(0.006)	(0.006)	(0.003)
	n.obs		**976**			**6605**			**1924**			**7212**	
MV	**coeffs**	0.422***	0.583***	-0.540***	0.194***	0.747***	0.169***	0.460***	0.551***	-0.414***	0.175***	0.748***	0.254***
	st.err.	(0.036)	(0.041)	(0.029)	(0.016)	(0.016)	(0.008)	(0.028)	(0.026)	(0.018)	(0.015)	(0.015)	(0.007)
	n.obs		**375**			**1159**			**728**			**1441**	
OTR	**coeffs**	0.440**	0.512**	-0.719***	0.105**	0.800***	0.132***	0.147	0.739**	-0.609***	0.074**	0.823**	0.226***
	st.err.	(0.145)	(0.140)	(0.071)	(0.022)	(0.022)	(0.010)	(0.086)	(0.100)	(0.051)	(0.025)	(0.024)	(0.012)
	n.obs		**85**			**558**			**190**			**519**	

Bootstrapped standard errors (100 replications) in parenthesis.
***,**,* significant values at 99, 95, 90%

Table 9: Robustness, flexible number of clusters - LR test.

SECTOR	**LR (M=1)**	**LR (M=2)**	**LR (M=3)**	**LR (M=4)**
CH	0.05	0.05	**0.25**	
RP	0.02	0.02	**0.38**	
ONM	0.02	0.02	**0.71**	
BM	0.02	**0.08**		
ME	0.02	0.04	0.02	**0.29**
EL	0.02	0.04	**0.58**	
MA	0.02	0.04	0.04	**0.52**
MV	0.02	0.04	0.04	**0.57**
OTR	0.02	0.04	**0.54**	

LR = log-likelihood ratio test values for H_0 : numb. of segments $= M, H_1$: numb. of segments $> M$
Bootstrapped tests (25 replications).
Decisive tests in boldface.

Table 10: Robustness, flexible number of clusters - mixture regression output.

		Cluster 1			**Cluster 2**			**Cluster 3**			**Cluster 4**		
		β_K	β_L	**const**	β_K	β_L	**const**	β_K	β_L	**const**	β_K	β_L	**const**
CH	**coeffs**	0.381***	0.467***	-0.571***	0.272***	0.781***	0.016***	0.155***	0.771***	0.056***			
		(0.041)	(0.041)	(0.045)	(0.026)	(0.025)	(0.017)	(0.014)	(0.011)	(0.009)			
	n.obs		**573**			**696**			**12585**				
RP	**coeffs**	0.495***	0.413***	-0.405***	0.413**	0.436**	-1.522***	0.154***	0.796***	0.149***			
		(0.018)	(0.018)	(0.021)	(0.191)	(0.212)	(0.252)	(0.006)	(0.007)	(0.004)			
	n.obs		**926**			**1842**			**7760**				
ONM	**coeffs**	0.549***	0.308***	-0.381***	0.297***	0.662***	0.157***	0.097***	0.896***	-0.036**			
		(0.024)	(0.025)	(0.026)	(0.010)	(0.011)	(0.011)	(0.021)	(0.024)	(0.016)			
	n.obs		**1130**			**6410**			**364**				
BM	**coeffs**	0.537***	0.322***	-0.574***	0.249***	0.640***	0.256***						
		(0.037)	(0.039)	(0.044)	(0.013)	(0.012)	(0.006)						
	n.obs		**671**			**2297**							
ME	**coeffs**	0.479***	0.247***	-0.672***	0.245***	0.534***	0.326***	0.134***	0.758***	0.272***	0.124***	0.738***	.738***
		(0.019)	(0.021)	(0.021)	(0.023)	(0.034)	(0.020)	(0.011)	(0.014)	(0.011)	(0.021)	(0.020)	(0.037)
	n.obs		**2180**			**112**			**5301**			**1030**	
EL	**coeffs**	0.456***	0.339***	-0.383***	0.406*	0.397*	-1.783***	0.040***	0.908***	0.167***			
		(0.017)	(0.016)	(0.019)	(0.200)	(0.180)	(0.292)	(0.008)	(0.009)	(0.004)			
	n.obs		**2140**			**2364**			**9280**				
MA	**coeffs**	0.452**	0.239	-1.593***	0.433***	0.315***	-0.509***	0.070***	0.882***	0.129***	0.017	0.930***	0.648***
		(0.138)	(0.172)	(0.240)	(0.016)	(0.016)	(0.016)	(0.004)	(0.005)	(0.003)	(0.012)	(0.011)	(0.013)
	n.obs		**350**			**2070**			**9058**			**5239**	
MV	**coeffs**	0.516***	0.552***	-0.440***	0.379***	0.391***	-0.013	0.122***	0.831***	0.181***	0.070**	0.806***	0.502***
		(-0.030)	(-0.033)	(-0.036)	(0.041)	(0.039)	(0.044)	(0.019)	(0.021)	(0.012)	(0.026)	(0.027)	(0.023)
	n.obs		**773**			**401**			**2160**			**369**	
OTR	**coeffs**	0.368**	0.574***	-0.553***	0.116***	0.796***	0.121***	0.018	0.855***	0.462***			
		(0.09)	(0.089)	(0.053)	(0.018)	(0.019)	(0.013)	(0.030)	(0.029)	(0.022)			
	n.obs		**241**			**928**			**183**				

Bootstrapped standard errors (100 replications) in parenthesis.
***,**,* significant values at 99, 95, 90%

Table 11: Robustness, re-run estimations.

	Clustering over sub-periods		Flexible number of clusters
	Technology adoption effects	*tfp* **effects**	*tfp* **effects**
	Coeff.	Coeff.	Coeff.
Firm Intangibles (log, instrumented)	0.058 (0.008)***	0.012 (0.006)**	0.023 (0.009)**
Firm Age	-0.005 (0.009)***	-0.023 (0.007)***	-0.050 (0.013)***
Listed Firm	-0.528 (0.169)***	-0.191 (0.178)	-0.169 (0.264)
Sales (log)	0.265 (0.015)***	0.346 (0.011)***	0.305 (0.016)***
Regional R&D	0.001 (0.000)***	-0.000 (0.000)	0.000 (0.000)
Region Accessibility	0.000 (0.000)*	0.000 (0.000)	0.000 (0.000)
Neighbouring Regions R&D	15.944 (11.711)	-47.710 (146.513)	dropped
Labour Cost	-0.037 (0.045)	0.059 (0.010)***	0.080 (0.016)***
Country EPL	-0.171 (0.514)	0.167 (0.056)***	0.277 (0.094)***
Shareholder Rights	-0.181 (0.370)	-0.500 (0.039)***	-0.452 (0.064)***
Independent Directors	-0.001 (0.007)	0.014 (0.001)***	0.014 (0.001)***
Constant	-0.274 (1.580)	-2.255 (0.277)***	-2.789 (0.167)***
First-stage R2	0.991	0.966	0.965
Wald χ^2	5.52		
[Prob> χ^2]	[0.018]		
F-stat	-	2.1e+05	1.9e+05
[Prob>F]	-	[0.000]	[0.000]
Null hyp. of weak IV (Cragg-Donald test)	-	rejected	rejected
Firm, country, sector, year effects	yes	yes	yes
Number of obs.	15358	13470	12541
Dependent variable:	*Group* $\mathcal{H}$	*tfp*	*tfp*
Estimation method:	FE panel logit	FE panel GLS	FE panel GLS

Standard errors in parenthesis.
***,**,* significant values at 99, 95, 90%

Table 12: Robustness, country selection - within country technology composition (sectoral averages).

Technology Group	**AT**	**BE**	**CZ**	**DE**	**ES**	**FI**	**FR**	**GB**
$\Theta_{\mathcal{H}}$	97.1	98.0	22.7	97.1	88.6	93.4	95.2	94.5
$\Theta_{\mathcal{L}}$	2.9	2.0	77.3	2.9	11.4	6.6	4.8	5.5

Technology Group	**HU**	**IT**	**NL**	**NO**	**PT**	**SE**	**SI**	**SK**
$\Theta_{\mathcal{H}}$	22.3	95.7	95.9	93.5	60.8	93.4	44.8	32.7
$\Theta_{\mathcal{L}}$	77.7	4.3	4.1	6.5	39.2	6.6	55.2	67.3

Average sectoral shares of total country-sector obs (%).

Table 13: Robustness, comparison between cross-country and within country clustering (selected countries).

COUNTRY	**SECTOR**	within country technology composition (from cross-country mixture model)		within country number of technology clusters (from within-country mixture model)
		$\Theta_{\mathcal{H}}$	$\Theta_{\mathcal{L}}$	
FRANCE	CH	98.74	1.26	1
	RP	97.79	2.21	1
	ONM	96.87	3.13	1
	BM	89.06	10.94	2
	ME	96.04	3.96	1
	EL	96.85	3.15	2
	MA	96.86	3.14	1
	MV	90.76	9.24	2
	OTR	94.15	5.85	2
NORWAY	CH	100	0.00	1
	RP	100	0.00	2
	ONM	96.55	3.45	2
	BM	88.89	11.11	2
	ME	88.57	11.43	1
	EL	96.30	3.70	2
	MA	95.24	4.76	1
	MV	85.71	14.29	1
	OTR	96.67	3.33	2
SLOVAK REPUBLIC	CH	36.63	63.37	2
	RP	49.71	50.29	1
	ONM	50.00	50.00	2
	BM	18.92	81.08	1
	ME	7.98	92.02	1
	EL	20.06	79.94	2
	MA	26.61	73.39	2
	MV	52.83	47.17	2
	OTR	32.00	68.00	2

Table 14: Robustness, production function coefficients.

		OPACF			OLS			OPACF - $\Theta_{\mathcal{H}}$			OPACF - $\Theta_{\mathcal{L}}$		
SECTOR		β_K	β_L	$\beta_K + \beta_L$	β_K	β_L	$\beta_K + \beta_L$	β_K	β_L	$\beta_K + \beta_L$	β_K	β_L	$\beta_K + \beta_L$
CH	**coeffs**	0.15	0.57	0.72	0.22	0.73	0.95	0.14	0.51	0.65	0.10	0.85	0.95
	st.err.	0.043	0.084	-	0.006	0.006	-	0.038	0.060	-	0.358	0.146	-
RP	**coeffs**	0.21	0.34	0.55	0.28	0.66	0.94	0.14	0.65	0.80	0.27	0.63	0.89
	st.err.	0.053	0.066	-	0.007	0.007	-	0.035	0.063	-	0.114	0.203	-
ONM	**coeffs**	0.22	0.75	0.97	0.40	0.55	0.95	0.20	0.79	0.98	0.31	0.71	1.02
	st.err.	0.068	0.090	-	0.008	0.008	-	0.039	0.055	-	0.244	0.138	-
BM	**coeffs**	0.49	0.76	1.25	0.47	0.41	0.88	0.13	0.79	0.91	0.48	0.49	0.96
	st.err.	0.148	0.247	-	0.018	0.018	-	0.087	0.108	-	0.171	0.134	-
ME	**coeffs**	0.31	0.32	0.63	0.36	0.47	0.83	0.07	0.74	0.82	0.40	0.58	0.98
	st.err.	0.102	0.148	-	0.010	0.010	-	0.044	0.069	-	0.089	0.117	-
EL	**coeffs**	0.21	0.51	0.71	0.22	0.69	0.90	0.03	0.81	0.84	0.35	0.32	0.67
	st.err.	0.057	0.085	-	0.007	0.007	-	0.038	0.055	-	0.068	0.070	-
MA	**coeffs**	0.17	0.80	0.97	0.20	0.72	0.92	0.05	0.79	0.83	0.28	0.66	0.94
	st.err.	0.039	0.074	-	0.006	0.006	-	0.031	0.050	-	0.060	0.046	-
MV	**coeffs**	0.10	0.52	0.62	0.36	0.58	0.94	0.09	0.74	0.83	0.31	0.67	0.98
	st.err.	0.110	0.147	-	0.014	0.014	-	0.083	0.100	-	0.103	0.097	-
OTR	**coeffs**	0.30	0.89	1.19	0.20	0.71	0.91	-0.08	0.78	0.70	-0.05	0.63	0.58
	st.err.	0.237	0.263	-	0.028	0.027	-	0.121	0.143	-	0.468	0.344	-