The Role of 'Research' and 'Development' in Technology Upgrading of a Firm*

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Abstract

In this paper I use longitudinal data from the Spanish innovation panel (PITEC) to uncover separate effects of 'Research' and 'Development' on productivity growth at the firm level. I report expected dynamic gains (discounted flow of profits) as well as fixed costs associated with both types of R&D activities. By bringing together the ideas from the structural productivity estimation literature and treating R&D as a search process, I develop a model of innovation and productivity dynamics that accounts for intrinsic differences between 'Research' and 'Development' (unlike previous models considering R&D as a uniform activity). In the model firms invest in 'Development' to search for higher productivity levels on intervals of the technology distribution, while investments in 'Research' expand frontiers of firm-specific search intervals. Given the observable entry into 'Research' and 'Development', the model is used to identify fixed costs of the two activities. The findings show that 'Research' is a primary contributor to the productivity growth, when both direct and indirect effects are taken into account. 'Research' significantly improves success rates of 'Development' in the long run. At the same time, it turns out that fixed costs of R&D have been largely underestimated in the previous literature, where 'Research' and 'Development' expenses are not differentiated. For instance, I find 'Research' to be almost ten times more expensive than 'Development' when it comes to fixed costs. It implies that only a narrow class of firms with 'Research' as a potentially optimal strategy can in practice afford to invest in this activity and bear the risks connected to it. Hence, policies using R&D subsidies to boost productivity have to consider structural differences between 'Research' and 'Development'.

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1 Introduction

The vast literature on technological change agrees that R&D is a key contributor to the economic growth in the long run (Acemoglu et al., 2018). When resources are scarce, it is better technologies (productivity) that allow firms to expand and generate higher profits. Nowadays, many economies experience the consequences of the global productivity slowdown (Goldin et al., 2022). Some studies suggest that it is the researchers that are becoming less productive (Bloom et al., 2020). Others highlight diminished allocative efficiency gains as a primary reason (Decker et al., 2017). However, both strands of the literature point out that the link between R&D and productivity is far from being well-understood. In this paper I will show that a proper evaluation of long-term technological changes requires separate accounting for 'Research' (R) and 'Development' (D). Most often economists treat R&D as a uniform activity, while, in fact, the tasks performed by researchers and developers differ significantly.

Hereinafter the 'Research' term covers basic and applied research, while 'Development' stands for the experimental development. The given classification of R&D types has been standardised by OECD already in the 1960s in the Frascati Manual (OECD, 2015) and definitions did not change much since then.[1] Basic research is performed 'to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view'. Applied research is 'original investigation undertaken in order to acquire new knowledge, however, directed primarily towards a specific, practical aim or objective'. Finally, experimental development 'draws on knowledge gained from research and produces additional knowledge, which is directed to producing new products or processes or to improving existing products or processes'.

The current paper is aimed at disentangling individual effects of R and D on firm-level productivity and estimating monetary gains from both activities. Traditionally, in the productivity literature, even when certain studies did differentiate between R and D components, their channels of influence on productivity were assumed to be similar. However, I show that it is not necessarily the case. In order to do so I impose an explicit structure on the productivity process in the form of a technology search model. Essentially, it is assumed that all available technologies (productivity levels) can be summarised by some distribution. Then the state of each firm is comprised of two parameters – current productivity level and potential productivity level that it can achieve (frontier). Both parameters are firm-specific. Investment in development allows a firm to improve current productivity level while aiming at its potential productivity, which is not always successful. Investment in research makes it possible to increase the firm's potential productivity level only, hence, not directly affecting productivity. At the same time, higher potential productivity levels

[1] Some consider the terminology outdated and irrelevant, others point to the fact that it is very hard to distinguish between basic and applied research within a single R&D project. It becomes even more problematic at the level of a single firm where the same team can participate in multiple projects. Nevertheless, it is hard to find any other consistent way of measuring such an elusive process as R&D and knowledge in general. As mentioned in Hall et al. (2010), it might not be of benefit to make definitions more complex and disaggregate R&D into many separate activities. They suggest to identify R&D types in terms of their distance to commercial output. Development is the closest stage and gets the highest share in total R&D spending, while basic research is the activity most remote from the final product with the lowest share in total R&D spending (in an average manufacturing firm).

provide more options to choose from while conducting development projects.

I combine the technology search model with a standard structural productivity estimation framework and perform the analysis in three steps. First, I specify the short-run problem of a firm and estimate revenue productivity from the optimality conditions using inverted demand for labour. Next, I treat these estimates as draws from the technology search distribution. Therefore, it becomes possible to estimate parameters of the search distribution in the second step given the observed R&D decisions of firms. After recovering firm-level technology frontier levels, there is enough information to construct the state-space and perform dynamic estimations. I apply the value function iteration algorithm and maximise the log-likelihood in order to get estimates of fixed costs parameters. Then, I compute expected dynamic gains associated with different R&D choices across observed productivity and technology frontier levels. Simulating a decline in R&D fixed costs, I perform counterfactual analysis and study industry-level responses in terms of productivity and total share of innovative firms.

The foundation of the model relies on two well-established strands of economic literature that have been rarely combined before. On the productivity side, the paper follows the idea of using short-run optimality conditions similar to Aw et al. (2011) and Peters et al. (2017) among others, which is primarily motivated by the data at hand. When it comes to the innovation process, there is a huge variety of theoretical frameworks modelling the arrival of new technologies. Purposes of using such models differ widely as well. In this paper the choice is to treat R&D as a search process in the spirit of Evenson and Kislev (1976) and Lee (1982). It allows me to capture intrinsic differences between R and D.[2] Moreover, the idea can be smoothly integrated into the chosen productivity estimation model. Thus, by bridging the gap between two theoretical frameworks, it is finally possible to reveal interactions between R and D in the productivity process and separately estimate fixed costs associated with each activity.

The paper provides several major findings. Most importantly, I show that fixed costs associated with R&D have been underestimated in previous studies (though the empirical sample tends to be biased towards large firms). When total R&D expenses are used to evaluate the fixed costs of R&D, it is only the fixed costs of the least expensive component that can be captured because the investment in R&D can either be an investment in R, D or both. I evaluate fixed costs of R to be almost ten times higher than fixed costs of D (when treating them as separate activities). Along with that, it is the research component that accounts for a larger part of the productivity growth. Further dynamic estimates demonstrate that the optimal choice of investing in R&D depends on very specific combinations of productivity and technology frontier levels. Finally, I show that development becomes riskier at higher productivity levels.

The remainder of this paper is structured as follows. In Section 2 I provide a comprehensive review of the literature in the field in order to determine common assumptions about key differences between research and development activities. In Section 3 I develop a structural model of productivity dynamics with research and development. Section 4 contains an overview of the dataset and

[2]See, for example, the Frascati Manual (OECD, 2015).

key variables. Section 5 is devoted to the empirical strategy and identification. Section 6 analyses the results. Section 7 deals with counterfactuals. Section 8 concludes.

2 Literature

One of the first comprehensive economic reviews of different R&D types and their contribution to firm performance has been presented in Nelson (1959). The major discussion point is related to the existence of basic research in many of the private sector firms. The author argues that if markets were to be perfect and competitive, there would be no resources drawn to basic research in the private sector. Hence, the evidence of within-firm basic research activities requires an economic explanation of its own. The following argumentation suggests that basic research in the private sector is highly heterogeneous in its nature and differs tremendously from research in the public sector. Namely, firms do not need to invest in all fields of basic research, they only need to cover what is relevant for their industry. It implies that more focused private research can potentially push development further at faster rates than research in the public sector (where optimal investment strategies are chosen by the social planner). Thus, private firms have the opportunity to endogenously direct the evolution of technologies they use. The key challenge, however, is to test these theoretical propositions. For instance, comprehensive firm-level datasets with highly-disaggregated R&D information are still relatively new. Moreover, the dynamic estimation of firm-level technological changes is associated with a range of econometric challenges in itself.

Mansfield (1980) was one of the first to investigate the role of basic research in manufacturing sector empirically. He expresses that data on the composition of R&D expenditures at the firm level is rare, thus, there is space primarily for the theoretical work in the field. Nevertheless, the study uncovers a statistically significant and direct relationship between the amount of basic research carried out by an industry or a firm and its rate of increase of total factor productivity, when its expenditures on applied research (incl. development) are held constant. Namely, total returns to R&D constitute about 27% of productivity growth in the long-run with basic research (or long-term research) accounting for more than half of it. At the same time, it is highlighted that firm-level expenses on basic research have been declining throughout the sample period. The study, however, does not provide a clear perspective on the interaction mechanism between basic and applied research. It is also puzzling that it is basic research that is of importance considering its remoteness from the commercial product.[3] The results could also mean that firms performing basic research become more successful in applied research, but it is still applied research that contributes directly to productivity. When there is not enough variation in the sample, it becomes harder to capture effects stemming from applied activities with standard regressions. Therefore, in order to resolve this ambiguity, I will try to look deeper into the complementarity and substitutability of R and D activities by explicitly modelling the innovation process and its effects on productivity.

Several options exist when it comes to modelling the link between R&D and productivity. The

[3] See the discussion in Section 1 and Hall et al. (2010).

development of the first approach to measure R&D capital and quantify R&D contribution to productivity at the firm level is usually attributed to Griliches (1979).[4] The knowledge capital model has been suggested to account for the simultaneity problem in productivity estimation while providing causal estimates of R&D effects on productivity growth. Later, the CDM model appeared and improved our understanding of the relationship between R&D and firm performance (Crépon et al., 1998). It is a structural model where productivity depends on the innovation output, and equations for innovation output rely on R&D inputs. Most often the model is applied to the data from Community Innovation Surveys (CIS) conducted in the EU. Data from the Spanish innovation panel (PITEC) follows the CIS design, therefore, it is also possible to apply structural methods. Moreover, the findings in this paper become potentially comparable to results reported in other empirical papers using CIS surveys.

Some of the recent literature has advanced the CDM and Griliches frameworks and developed more robust techniques of productivity estimation under different R&D regimes. However, all of the papers to my knowledge deal with total R&D expenditures and do not estimate contributions of research and development separately. Doraszelski and Jaumandreu (2013) develop a comprehensive framework to measure R&D contribution to productivity in the Spanish manufacturing sector. The model relies on non-parametric estimation of productivity and requires information on input and output prices. They find one-year R&D returns to account for about 5% of productivity growth. Peters et al. (2017) expand the model with an additional estimation stage. First, they calculate the probability of innovation based on previous period R&D expenses. Then, successful innovations contribute to productivity improvement. The study shows that product innovations are more important in high-tech industries, raising productivity by 3.6%, whereas process innovations are more important for firms in low-tech industries, raising productivity by 3.5%. There are also studies measuring interactions between R&D and exports. For instance, Aw et al. (2011) use plant-level data for the Taiwan electronics industry from the period 2000-2004 and find that export market participation raises future productivity by 1.96%, while R&D investment raises it by 4.79%. Bøler et al. (2015) use the Norwegian register data and exploit the introduction of an R&D tax credit in Norway in 2002. They find that the short-run impact of R&D investment on revenue is in the vicinity of 8%. In this paper I apply similar estimation techniques when it comes to static decisions, but use a novel approach to solve the dynamic problem of a firm and accommodate individual effects of R and D.

The key novelty relies on modelling R&D and innovation as a search process. Evenson and Kislev (1976) build up a stochastic model of basic and applied research that has been primarily used to study innovations in agriculture. The setting allows modelling the discovery of new technologies (productivities) as an opening of new exponential distributions to search. It leads to two main consequences: (i) the model makes it possible to rationalise the interactions between basic and applied research by explicitly differentiating between the effects of these activities on the productivity distribution; (ii) the framework works with observable outcomes, hence, becomes problematic when

[4]See Griliches (1990) for a later review of estimation techniques and measurement approaches.

productivity of a firm is hidden from the econometrician. In this paper I will try to to utilise the advantages of the search model while combining it with standard methods of structural productivity estimation in order to account for possible endogeneities.

It is important to highlight several empirical studies investigating differences between R and D activities at different levels. The findings will motivate the modelling choices in this paper. Most of the literature is focused on macro-level or industry-wide outcomes. Traditional view is to assume that basic research comes from the public sector while private sector is engaged in applied research and development activities.[5] Gersbach et al. (2018) develop such a model where basic research extends the knowledge base, while applied research (incl. experimental development) commercialises it. The model is constructed from the hierarchy of basic and applied research. Authors assume that basic research is exclusively funded by the public sector and produces no commercial output. Applied research is done by private firms where they learn about prototypes developed in the public sector and try to modify them for commercial purposes. They report that higher public funding of basic research always translates into higher growth as long as it does not attract all the labour force and the private sector actively sources knowledge from the public sector. At the same time, despite the fact that the process of commercialising basic research is not immediate (their estimate for the US is about eleven years), the knowledge frontier might soon become a constraint. The study accounts for generous research subsidies increasing catch-up rates in the private sector. Similar implications can be found in Cozzi and Galli (2009). However, they also report that a lot of basic research projects in the public sector are originally motivated by problems arising in the private sector. Since public sector researchers are usually motivated by patents, establishment of a solid link between R&D projects in public and private sectors proves to have positive welfare effects. Naturally, in a later study they extend the idea and account for an important empirical fact that is often neglected – private firms can perform basic research themselves (Cozzi and Galli, 2014). They find that there is a stronger positive externality from private research on private development than from public research on private development.

The paper by Czarnitzki and Thorwarth (2012) is one example of a micro-level study aimed at disentangling R and D effects on different variables related to firm performance. Using a sample of Belgian firms, the study reveals a premium for basic research on a firm's net output and shows that it is observed predominantly in high-tech manufacturing industries. They report that effects of investing in basic research are almost three times higher in terms of productivity growth compared to investments in applied research and development. Total stocks of R&D capital have a positive impact on productivity growth both in high-tech and low-tech manufacturing sectors. The methodology is based on a model in the spirit of Griliches (1979) with two types of knowledge capital: basic and applied (incl. development). The assumption is that knowledge capital directly enters the production function. Investment in basic research exhibits a premium over investments in applied research and, thus, has a stronger impact on total knowledge capital accumulation. Basic research premium is the main parameter of interest in the model. It is estimated with a linear feedback

[5] For instance, see the discussion in Faulkner and Senker (1994), Salter and Martin (2001), Toole (2012), Prettner and Werner (2016).

model, hence, utilises information from the pooled cross-section dataset where pre-sample period means are used to approximate for unobserved heterogeneities. Original dataset is a panel from the Flemish Research and Development Survey similar to Community Innovation Surveys (CIS). The authors touch upon some important issues when discussing the results of their investigation. For instance, it is clear that firms in high-tech industries benefit a lot from basic research. However, it seems that the appropriability conditions for basic research are more favourable in low-tech rather than high-tech industries. It means that firms in low-tech manufacturing might as well be technology intensive and adopt basic knowledge even faster than their peers in high-tech manufacturing (e.g., advanced optical equipment to cut wood or biotechnologies in food sector). The study, however, abstracts from structural interactions between R and D as determinants of productivity dynamics.

The problem is addressed in the paper by Akcigit et al. (2020). They present motivating evidence and estimate moments to be used in calibration exercise from the micro-level data, even though their primary focus is on macroeconomic outcomes. The dataset comes from the French Research and Development Survey (similar to the CIS design), French accounting registers and NBER patent database. Time coverage is rather short and spans from 2000 to 2006. The key observation is that firms involved in basic research tend to have more diversified activities. Not only are they generally larger, but they sell varieties of differentiated products and conduct activities in several industries at the same time. For example, some firms in computer and electronics manufacturing sell software and invest in IT research. Likewise, companies producing household chemicals in some instances are also involved in the production of over-the-counter (OTC) drugs. Therefore, in the model, the firm is the collection of product lines that might belong to different industries. The portfolio of products evolves over time due to acquisition of new product lines (innovation) and loss of outdated product lines (competition). Basic research allows a firm to move on to new product lines while applied research improves quality of existing product lines. The authors report overinvestment in applied research and underinvestment in basic research in equilibrium. Hence, uniform R&D subsidies turn out to be inefficient. The framework estimates productivity as an aggregate over productivity of product lines which is a constant per unit of labour. Thus, the approach is useful to explain aggregate fluctuations, but becomes less flexible when it comes to micro-level problems of endogeneity and simultaneity when estimating unobservable productivity measures. It, however, gives an idea about additional factors that force firms to do research. In the model, I will try to account for multiple product lines by introducing respective cost shifters in the static problem of a firm.

When it comes to studies of research and development at the firm level, a wide array of literature in management science has to be mentioned. Researchers highlight the fact that the degree of switching between R and D has a huge impact on firm performance (in terms of output, profits and productivity).[6] Mavroudi et al. (2020) provide a recent investigation based on the firm-level longitudinal data from the Spanish innovation panel (PITEC). They estimate productivity as a

[6]Non-exhaustive list of papers on the topic includes He and Wong (2004), Jansen et al. (2006), Lisboa et al. (2011), Hsu et al. (2013), Mudambi and Swift (2014), Ngo et al. (2019).

residual from the Cobb-Douglas production function and use the frequency of switching between research and development as an explanatory variable. In line with previous research, they find that the faster the switching, the better the performance (on average). However, firms in high-tech manufacturing industries can afford to switch more often while firms in low-tech manufacturing industries perform better when they switch less. Hence, it becomes crucial to understand when flexibility contributes positively to productivity and when it compromises organisational learning. This paper attempts to develop a flexible framework that would allow accounting for switches between innovation choices. Even though R&D decisions demonstrate a lot of persistence in the Spanish innovation panel (PITEC), there are substantial proportions of firms switching back and forth between research and development during short periods of time. In the model, the relationship between the parameters of the technology search distribution and fixed costs of R and D will affect the incentives to switch between the two activities at faster or slower rates (optimal allocation of R and D choices in time).

3 Model

In this section I develop a theoretical model that rationalises a firm's choice to invest in 'Research' (R) and 'Development' (D). The key parameters of the model are (i) realised productivity levels ($\tilde{\omega}_{it}$) and (ii) technology frontier levels (τ_{it}). They will set the borders for technology search intervals defining a sequence of per-period states for each firm to be used in the dynamic estimation. First, I provide a model of production in the short run similar to Aw et al. (2011) and Peters et al. (2017). Next, I describe the innovation process in greater detail following the early works of Evenson and Kislev (1976) and Lee (1982). Thus, the extended productivity estimation framework allows me to account separately for R and D contribution to the technology upgrading at the firm level.

3.1 Production in the short run

The model of production in the short run follows directly the ideas from Aw et al. (2011) and Peters et al. (2017). I start by specifying firm-level product demand. Suppose that for a firm i in time period t it takes the Dixit-Stiglitz form:

$$q_{it} = Q_t \left(\frac{p_{it}}{P_t} \right)^{\eta} \exp(z_{it}) = \Phi_t (p_{it})^{\eta} \exp(z_{it}) \tag{1}$$

where Q_t and P_t represent aggregate industry output and price index respectively, p_{it} and z_{it} are firm-level output price and demand shifter, η is the constant elasticity of demand relevant for all firms in an industry.[7] Industry aggregates are further combined into a single variable Φ_t.

Next, short-run marginal cost of the firm (in logs) is determined by:

$$c_{it} = c(k_{it}, d_{it}, w_t) - \omega_{it} = \beta_0 + \beta_k k_{it} + \beta_d d_{it} + \beta_w w_t - \omega_{it} \tag{2}$$

[7] It is possible to specify a time-varying elasticity of demand η_t in this model, similar to Jaumandreu and Yin (2017), however, it is not possible to recover these values empirically due to data limitations.

where k_{it} is the capital stock, w_t is a vector of variable input prices faced by all firms in the industry, d_{it} accounts for other potential observable firm-level cost shifters (such as age and ownership information). The final term ω_{it} represents productivity component (or technological capacity) observed by a firm but unavailable in the data.

Market structure is defined by monopolistic competition between firms, therefore, constant mark-up pricing applies: $p_{it} = \left(\frac{\eta}{1+\eta}\right)\exp(c_{it})$. First-order condition for a market price leads to the following revenue function:

$$\begin{aligned} r_{it} &= (1+\eta)\ln\left(\frac{\eta}{1+\eta}\right) + \ln\Phi_t + (1+\eta)(\beta_0 + \beta_k k_{it} + \beta_d d_{it} + \beta_w w_t - \omega_{it}) + z_{it} \\ &= (1+\eta)\ln\left(\frac{\eta}{1+\eta}\right) + \ln\Phi_t + (1+\eta)(\beta_0 + \beta_k k_{it} + \beta_d d_{it} + \beta_w w_t - \tilde{\omega}_{it}) \end{aligned} \tag{3}$$

where $\tilde{\omega}_{it} = \omega_{it} - \frac{z_{it}}{1+\eta}$ is a measure of revenue productivity of a firm I am going to focus my attention on. It is important to highlight that the measure of $\tilde{\omega}_{it}$ will be affected both by changes in technology and product appeal (potentially as well as mark-ups). However, I do not aim to separately identify the relative importance of these channels.[8] More specifically, I assume that R&D activities of a firm might affect both the demand side – z_{it} (customer preference towards high-tech products), and the production side – ω_{it} (R&D leading to product and process innovations within a firm). Thus, I am predominantly interested in how changes in $\tilde{\omega}_{it}$ induced by R&D activities (either through demand or costs) are reflected in firm sales and profits. The structure of the model will help me to quantify these effects.

Finally, the chosen specification can be characterised by the following relationship between short-run profits of a firm and its revenue:

$$\pi_{it} = \pi(\tilde{\omega}_{it}) = -\frac{1}{\eta}\exp(r_{it}) \tag{4}$$

Short-run profits of a firm will be used to further rationalise firm-level choice and mix of R&D activities in a dynamic setting. Importantly, there is a one-to-one mapping between productivity $\tilde{\omega}_{it}$ and short-run profits. I follow Aw et al. (2011) and assume that capital stock k_i is fixed over time when it comes to modelling dynamic decisions of a firm. The variation from $\ln\Phi_t$ will be absorbed by time fixed effects.

3.2 Innovation process

This part of the model is inspired by the literature on R&D as a search process (see Evenson and Kislev, 1976; Lee, 1982). The firm can decide to engage in R&D activities that would endogenously affect the productivity process – $\tilde{\omega}_{it}$. The technology state of a firm i in time period t is characterised by two variables $(\tilde{\omega}_{it}, \tau_{it})$, where $\tilde{\omega}_{it}$ is the realised productivity and τ_{it} is the best available

[8] It is not possible to identify demand shifters in the Spanish data, since there is no information on firm-level output prices. Studies that focus on disentangling pure technology change from shifts in consumer demand include among others Foster et al. (2008), Roberts et al. (2017), Gandhi et al. (2020).

technology (frontier). In time period $t = 0$ each firm is randomly assigned a realised productivity level $\tilde{\omega}_{i0}$ and $\tau_{i0} = \tilde{\omega}_{i0} + \varepsilon$. The value of ε represents the state of publicly available research that is exogenous to a firm.[9] Every period the firm chooses between doing research (ρ_{it}), development (δ_{it}), or both.[10] The decision is sequential in a sense that a firm decides on research activities first, and then optimally chooses development.[11] That assumption is in line with practical differences between research and development activities.

If a firm does not engage in R&D activities, then no endogenous relationship between R&D and productivity can be established. In that case I simply assume that productivity evolves as an exogenous Markov process: $\tilde{\omega}_{it} = \alpha \cdot \tilde{\omega}_{it-1} + \xi_{it}$. Here $\alpha \in (0, 1)$ can be interpreted as a known depreciation rate of technology, while ξ_{it} is an i.i.d. exogenous shock to productivity. Since the firm cannot observe ξ_{it}, innovative decisions are based on the value of α.

Initial productivity levels and technological opportunities are drawn from a probability distribution $F(\cdot)$. A firm that decides to proceed with development draws a new value of realised productivity from the interval $[\tilde{\omega}_{it}, \tau_{it}]$ and behaves optimally after that. Development is associated with fixed costs of γ^{δ}. Research allows a firm to update its best available technology by drawing a new value of τ_{it} from the interval $[\tau_{it}, \infty)$ at a cost γ^{ρ}.[12] Hence, realised productivity level changes only when development activities are performed. Research in itself does not affect the realised productivity level but rather gives access to better productivity draws that can be potentially implemented through development at a later stage.

The stylised search mechanism is illustrated in Figure 1. Here I assume that all existing technologies are represented by the distribution $F(\cdot)$, but firms have access to technologies only on the specific interval $[\tilde{\omega}_{it}, \tau_{it}]$. Hence, if they want to improve productivity, they have to perform R&D. At the same time, pure research affects only the technology frontier. Therefore, investment in research suggests commitment to conduct development in the future.

To summarise, every firm potentially has four different modes of innovative behaviour in a given period:

(i) do not perform R&D at all;

(ii) perform only development activities (δ_{it});

(iii) perform only research activities (ρ_{it});

[9] In the model all firms face the same value of ε that is fixed over time. It can also be specified as a process ε_t evolving over time. It is not very relevant for the purposes of this study since the focus here is on the within-firm dynamics.

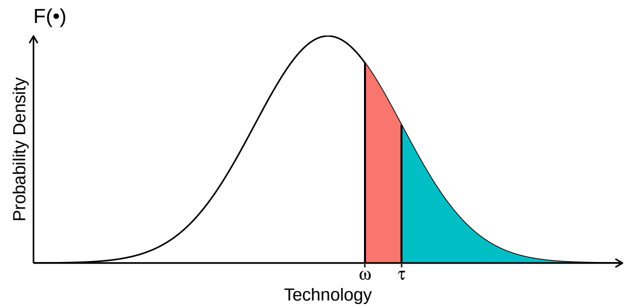
[10] R&D variables are specified as indicators in a basic setting. It is possible to extend the model to account for varying R&D intensities. However, it would require to specify additional parameters of Poisson distributions controlling the arrival of realised productivity levels and best available technologies. Moreover, R&D intensity levels do not show a lot of variation in the Spanish data over time at the firm level. Therefore, estimation possibilities would be rather limited when using continuous variables.

[11] The case of joint decisions is possible, but leads to a multinomial model requiring more complicated estimation techniques.

[12] Fixed costs can also be specified as varying across firms over time – γ^{δ}_{it} and γ^{ρ}_{it}. However, I do not find any evidence that this is the case in the PITEC dataset.

(iv) perform both research and development.

Figure 1: *Search over Technology Distribution*



Notes: Theoretical search distribution (normal assumptions), where ω stands for current productivity and τ reflects current level of the best available technology. If a firm chooses to invest in development in current period, it draws new productivity level from the interval $[\omega, \tau]$ in the next period (in red). If a firm chooses to invest in research, it draws new technology frontier level from the interval $[\tau, \infty)$ in the next period (in blue).

If a firm chooses to do research, then it would imply giving up current period productivity gains that could have been achieved by means of development in favour of expanding its search horizon in the future. At the same time, firms have additional motivation to participate in development projects because it allows to prevent realised productivity $\tilde{\omega}_{it}$ from declining. Therefore, development should be more common than research depending on the relationship between relevant components in fixed costs of R&D.[13]

Given the four options for a firm to choose from, the functional equation can be specified as follows:

$$V(\tilde{\omega}_{it}, \tau_{it}) = \pi(\tilde{\omega}_{it}) + \max\{u_{00}(\tilde{\omega}_{it}, \tau_{it}), u_{01}(\tilde{\omega}_{it}, \tau_{it}), u_{10}(\tilde{\omega}_{it}, \tau_{it}), u_{11}(\tilde{\omega}_{it}, \tau_{it})\} \tag{5}$$

where $\{u_{00}(\tilde{\omega}_{it}, \tau_{it}), u_{01}(\tilde{\omega}_{it}, \tau_{it}), u_{10}(\tilde{\omega}_{it}, \tau_{it}), u_{11}(\tilde{\omega}_{it}, \tau_{it})\}$ are additional discounted profits generated due to the choice of innovation policy by a firm i in time period t (policies i-iv respectively).

Suppose that discount factor is λ, then for a firm that does not engage in R&D, the flow of additional discounted profits will look as follows:

$$u_{00}(\tilde{\omega}_{it}, \tau_{it}) = \lambda V(\tilde{\omega}_{it}, \tau_{it}) \tag{6}$$

If a firm performs development activities in a period, the reward will be represented by the following equation:

$$u_{01}(\tilde{\omega}_{it}, \tau_{it}) = -\gamma^{\delta} + \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} V(\tilde{\omega}_{it+1}, \tau_{it}) dF(\tilde{\omega}_{it+1}) + \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tilde{\omega}_{it}) \tag{7}$$

[13]The general idea in the literature that research is associated with higher costs than development.

Here the last two terms summarise respectively expected additional flow of discounted profits in case a firm acquires higher realised productivity level through development and in case development turns out to be unsuccessful.

Next, if a firm participates only in research, it gets:

$$u_{10}(\tilde{\omega}_{it}, \tau_{it}) = -\gamma^{\rho} + \lambda \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it}, \tau_{it+1}) dF(\tau_{it+1}) + \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tau_{it}) \tag{8}$$

Similarly, the last two terms summarise expected additional flow of discounted profits in case a firm updates the best available technology through research and in case research turns out to be unsuccessful.

Finally, in case the firm performs both activities:

$$\begin{aligned} u_{11}(\tilde{\omega}_{it}, \tau_{it}) = -\gamma^{\rho} - \gamma^{\delta} &+ \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it+1}, \tau_{it+1}) dF(\tau_{it+1}) dF(\tilde{\omega}_{it+1}) \\ &+ \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} V(\tilde{\omega}_{it+1}, \tau_{it}) dF(\tilde{\omega}_{it+1}) F(\tau_{it}) \\ &+ \lambda \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it}, \tau_{it+1}) dF(\tau_{it+1}) F(\tilde{\omega}_{it}) \\ &+ \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tilde{\omega}_{it}) F(\tau_{it}) \end{aligned} \tag{9}$$

Decisions about research and development are assumed to be disjoint, hence, I can separately estimate gains from these activities considering one or the other as fixed. Furthermore, on a one-period horizon the choice of research does not affect the realisation of $\tilde{\omega}_{it}$ even in case when a firm is doing development as well. Based on that several indifference conditions can be specified.

The following two are sufficient to identify fixed costs associated with particular R&D activities:

$$(u_{00} = u_{01}) : \gamma^{\delta} = \lambda \left(\int_{\tilde{\omega}_{it}}^{\tau_{it}} \left[V(\tilde{\omega}_{it+1}, \tau_{it}) - V(\tilde{\omega}_{it}, \tau_{it}) \right] dF(\tilde{\omega}_{it+1}) \right) \tag{10}$$

$$(u_{00} = u_{10}) : \gamma^{\rho} = \lambda \left(\int_{\tau_{it}}^{\infty} \left[V(\tilde{\omega}_{it}, \tau_{it+1}) - V(\tilde{\omega}_{it}, \tau_{it}) \right] dF(\tau_{it+1}) \right) \tag{11}$$

Here I derive indifference conditions between policies of (i) no R&D, (ii) only development, (iii) and only research. By using the case of 'no R&D' as a baseline in the estimations, I will be able to separate fixed costs (as well as expected dynamic payoffs) by types of R&D activities. As long as expected discounted profits in case of no R&D do not exceed fixed costs of development or research, the firm will not be involved into R&D activities.

The model produces a useful implication. Namely, the optimal R&D decision will depend on the current distance between $\tilde{\omega}_{it}$ and τ_{it}. If current productivity level is close to the frontier, then the expected gains from development will be low due to low probability of a significant improvement in productivity in the next period. On the contrary, the expected gains from research will be high because it will imply higher probability of success for development activities in the next period. If current productivity level is far below the frontier, then it does not make sense to invest in research anymore. It requires to cover additional monetary and time costs of development to get closer to the frontier level of technology. Hence, it will be optimal to focus exclusively on development activities. Only later, when productivity levels get closer to the frontier, it is again optimal to invest in research. The case when a firm chooses to simultaneously perform research and development is rather specific. It is possible that given the empirical approach to the discretisation of the time periods (since time is discrete in empirical datasets), the gains from both activities will be observed at the same time horizon. Then, a firm updates both $\tilde{\omega}_{it}$ and τ_{it} in the same time period. I assume that it does not change the parameters of the general productivity process.

In what follows, I will formalise the above discussion by analysing the value function. In order to do so I compute its derivatives with respect to the state variables (see the Appendix A.1). The differentiability of the value function is guaranteed by the envelope theorem assuming that the value function is continuous on the full interval. Following the assumptions that $F(\cdot)$ satisfies general properties of probability distributions and profits are increasing in productivity, it becomes possible to establish the set of inequalities describing the behaviour of the value function with respect to productivity and technology frontier values:

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} \geq 0,$$
$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it}} > 0,$$
$$\frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} = 0.$$

These inequalities, in turn, lead directly to the dynamic relationship between productivity, technology frontier, and fixed costs values.

Proposition 1 *Incentives to perform development decline with an increase in fixed costs of development:* $\frac{d\tilde{\omega}_{it}}{d\gamma^{\delta}} < 0$.

Proposition 2 *Incentives to perform development decline with an increase in fixed costs of research:* $\frac{d\tilde{\omega}_{it}}{d\gamma^{\rho}} < 0$.

Proposition 3 *Incentives to perform research increase or do not change with an increase in fixed costs of development:* $\frac{d\tau_{it}}{d\gamma^{\delta}} \geq 0$.

Proposition 4 *Incentives to perform research decline with an increase in fixed costs of research:* $\frac{d\tau_{it}}{d\gamma^{\rho}} < 0$.

Therefore, if research gets more expensive, then it affects negatively the whole R&D pipeline. On the other hand, if it is development that gets more expensive, then firms can postpone development activities for later but continue performing research. If it is optimal for a firm to perform only one type of activity per period, then it might choose to invest even more in research, redistributing the resources within its total R&D budget. Furthermore, if both γ^δ and γ^ρ are very high, it will never be optimal to perform both R and D at the same time. The key condition for that is that development activities should bring high enough profits already at very low productivity increments. Otherwise, it only makes sense for a firm to establish a knowledge base first (research) and then move on to development. Finally, if the search distribution $F(\cdot)$ does not change, then it will always be optimal to stop at the upper bound of it. Therefore, an important caveat is that in this paper it is not possible to infer 'true' boundaries of the search distribution in the empirical setting.

The result raises an important discussion. Fixed costs of research affect both directly and indirectly firm-level R&D decisions, which in turn implies different dynamic trajectories for productivity. Even if it is not optimal for a firm to perform research at the moment, the costs of research will nevertheless affect its judgement about current development activities. Knowing that research is too expensive anyway, a firm will choose to redistribute development expenditures over a longer period of time instead of pushing development activities further in the very early periods. Hence, industrial productivity growth will potentially be slower than it could have been under lower fixed costs of research. Fixed costs of development are also important, however, they primarily affect only development activities. If fixed costs of development are high, then firms bring new technologies to the production process at slower rates and industrial productivity growth slows down. At the same time, under certain conditions, the negative effect might still be alleviated if firms shift their focus to research, which would increase marginal benefits from development. Thus, high fixed costs of research are prohibitive both for research and development, always leading to a lower productivity growth; while high fixed costs of development are prohibitive for development but not for research, hence, not always resulting in a lower productivity growth.

4 Data

The data comes from the Spanish innovation panel – PITEC.[14] The sample covers a period of 14 years between 2003 and 2016. Sampling strategy in 2003 was to target all firms that potentially perform R&D activities in Spain. Naturally, the survey presents a better coverage of larger enterprises. Therefore, the quantitative estimates might be of lower relevance for the group of small firms (for example, when it comes to fixed costs). The qualitative results are still valid, unless the R&D process looks completely different within the group of small firms (a caveat applicable to most studies based on the CIS surveys). By 2016 the split between R&D and non-R&D firms is about 50/50. Every year it is aimed to keep the same firms in the survey, however, there are also firms that enter and exit the panel. First, the firms from the directory of possible research companies (DIRID) are selected. Firms get into the DIRID either because they have been classified as research companies in previous periods, or because they have received public R&D funds during

[14]The general structure and methodology of the survey are extensively described in Barge-Gil and López (2014). There authors study the differential impact of R and D on product and process innovations. They also explain why selection bias is not a huge issue in the survey sample. Current paper makes use of the same data assumptions and interprets innovation variables in a similar way.

the reference year of the survey. This register is updated annually. Then, a random sample of firms is added to the survey (based on size, location and industry stratifications). In that way the survey is representative of the total R&D activity in Spain. The responses can be collected through various channels: physical post, electronic devices, phone interviews. The survey covers both manufacturing and services sectors. In this study I focus exclusively on manufacturing industries.

The survey allows a researcher to choose between five representative subsamples (muestras). Namely, (i) all firms with more than 200 workers; (ii) all firms that carry out R&D activities internally; (iii) firms with more than 200 workers that carry out R&D activities internally; (iv) companies with less than 200 workers that buy external R&D and do not carry out R&D activities internally; (v) companies with less than 200 workers that do not perform any of the innovative activities. Since my primary interest lies in disentangling productivity effects from own R and own D, in the dynamic estimation I am going to focus on all firms classified as performers of internal R&D. The estimation approach, however, can easily be applied to all firms in the PITEC sample.

Overall, after keeping only active observations, there are about 6,000 unique firms participating in the survey. It corresponds to 3,500 manufacturing firms per year on average. Out of these firms, for the dynamic study, it is possible to select a subsample of 1,779 firms that are available every year between 2003 and 2016 (about 50% of all observations and 70% of total sales volume). R&D activities are classified in accordance with the OECD guidelines. In 2016 the average share of spending on research activities was at the level of 46% while 54% were attracted to development activities. Over the years these shares were quite stable, hence, I will be mostly relying on indicators for R and D in the analysis.

Table 1: *Descriptive Statistics, by Industry*

		Revenue		**Capital**		**Labour**		**Age**		**Foreign**		**Obs.**
	Industry	*rd*	*no rd*	*rd*	*no rd*	*rd*	*no rd*	*rd*	*no rd*	*rd*	*no rd*	
1	Food, beverages and tobacco	16.93	16.20	15.11	14.54	4.52	4.03	3.16	3.18	0.14	0.11	4449 / 3942
2	Textile and clothing	15.98	15.33	13.76	13.45	4.14	3.80	3.16	3.22	0.11	0.09	1639 / 1425
3	Leather and footwear	15.95	14.94	13.47	12.82	4.05	3.46	2.92	2.92	0.09	0.03	278 / 392
4	Wood, paper and furniture	16.15	15.60	14.22	13.82	4.31	3.90	3.04	3.07	0.13	0.12	2382 / 3360
5	Chemicals and pharmaceuticals	16.49	15.73	14.55	14.11	4.25	3.68	3.18	3.15	0.26	0.26	8986 / 3705
6	Metals and minerals	16.55	15.60	14.78	14.07	4.49	3.76	3.15	3.11	0.15	0.11	6036 / 5412
7	Computers and electronics	15.74	15.03	13.64	13.08	3.94	3.36	2.96	3.01	0.16	0.17	5452 / 1939
8	Machinery	16.21	15.39	13.95	13.55	4.25	3.63	3.09	3.08	0.18	0.19	7123 / 3893
9	Transportation equipment	16.85	15.83	15.18	14.15	4.83	4.23	3.05	2.98	0.26	0.16	618 / 359
10	Other manufacturing	15.60	14.72	13.44	12.85	3.85	3.13	3.12	2.98	0.05	0.12	408 / 393

Notes: All continuous variables are reported in logs. Last column shows number of observations per group (with internal R&D activities / without internal R&D activities). Stock of capital is calculated using perpetual inventory method from yearly capital investment observations. Age is the difference between current year and establishment year of a firm. Foreign owned firms are defined as companies with at least 10% of foreign capital (cumulative).

In Table 1 I provide detailed summary statistics for some of the key variables and compare observations based on the performance of internal R&D activities. Revenue is the reported turnover of a firm in a given year. Across all industries it seems that R&D activities are generally associated with larger sales volumes. Further, I construct the stock of capital using yearly information on gross investments. I apply perpetual inventory method and assume that the depreciation rate of capital equals to 5%. It can be seen from the table that stocks of capital are also on average higher when internal R&D activities are performed. Next, I move on to labour which is measured as the number of workers in a given year. Likewise, employment seems to be higher when internal R&D activities are performed. There is no information about material purchases in the survey. Thus, I use inverted demand for labour instead to estimate revenue productivity of a firm. It is also believed that labour is a more robust variable relative to materials for that purpose. There is a higher consistency in the measurement of employment over the years, hence, a lower chance of significant errors. Finally, I use two additional variables to account for potential unobserved firm-level cost shifters: age and foreign ownership. From the dataset I acquire the establishment year of a firm and calculation of its age is straightforward. Foreign ownership classification changed during the sample period, therefore, I use a broad definition and identify all firms with more than 10% of foreign capital (cumulative) as foreign owned. There are no strong differences between observations with and without R&D activities in terms of age and foreign ownership. Many firms have joined the sample in 2003 when they were about five years old. Thus, it is a great opportunity to study innovation processes over a long time horizon. At the same time, there are not so many firms with foreign capital in general. It is possible to identify only about 15% of all firms as foreign owned in the sample using the broad definition. Here I consider it an advantage because the focus of the paper is on own R&D activities. If there are primarily foreign-owned firms in the sample, then it is hard to control for cases when innovations arrive from innovative parents. As for purchases of foreign technologies, it is possible to control for that using respective variables in the dataset.

It can also be noticed that the distribution of observations across industries is relatively uneven. It, however, reflects the major difference between high-tech and low-tech industries. Often it is easier to find an R&D firm in chemicals and pharmaceuticals than in leather and footwear. Nevertheless, even in industries with less firms there is a good representation of R&D performers as well as non-performers. Throughout the paper I focus on the following grouping of industries into sectors: (i) high-tech (chemicals and pharmaceuticals; metals and minerals; computers and electronics; machinery), and (ii) low-tech (food, beverages and tobacco; textile and clothing; leather and footwear; wood, paper and furniture; transportation equipment; other manufacturing). Some of the final dynamic estimates for the high-tech sector are also provided at the disaggregated industry level. In Table 2 I show detailed R&D summary statistics for the balanced subsample of 1,779 firms that enter final dynamic estimations.

Overall, in the balanced subsample the share of firms with zero investments in R&D increased in 2016 relative to 2003. In the low-tech sector it is 46% of firms in 2016 that do not perform R&D at all, while in the high-tech sector the same is true for about 30% of firms. If firms do perform R&D, then the largest share of firms performs both R and D across almost all of the industries. Only in machinery the majority tends to invest in D, while in chemicals and pharmaceuticals the second popular choice is investments only in R. When it comes to average expenses, they seem to have increased over the years. It is especially relevant for firms performing both R and D. Within

Table 2: *R&D Summary Statistics for the Balanced Sample*

A. Share of R&D firms		**Year**							
		2003				**2016**			
Sample	Firms	None	D	R	R&D	None	D	R	R&D
Full	1779	15.8	23.7	23.5	37.0	34.6	19.9	16.6	28.8
High-tech	1277	11.5	26.1	23.0	39.4	30.1	21.4	16.5	31.9
Chemicals and pharmaceuticals	452	8.0	16.6	33.6	41.8	25.4	13.7	25.0	35.8
Metals and minerals	285	22.5	28.8	18.2	30.5	37.2	22.8	15.8	24.2
Computers and electronics	224	4.9	29.9	17.9	47.3	23.7	22.3	14.3	39.7
Machinery	316	11.4	34.5	15.8	38.3	35.1	30.4	6.6	27.8
Low-tech	502	26.7	17.7	24.7	30.9	46.0	16.1	16.9	20.9

B. Average R&D expenses million EUR	**Year**							
	2003				**2016**			
	R or D		*R and D*		*R or D*		*R and D*	
Sample	D	R	D	R	D	R	D	R
Full	7.510	3.584	2.324	2.091	7.166	2.690	18.933	8.458
High-tech	8.217	4.829	1.389	2.564	8.098	4.377	21.718	9.961
Chemicals and pharmaceuticals	1.078	6.734	0.954	3.847	3.824	5.692	1.680	7.382
Metals and minerals	1.248	0.664	0.706	1.243	1.041	2.444	0.587	0.544
Computers and electronics	1.570	2.247	2.587	3.119	1.561	0.769	6.320	3.554
Machinery	9.662	1.282	2.164	0.860	10.672	0.984	49.260	17.342
Low-tech	2.035	0.830	3.831	1.328	0.614	0.449	11.365	4.374

Notes: R&D summary statistics for the balanced sample of continuing firms (available in each of the 14 years of the survey). Statistics are represented as averages for the full balanced sample, high-tech sector, low-tech sector, and every industry in the high-tech sector. Comparison between 2003 and 2016 is provided. Panel A shows the number of firms and shares of firms choosing one of the four possible modes of investing in R&D – (i) no R&D; (ii) only D; (iii) only R; (iv) both R and D. Panel B contains weighted average expenses on R&D in million EUR. Firm-level sales in a given year are used as weights. If a firm invests both in R and D, then separate averages for R and D are given to reflect the composition of total expenses.

that group expenses both on R and on D are substantially higher in 2016 relative to 2003. In case a firm performs only R or only D, then the level of expenses seems to remain stable over the years. Generally, expenses on D exceed the amount of resources devoted to R. Only in chemicals and pharmaceuticals as well as in computers and electronics the research expenses represent the largest share in total R&D expenditures. In machinery there has been a huge surge in R&D expenditures over the years. The composition of expenditures did not change very much though, with development expenses still representing about 70% of total R&D expenditures.

The sample displays a lot of variation in terms of firm-level R&D choices. Since the focus is on indicators for R&D variables, it is important to observe the variability in inter-temporal dynamics along with different patterns of investing in R&D across industries. Raw R&D expenditure variables could be used as a common point of reference for monetary fixed costs estimates during later stages of the dynamic estimation.

5 Empirical strategy

In this section I provide some details related to the empirical identification of the model parameters and construction of value functions to be used in the estimation of fixed costs and dynamic

R&D gains. The key innovation variables (δ_{it}, ρ_{it}) take discrete values of either 0 or 1. It allows me to significantly simplify the problem by considering the dynamics of a continuous variable $\tilde{\omega}_{it}$ affected only by four possible actions of a firm. Estimation is divided into three stages. In the first step I recover productivity measures using static functional equations and information about the productivity process following Aw et al. (2011) and Peters et al. (2017). In the second step I recover technology frontier estimates and parameters of the search distribution imposing a structure on the productivity process. In the last step I use one-to-one correspondence between the productivity measure and short-run profits to construct value functions and solve the dynamic problem for parameters of the technology distribution and costs.

5.1 Static parameters

From the static model it is easy to derive variable input demand functions.[15] The equation either for labour or materials (or both) can be potentially used. Here I focus on the equation for labour since the information about materials is not available in the Spanish innovation panel.

The demand for labour is specified as a function of capital stock (k_{it}), additional cost shifters (d_{it}) and observed productivity $(\tilde{\omega}_{it})$:

$$l_{it} = h_t(k_{it}, d_{it}, \tilde{\omega}_{it}) \tag{12}$$

The function h_t is then inverted to account for productivity:

$$\tilde{\omega}_{it} = h_t^{-1}(k_{it}, d_{it}, l_{it}) \tag{13}$$

Substituting into the revenue equation (3) yields:

$$\begin{aligned} r_{it} =& (1+\eta)\left[\beta_0 + \ln\left(\frac{\eta}{1+\eta}\right)\right] \\ & + \ln \Phi_t + (1+\eta)\beta_w w_t \\ & + (1+\eta)\left[\beta_k k_{it} + \beta_d d_{it} - h_t^{-1}(k_{it}, d_{it}, l_{it})\right] \\ & + \epsilon_{it} \\ =& \beta_0^{'} + \beta_t^{'} + g(k_{it}, d_{it}, l_{it}) + \epsilon_{it} \end{aligned} \tag{14}$$

where $\beta_0^{'}$ is a constant, $\beta_t^{'}$ stands for time fixed effects, $g(k_{it}, d_{it}, l_{it})$ is approximated as a third order polynomial in k_{it}, d_{it}, l_{it}, and ϵ_{it} is an error term. The revenue equation returns the estimates of $\hat{g}_{it}$.

Note also that:

$$\tilde{\omega}_{it} = \beta_k k_{it} + \beta_d d_{it} - \frac{1}{1+\eta}\hat{g}_{it} \tag{15}$$

One can combine this equation with the law of motion for productivity and recover β_k, β_d and α.

[15] See Aw et al. (2011) and Peters et al. (2017) for details.

Thus, I construct the following estimation equation:

$$\begin{aligned}\hat{g}_{it} = & -\alpha_0(1+\eta) + \beta_k k_{it}(1+\eta) + \beta_d d_{it}(1+\eta) \\ & + \alpha_1(\hat{g}_{it-1} - \beta_k k_{it-1}(1+\eta) - \beta_d d_{it-1}(1+\eta)) \\ & - \frac{\alpha_2}{1+\eta}(\hat{g}_{it-1} - \beta_k k_{it-1}(1+\eta) - \beta_d d_{it-1}(1+\eta))^2 \\ & + \frac{\alpha_3}{(1+\eta)^2}(\hat{g}_{it-1} - \beta_k k_{it-1}(1+\eta) - \beta_d d_{it-1}(1+\eta))^3 \\ & - \alpha_4(1+\eta)\rho_{it-1} - \alpha_5(1+\eta)\delta_{it-1} - \alpha_6(1+\eta)\rho_{it-1}\delta_{it-1}\end{aligned} \tag{16}$$

Here I use a third-order polynomial in productivity as well as controls for R&D decisions. Empirically the cost shifter will be constructed from two variables – age (β_a) and foreign ownership (β_f). Estimates of η can be acquired from the standard regression of total variable cost on total turnover. They, however, cannot be recovered directly from the Spanish innovation panel, therefore, I apply industry-level measures estimated from another firm-level Spanish dataset (ESEE) with the same classification of industries.[16] Parameters β_k, β_d, η and $\hat{g}_{it}$ represent sufficient statistics to compute productivity measures $\tilde{\omega}_{it}$ for all firms. Non-linear least squares method is used to estimate the equation.

5.2 Technology frontier

In the second stage, firm-level estimates of best available technologies (frontier, τ_{it}) have to be constructed in each time period. Here it is required to discuss several important cases. First, there are some firms in the sample that never perform development activities (228 firms). It implies that the draws from the search distribution are never observed. Thus, it is not possible to derive valid estimates of τ_{it}. In such a case, the productivity process is assumed to follow an AR(1) process. Still, a lower bound for τ_{it} can be calculated, though it cannot be used in the value function iteration algorithm. Second, there are firms that never perform research activities (275 firms). Recovered estimates of τ_{it} for these firms are only lower bounds, since there is no information on potential out-of-sample research activities. Nonetheless, they will be used in the value function iteration because there are still observable draws from the search distribution for these firms through their development activities. Lastly, since the strategy will be to run a grid search for τ_{it}, some low-productive firms will receive similar starting values of τ_{i0}. It is a small number of firms (about 15), hence, the quality of the estimation is likely to remain unaffected.

The estimation algorithm proceeds as follows. The firms with at least three years of observations are kept in the dataset. Then, it begins with an initial guess for τ_{i0} for each firm given the search distribution parameters – $\mathcal{N}(\mu_s, \sigma_s^2)$. The assumption is that the search distribution can be well approximated by a normal distribution.[17] After that, given R&D choices of a firm, the evolution of τ_{it} and $\hat{\omega}_{it}$ is modelled. The value of $\hat{\omega}_{it}$ is the productivity level predicted by the search model.

[16] Details provided in the Appendix A.2.

[17] At the same time, the model is flexible enough to be used with any desired distribution as an approximation of the search distribution.

It is assumed that $\hat{\omega}_{i0} = \tilde{\omega}_{i0}$ and in all other periods the difference between predicted productivity ($\hat{\omega}_{it}$) and true productivity ($\tilde{\omega}_{it}$) is an error term (ξ_{it}). The algorithm searches for an optimal τ_{i0} (minimising the sum of squared errors – $\sum\limits_t \xi_{it}^2$) given $\mathcal{N}(\mu_s,\, \sigma_s^2)$ over a fine grid represented by 1000 points in the interval covering observed $\tilde{\omega}_{it}$ levels. Parameters μ_s and σ_s are also identified using the grid search method. Here, however, optimisation is performed not at the firm level but for the whole sample (minimising $\sum\limits_i \sum\limits_t \xi_{it}^2$).

5.3 Value function iteration

Given the derived values of realised productivity ($\tilde{\omega}_{it}$) and technology frontier (τ_{it}), it is possible to construct a discretised state-space $s_{it} = (\tilde{\omega}_{it}, \tau_{it})$ to be used in the dynamic estimation. I follow the nested fixed-point algorithm suggested by Rust (1987) and select 50 grid points for $\tilde{\omega}_{it}$ as well as 50 grid points for τ_{it}. Hence, firms are grouped according to $50 \times 50 = 2500$ discrete states. Further, value functions are allowed to differ across two firm size categories (large and small), four capital stock categories, and seven estimation samples (full sample, high-tech, low-tech, chemicals and pharmaceuticals, metals and minerals, computers and electronics, machinery). I calculate the value of a firm at each discrete state and construct payoffs – $\{u_{00}(s_{it}), u_{01}(s_{it}), u_{10}(s_{it}), u_{11}(s_{it})\}$. Payoffs depend on probabilities of transiting between states conditional on R&D decisions (four choice options). Therefore, I construct four transition probability matrices that depend on parameters of the previously estimated technology search distribution – $\mathcal{N}(\mu_s,\, \sigma_s^2)$.

Starting values of the value function in each state are set at $V_0(s_{it}) = 0$. The temporal discount factor is set at $\lambda = 0.9$ and there is no aim to estimate it in the model. The value function is updated throughout multiple iterations: $V_{i+1}(s_t) = \max\big(\pi_t - \rho_t\gamma^\rho - \delta_t\gamma^\delta + \lambda E V_i(s_{t+1}|s_t, \rho_t, \delta_t)\big)$. The stopping rule for the algorithm is set as follows: $|V_{i+1}(s_t) - V_i(s_t)| \leqslant \frac{2\varepsilon\lambda}{1-\lambda}$, where $\varepsilon = 10^{-6}$. As the number of iterations increases ($i \to \infty$), the value function is getting closer to the fixed point. In these approximations the algorithm never exceeds 200 iterations to get to the fixed point. In a next step, the cubic spline method is applied to extrapolate values from the discrete grid to a continuous scale for $\tilde{\omega}_{it}$ and τ_{it}.

In order to estimate fixed costs, the log-likelihood function ($\ell = \ln L$) is maximised. Optimising over parameters γ^ρ and γ^δ, the probability of predicting observable firm-level R&D choices is maximised as follows:

$$L(\gamma^\rho, \gamma^\delta) = \prod_i \prod_t P(\rho_{it}, \delta_{it}|s_{it}, \gamma^\rho, \gamma^\delta) \tag{17}$$

Here I apply the standard Broyden–Fletcher–Goldfarb–Shanno (BFGS) numerical optimisation algorithm and set two restrictions on parameter values: $\gamma^\rho > 0$ and $\gamma^\delta > 0$. Standard errors are derived from the Hessian evaluated at optimal values of fixed costs parameters. In a case when fixed costs exceed payoffs, the probabilities are set close to zero.

6 Results

In this section I present the results of the empirical estimation. I start by providing first stage estimates of static parameters to recover realised productivity levels ($\tilde{\omega}_{it}$). Then, I briefly summarise transition patterns between innovation choices in the sample. After that, I present estimates of the technology search distribution and firm-level technology frontier levels (τ_{it}). Given the estimates of $\tilde{\omega}_{it}$ and τ_{it}, I evaluate the general productivity process. Finally, I report dynamic estimates of fixed costs and expected gains from R&D activities.

6.1 Productivity estimates

In order to proceed with the estimation of productivity levels, there should be a value set for the final demand elasticity – η. The approach is to run industry-by-industry regressions of total variable cost on total turnover. Estimates are derived from the ESEE dataset and reported in Table A1 in the Appendix. There seems to be low variation across industries, but generally the estimates are similar to the ones reported in other studies using Spanish data.

In Table 3 the results from the first stage of estimations are presented (equation 16). Coefficient α_0 is a constant, while α_1, α_2 and α_3 represent coefficients of first, second and third-order polynomials in productivity respectively. All coefficients are significant at the 1% level except for constants in high-tech and low-tech samples, and interaction between R and D in the low-tech sample. The productivity process does show signs of non-linearity, however, the first-order approximation seems to be sufficient enough. Further, β_k demonstrates that firms with higher capital stock tend to have lower variable costs and this effect is stronger in the low-tech sample. Foreign owned firms (β_f) also tend to have lower variable costs, but this effect is now stronger in the high-tech sample. Firms that had been established earlier than their competitors seem to have higher variable costs in the PITEC sample on average (β_a).

Table 3: *First Stage Estimation Results*

A. Full sample			**B. High-tech**			**C. Low-tech**		
Parameter	Coefficient	Std. Err.	Parameter	Coefficient	Std. Err.	Parameter	Coefficient	Std. Err.
α_0	0.0224	0.0045	α_0	0.0033	0.0048	α_0	-0.0009	0.0063
α_1	0.9068	0.0040	α_1	0.9196	0.0040	α_1	0.9400	0.0068
α_2	0.0442	0.0016	α_2	0.0428	0.0015	α_2	0.0367	0.0035
α_3	-0.0061	0.0003	α_3	-0.0063	0.0003	α_3	-0.0062	0.0007
β_k	-0.1196	0.0016	β_k	-0.1109	0.0019	β_k	-0.1374	0.0028
β_a	0.0945	0.0102	β_a	0.1278	0.0126	β_a	0.0584	0.0180
β_f	-0.1361	0.0044	β_f	-0.1470	0.0051	β_f	-0.1078	0.0083
R	0.0277	0.0024	R	0.0333	0.0029	R	0.0165	0.0040
D	0.0295	0.0022	D	0.0331	0.0026	D	0.0217	0.0041
R $\times$ D	-0.0244	0.0033	R $\times$ D	-0.0312	0.0040	R $\times$ D	-0.0073	0.0063
Obs.	56,059		Obs.	38,425		Obs.	17,634	
Root MSE	0.2665		Root MSE	0.2659		Root MSE	0.2630	

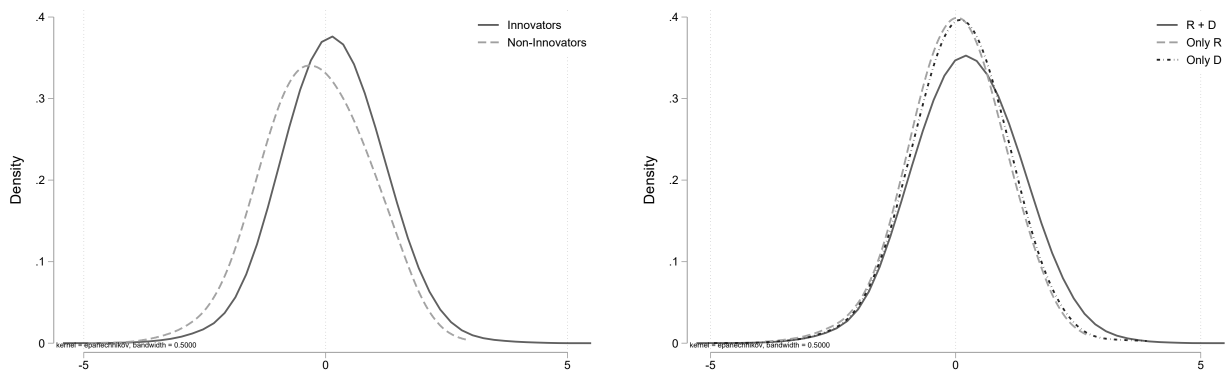
The last three parameters (R, D, R $\times$ D) indicate differences in productivity dynamics depending on the firm-level choice of R and D. A firm that performed only research activities in a given period is expected to achieve 2.77% higher productivity level in the next period. The effect is larger for high-tech firms (3.33%) and smaller for low-tech firms (1.65%). Analogously, a firm that performed only development activities in a given period is expected to achieve 2.95% higher productivity level in the next period. The effect is again higher for high-tech firms (3.31%) and lower for low-tech firms (2.17%). The results suggest that individual gains of R and D are not very different when compared based on their short-run productivity contribution. It is important to highlight that the interaction term between R and D is also significant and is of high magnitude (full and high-tech samples). It results in a firm performing both R and D in a given period being able to achieve 3.28% higher productivity level in the next period. Considering that costs of R&D are high, it would seem like a minor incentive to perform both activities at the same time. In the long run a firm performing R&D every year during 14 years could be expected to increase its productivity by about 50% by the end of the period.

The R&D coefficients at this stage should be interpreted with caution. Though the chosen estimation approach proves to be useful in recovering productivity measures, it does not yet account for potentially more complicated interactions between R and D activities in the long run. That is why in the next stage I am going to apply the search model for productivity. Prior to that it is necessary to examine the distribution of realised productivity measures. It will be of assistance when making assumptions about parameters of the search distribution during later stages. In order to do so I divide all firms into categories of innovators and non-innovators. If a firm has been performing R&D over more than a half of its life in the sample, it is considered to be an innovative firm. Using the same principle, within the group of innovators I identify firms that primarily do only research, only development, or always predominantly do both. Results are presented in Figure 2. Panels (a) and (b) compare industry and year demeaned distributions of productivity measures. All measures are reported in logs. In Figure A1 in the Appendix I plot the dynamics of firm-level productivity measures over time to ensure that it follows the findings reported in other firm-level Spanish studies.[18]

From Figure 2a it can be inferred that productivity distribution for innovators dominates the distribution for non-innovators. The mean for innovators is at the level of $\mu = 0.147$ with standard deviation of $\sigma = 0.961$. When it comes to non-innovators, the mean is $\mu = -0.207$ and standard deviation is $\sigma = 1.015$. Hence, the distribution of productivity measures for non-innovators is also more dispersed. Within the group of innovators (Figure 2b) differences seem to be of smaller magnitude. The mean for predominantly researchers is $\mu = 0.008$ with standard deviation of $\sigma = 0.893$. The mean for predominantly developers is $\mu = 0.092$ with standard deviation of $\sigma = 0.915$. Finally, the mean for continuous performers of both activities is $\mu = 0.253$ with standard deviation of $\sigma = 1.012$. Thus, when accounted for industry and year fixed effects, performance of both R and D seems to be associated with higher levels of productivity. Among all of the innovators, firms with the lowest levels of productivity are those that perform most of the time only R with limited resources devoted to D. Such findings fit well with the search model, where research

[18] See, among others, Doraszelski and Jaumandreu (2013), Mavroudi et al. (2020), García-Santana et al. (2020).

Figure 2: *Distribution of the Firm-level Productivity Measures*



(a) Innovators vs. non-innovators

(b) Innovators by type

Notes: Productivity measures are reported in logs. Productivity measures in panels (a) and (b) are demeaned by industry and year. Innovators are firms performing R&D over more than a half of their life in a sample. For example, a firm active during 14 years in the sample should perform R&D in at least 8 periods to be considered innovative. Similarly, groups of firms doing only research, only development or always predominantly both are constructed.

discoveries can only be realised through development activities. Therefore, firms performing only research are not able to gain as much in terms of productivity as firms performing both research and development.

Note that results here do not yet reveal the mechanism behind R&D effects on productivity. Firms in the 'Only D' group could have performed research once but very successfully, so that further development led to even higher productivity levels. That is why there will be more structure added to the productivity process in an attempt to highlight the interplay between research and development in the long run.

6.2 Transition patterns

Since the focus of this paper is on dynamic decisions, it could be useful to look at the observed transition probabilities in the sample. Based on the R&D choice in a given period a set of four actions available to a firm during next periods is defined: (i) do not perform R&D; (ii) perform only research; (iii) perform only development; (iv) perform both research and development activities. Next, I calculate probabilities of choosing actions (i)-(iv) after 1, 2, 5, 10 years given the current choice of a firm in t. Results are shown in Table 4.

It is evident that the choice of R&D is rather persistent, especially in the short run. On a longer time horizon firms are most likely either to make the same R&D choice or to stop performing R&D at all. Comparing t and $t+10$, it is easy to notice that only firms performing both R and D in t are most likely to continue as innovators in $t+10$. In all other groups the probability of abandoning R&D in $t+10$ is the highest one relative to all other available choices.

Almost in 91% cases a firm not performing R&D in current period will not perform it in the

Table 4: *Empirical Transition Probability Matrices*

$t \to t+1$	Neither	Only R	Only D	Both	$t \to t+2$	Neither	Only R	Only D	Both
Neither	**0.9104**	0.0265	0.0380	0.0251	Neither	**0.8751**	0.0538	0.0361	0.0350
Only R	0.1460	**0.6316**	0.1177	0.1046	Only R	0.2179	**0.5743**	0.0946	0.1132
Only D	0.1450	0.0857	**0.6782**	0.0911	Only D	0.2121	0.1339	**0.5262**	0.1278
Both	0.0938	0.0705	0.0775	**0.7582**	Both	0.1441	0.1002	0.0868	**0.6689**
$t \to t+5$	Neither	Only R	Only D	Both	$t \to t+10$	Neither	Only R	Only D	Both
Neither	**0.8319**	0.0700	0.0471	0.0509	Neither	**0.7563**	0.0951	0.0636	0.0851
Only R	0.3263	**0.4249**	0.1107	0.1380	Only R	0.3975	**0.3285**	0.1136	0.1604
Only D	0.3189	0.1415	**0.3908**	0.1489	Only D	0.3583	0.1585	**0.3046**	0.1786
Both	0.2488	0.1297	0.1085	**0.5129**	Both	0.3098	0.1488	0.1291	**0.4123**

Notes: Rows – R&D choice in t. Columns – R&D choice in $t+1$, $t+2$, $t+5$, or $t+10$. The sample of continuing firms. Raw probabilities derived from the data.

next period. There is only a 4% chance that it will start performing development and slightly lower chances of performing only research or both research and development (3% each). At the same time, a firm currently performing only research is most likely to continue performing only research (63% chance). Similarly, firms currently performing only development or both R&D activities are most likely to continue with exact same choices of activities (68% and 76% respectively). The second most likely option is to drop out of all R&D activities. It reflects the long-term nature of many R&D projects, where it is not enough to invest into these activities during only a single period of time. Moreover, due to differences in goals and methods between research and development, it is the least likely option that a firm will start performing both activities at the same time. It is only probable when a firm had already begun performing either R or D, hence, possesses experience and a solid foundation to scale up its R&D activities.

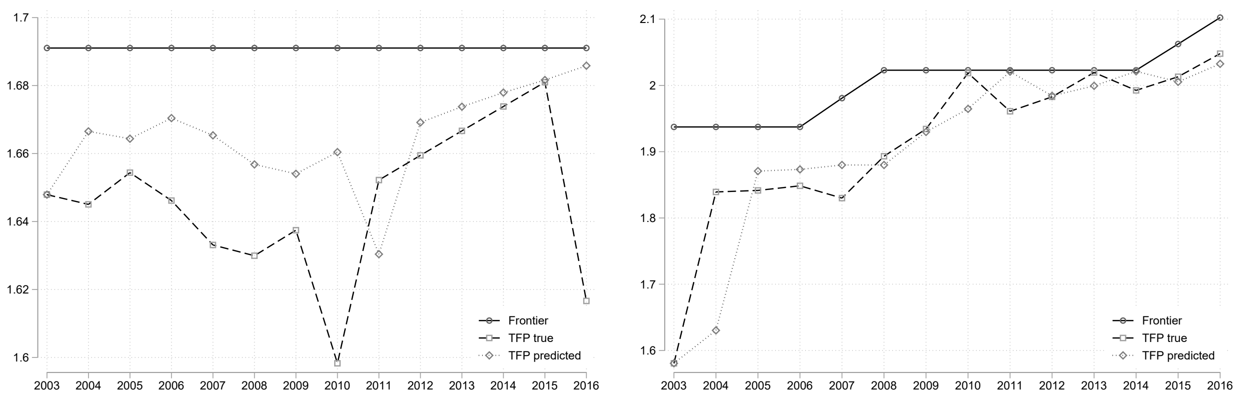
It is important to highlight that given the transition probability matrix from t to $t+1$ theoretical transition probability matrices to $t+2$, $t+5$ and $t+10$ could be easily obtained. However, they would significantly differ from their empirical counterparts. Namely, if transition probabilities between t and $t+1$ in Table 4 are true transition probabilities, then probabilities of making the same R&D choice should have been decreasing much faster relative to what is observed in the data. Again, it demonstrates that R&D investments are very persistent in the data. Firms make decisions about R&D investments optimising over the long time horizon.

Transition patterns highlight the importance of accounting for a long history of R and D in the model. Gains from development activities will differ depending on a firm's history of research decisions. Likewise, the decision to undertake research will be affected by successful completion of previous development projects. I account for that by keeping track of accessible technology search intervals at the firm level.

6.3 Frontier estimates

Technical details of the numerical estimation are summarised in the Appendix A.4. In Figure 3 I provide two examples of firm-level productivity dynamics. In panel (a) a firm that never performs research is shown. It, however, performs development, hence, the estimate of its frontier is a lower bound. Realisation of development projects is restricted by the fixed frontier level – $\bar{\tau}_i$. It can be observed that the firm has experienced a series of negative shocks to its productivity between 2003 and 2010. Consequently, it has been drifting away from the frontier level of technology. After 2010, development projects are seemingly becoming more successful, and the firm slowly starts to move towards its frontier level of technology. Given the design of the model, it would be plausible to say that the absence of research activities was due to negative shocks to productivity in the period prior to 2010. It could not have been feasible to invest in research when development projects were not leading to immediate productivity growth. If one were to make predictions, investments in research after 2016 could be expected, when the firm climbed closer to the frontier level of technology.

Figure 3: *Firm-level Examples of Productivity Dynamics*



(a) A firm that never performs research (b) A firm performing both R and D

Notes: TFP true is $\tilde{\omega}_{it}$ estimated from the first stage. TFP predicted is $\hat{\omega}_{it}$ estimated from the search model. Frontier is τ_{it} estimated from the search model. Search distribution parameters – $\mathcal{N}(-0.28,\, 0.31^2)$. Firm in (a) never performs research and τ_{it} is fixed. Firm in (b) is always involved in development and from time to time in research.

In Figure 3b I plot productivity dynamics for a firm that always performs development and from time to time also engages in research activities. Here the firm always seems to be on a trajectory of growth. In 2006 and 2007 it conducts research that increases the frontier technology level in 2007 and 2008 respectively. By 2010 the firm almost reaches its technology frontier and decides to invest more in research in 2014 and 2015. Not surprisingly, it leads to further growth in productivity through a series of multiple development activities. Potentially, one could expect the firm to continue investing in research since it approaches the frontier relatively fast.

The estimation of τ_{it} relies on the opportunity to follow a firm over a long period time. The more periods of time are available in the sample, then the more draws from the technology search distribution one has a chance to observe. It makes the technology frontier level estimates more robust. Therefore, one of the potential avenues of future research could be to explore that sensitivity. Here such an analysis is not performed since the study is limited to a single dataset.

6.4 Productivity process

Here I quantify the estimated productivity process. Formally, I rely on the following growth equation for the technology frontier:

$$\Delta\tau_{it} = \beta_1 \times \mathrm{R}_{it-1} + \beta_2 \times \tau_{it-1} \times \mathrm{R}_{it-1} + \mu_{st} + \epsilon_{it}, \tag{18}$$

where μ_{st} stands for industry-year fixed effects (most restrictive specification) and ϵ_{it} is an error term. Table 5 reports the results. The coefficients for τ_{it-1} are not included because the frontier remains unchanged in the absence of research activities by design.

Pure research effect (R_{it-1}) on the next period frontier (τ_{it}) is at the level of 30%. Interaction term ($\tau_{it-1}\times$ R_{it-1}) reveals that the net effect of research decreases when a firm approaches higher frontier productivity levels. It implies that it is getting harder to find new ideas when current knowledge is already advanced. Moreover, it could mean that more sophisticated technologies are associated with higher risks, hence, probability of conducting a successful research project decreases. The results reported in Table 5 provide a convenient way to study the search distribution. Note that the model could accommodate a depreciation rate for τ_{it} in the absence of research activities. However, I did not find any evidence that it would improve the estimates. Therefore, I simply assume that $\tau_{it} = \tau_{it-1}$ when $\mathrm{R}_{it-1} = 0$.

Table 5: *Dynamics for* τ_{it}

	$\Delta\tau_{it}$			
	(1)	(2)	(3)	(4)
R_{it-1}	0.284***	0.276***	0.279***	0.278***
	(0.00371)	(0.00367)	(0.00374)	(0.00373)
$\tau_{it-1}\times$ R_{it-1}	-0.0804***	-0.0786***	-0.0794***	-0.0788***
	(0.00120)	(0.00119)	(0.00119)	(0.00119)
Year FE	No	Yes	Yes	No
Industry FE	No	No	Yes	No
Industry-Year FE	No	No	No	Yes
Observations	23127	23127	23127	23127
R-squared	0.994	0.994	0.994	0.994

Estimating equation (18). Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Per period increase of 30% is quite high in terms of usually estimated per period productivity changes (3-5%) invoked by R&D, especially if extrapolated to the long run.[19] Therefore, it is quite important to remember that the aforementioned technology frontier expansion does not yet contribute to the productivity growth. Moreover, the higher the frontier, the lower becomes the probability of successfully updating the productivity due to complexity. As discussed in Section 3, it will always be optimal to stop performing R&D at the upper bound of the productivity distribution. Hence, it would not matter how big an update in a firm's technology frontier is if the firm has already

[19]See, e.g., Aw et al. (2011), Doraszelski and Jaumandreu (2013), Peters et al. (2017).

reached its maximum potential. Similarly, the reported increase is an average effect. The realised change in technology frontier will depend on the firm-specific technology state. The lagged research activity coefficient also accounts for the previous history of investments in research. To be more specific, it is not only the effect from the research activities performed in the previous period alone, but also from the research activities performed further back in time. I check that the inclusion of the second lag in the regression returns about 70/30 ratio between the contributions of the first and the second lag respectively.

Coefficients representing the most interest are those reported in Table 6. Here I re-evaluate firm-level productivity process for $\tilde{\omega}_{it}$. Formally, I rely on the following equation:

$$\tilde{\omega}_{it} = \gamma_1 \times \tilde{\omega}_{it-1} + \gamma_2 \times \mathrm{D}_{it-1} + \gamma_3 \times \tau_{it-1} + \gamma_4 \times \tau_{it-1} \times \mathrm{D}_{it-1} + \mu_{st} + \xi_{it}, \tag{19}$$

where μ_{st} stands for industry-year fixed effects (most restrictive specification) and ξ_{it} is an error term.

Table 6: *Dynamics for* $\tilde{\omega}_{it}$

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{\omega}_{it-1}$	0.976***	0.976***	0.976***	0.976***	0.976***	0.977***	0.976***	0.976***
	(0.00126)	(0.00125)	(0.00126)	(0.00126)	(0.00130)	(0.00129)	(0.00131)	(0.00130)
D_{it-1}	-0.0577***	-0.0584***	-0.0558***	-0.0559***	-0.0537***	-0.0538***	-0.0515***	-0.0517***
	(0.00461)	(0.00460)	(0.00464)	(0.00464)	(0.00482)	(0.00480)	(0.00484)	(0.00483)
τ_{it-1}	0.00175***	0.00186***	0.00177***	0.00176***	0.00162***	0.00170***	0.00160***	0.00158***
	(0.000524)	(0.000522)	(0.000524)	(0.000524)	(0.000551)	(0.000548)	(0.000551)	(0.000549)
$\tau_{it-1}\times \mathrm{D}_{it-1}$	0.0198***	0.0199***	0.0194***	0.0194***	0.0187***	0.0187***	0.0182***	0.0183***
	(0.00153)	(0.00152)	(0.00152)	(0.00152)	(0.00160)	(0.00159)	(0.00159)	(0.00159)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Industry-Year FE	No	No	No	Yes	No	No	No	Yes
Observations	23127	23127	23127	23127	21348	21348	21348	21348
R-squared	0.977	0.978	0.978	0.978	0.978	0.978	0.978	0.978

Estimating equation (19). Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In columns (1)-(4) I run regressions with industry-year fixed effects and in columns (5)-(8) results from 2SLS procedure are shown (τ_{it-1} is instrumented by τ_{it-2} and R_{it-2}). Coefficient for $\tilde{\omega}_{it-1}$ demonstrates high degree of persistence in productivity process similar to the findings reported in Table 3. Interestingly, pure development effect on productivity (D_{it-1}) becomes negative, and it is now of relatively high magnitude (about 5-6% productivity decline in t due to development in $t-1$). The only positive contribution comes from the frontier (τ_{it-1}) and the interaction term ($\tau_{it-1}\times \mathrm{D}_{it-1}$). Elasticities are rather small with interaction term accounting for most of the effect. The existence of an individual τ_{it-1} effect on future productivity implies that firms possessing more knowledge about better technologies are very likely to grow in the future and this prediction can be made without observing development activities. At the same time, it is only by combination of development and high frontier levels of technology a firm can successfully achieve productivity growth. If τ_{it} is low, then at some point it will no longer be sustainable to invest in development. In such a scenario, a firm might perform better without directing resources to R&D. If a firm aims to increase its productivity, then high enough τ_{it} becomes a major prerequisite for the success of development projects. It would make sense for a firm to start investing in research prior to returning back to development. At this point the technology search model reveals that the relationship between R&D and productivity is quite complex and depends on many firm-level factors. Hence, different firms will have different optimal R&D strategies.

Negative development coefficient does not immediately imply that development activities are useless and investments in development should be abandoned completely. Rather it indicates that successful development has certain prerequisites. One example is that a firm developing a new type of a product will be more successful in doing so if it has already developed similar products (or varieties) before. When developing a product from scratch, the risk of failure is much higher. The firm devotes resources to development that could have been used elsewhere. In case of failure, investments in development will simply become sunk costs. It is not surprising that productivity might actually decline in such a scenario. In a similar fashion, a firm will be more successful performing development activities in the areas related to its core business competences (plastic producer investing into new materials rather than developing plastic toys). Another important factor to consider is that technology depreciates with time (note that the lagged productivity coefficient is below unity). Negative development coefficient might also reflect the fact that if the development effort is not strong enough, then the available technology will become relatively more inferior with time.

Here arises an important question. Namely, what happens to firms that consistently perform only development and stay on the market? Earlier, in Table 4, it has been reported that almost 30% of all firms performing exclusively development in time t continue performing only development in $t + 10$. The theoretical framework suggests at least two explanations. One possibility is that these firms have started at very high technology frontier levels. At the same time, for various reasons, their development activities have not been rather successful over time. In the data, we observe cases when a firm's knowledge base is wide enough, while the efforts to commercialise that knowledge most often lead to failures. In order to properly investigate this relationship, there should be imposed additional heterogeneity on quality of the knowledge base. That would make it possible to account for the fact that sometimes even successful research efforts cannot be directly connected to the existing development practices of the firm. More specifically, when the results of research cannot be applied to that specific type of a good the firm produces. In this paper, I do not focus on the product dimension, therefore, do not elaborate why some firms do not succeed in development despite high technology frontier levels. Another possibility is related to the final part of the discussion in Section 3. Persistent performance of development activities over relatively long time periods without any research activities may signal that fixed costs of research are very high.

Consider a firm of relatively high productivity that has not yet reached the upper bound of the technology distribution. If fixed costs of research are prohibitively high, the firm will no longer find it optimal to invest in research given the risks associated with it. Thus, it will become preferable to slowly but steadily improve productivity exclusively through development. After that, the firm might stop performing R&D at all. The optimal period of investing into development activities will depend on the firm-specific technology state and its location relative to the boundaries of the technology search distribution.

Contribution of R and D to productivity can be specific to the PITEC sample. It is also possible that some firms have started performing R&D long before entering the survey. The primary controls to account for potential 'self-selection' in this study are capital stock, age and foreign ownership. Information on firm-level input and output prices could increase the reliability of the final estimates. However, datasets with such information often lack variables to analyze disaggregated R&D activities. Findings reported here are most probably only a lower bound for the research importance in the productivity process. Nevertheless, they already show that research is essentially the dominating force in terms of productivity improvement (even if the impact is indirect) while development is a complementary activity. In a way, research in itself implies commitment to perform development in the future. Therefore, decision to perform research has to account for future decisions to perform development (and costs associated with them). Thus, policies aimed at fostering private innovations should consider separately current state of research and development activities at the firm level. Another option to make R&D projects more successful would be to affect exogenous search distribution. For instance, it can be done by investing in public sector research and its transparency. Interactions between the private sector and public sector research are, though, out of scope of current paper. Finally, in richer datasets, the information on exports, technology outsourcing and other factors affecting productivity development could be added to the estimations in a similar framework.

6.5 Dynamic gains and costs of R&D

In the next step I am going to estimate fixed costs of research and development specific to the model. It is the last important component that will shed light on firm-level choices of the R&D portfolio. Depending on the value of fixed costs, different thresholds can be estimated revealing optimal conditions to invest in research vs. development activities.

Table 7 reveals estimates of fixed costs for the full sample, high-tech industries and low-tech industries. Industry-by-industry estimates for the high-tech sector are available in Table A2 in the Appendix. Estimates come from the comparison of payoffs $u_{01}(s_{it}), u_{10}(s_{it}), u_{11}(s_{it})$ to the baseline of $u_{00}(s_{it})$ (no R&D). In principle, two indifference conditions 10 and 11 were sufficient enough, but I am still estimating the total value of $(\gamma^{\rho} + \gamma^{\delta})$ instead of summing separate estimates of γ^{ρ} and γ^{δ} (last row – R&D). Estimates suggest that fixed costs of research are significantly larger in monetary terms than fixed costs of development. For instance, estimates for the full sample are about 296,000 EUR in case of development, and almost 2,945,000 EUR in case of research, making up total fixed costs of R&D at the level of 3,238,000 EUR. If the focus is exclusively on the low-tech sector, then fixed costs of research become almost two times lower and equal to 1,520,000 EUR. Thus, it seems cheaper to perform research in low-tech sectors, which might be driven by differences in quality of research performed in low-tech sectors as well as by lower revenue levels relative to the high-tech sector. Interestingly, fixed costs of development equal to 321,000 EUR in the low-tech sector which is similar to what is observed in the high-tech sector.

Table 7: *Fixed Costs Estimation (million EUR)*

A. Full sample				
	FC	Std. Err.	t-stat.	p-val.
Development	0.296	0.062	4.741	0.000
Research	2.945	0.299	9.857	0.000
R&D	3.238	0.296	10.953	0.000
B. High-tech				
	FC	Std. Err.	t-stat.	p-val.
Development	0.279	0.059	4.694	0.000
Research	3.606	0.370	9.751	0.000
R&D	3.882	0.366	10.610	0.000
C. Low-tech				
	FC	Std. Err.	t-stat.	p-val.
Development	0.321	0.069	4.642	0.000
Research	1.520	0.142	10.702	0.000
R&D	1.839	0.144	12.728	0.000

Notes: Maximum likelihood estimation, where fixed costs parameters are evaluated up to a constant. All parameter values are estimated against the baseline of not performing R&D at all. Therefore, the last line 'R&D' should give the sum of separate research and development fixed costs. Panel A aggregates across all industries, Panel B aggregates across high-tech industries (chemicals and pharmaceuticals; metals and minerals; computers and electronics; machinery), and Panel C aggregates across low-tech industries (food, beverages and tobacco; textile and clothing; leather and footwear; wood, paper and furniture; transportation equipment; other manufacturing). Estimates for each of the high-tech industries are provided in the Appendix A.5.

Within the group of high-tech industries, it is machinery along with computers and electronics that demonstrate the highest levels of research fixed costs – 5,084,000 EUR in both cases. At the same time, fixed costs of development in computers and electronics are almost three times lower than in machinery. Fixed costs of research in metals and minerals are lower than the average in the low-tech sector. The same is true for fixed costs of development. Levels of fixed costs in chemicals and pharmaceuticals are generally in line with the averages reported for the whole high-tech sector.

Overall, the estimates of development fixed costs are in line with other studies using similar approach.[20] There, however, that value is attributed to the total R&D fixed cost. It is due to the fact that previous literature does not consider research as a separate activity, hence, does not

[20]See, e.g., Aw et al. (2011), Peters et al. (2017).

account for the dynamics of a firm's investment in research. When a firm invests in R&D in their data, it is possible to account only for the least costly type of R&D activities. Here I show that the difference between research and development fixed costs is, in fact, almost tenfold. Thus, it has to be taken into consideration if one wants to design policies with monetary incentives to invest in R&D and if the goal is to boost productivity growth.

As a robustness check, I calculate fixed costs of R&D without separating between R and D (traditional approach). Results are presented in Table A3 in the Appendix. The findings are broadly in line with the previous literature in the field.[21] On average, fixed costs of R&D vary between 10 to 30% of firm sales. At the same time, it is evident that total costs of R&D are significantly underestimated. For instance, in machinery, they are only at the level of 960,000 EUR. Hence, it is highly important to differentiate between different types of activities united under a very broad umbrella of R&D.

Figure 4 shows six plots of gains expected from different R&D choices for varying levels of productivity and technology frontier (long-term discounted profits vs. baseline payoff in case of no R&D, accounted for fixed costs). Panel A combines two graphs for the full sample, Panel B – for the high-tech sample, and Panel C – for the low-tech sample. Graphs to the left compare payoffs across productivity levels given that frontier is fixed. Graphs to the right compare payoffs across frontier levels given that productivity is fixed.

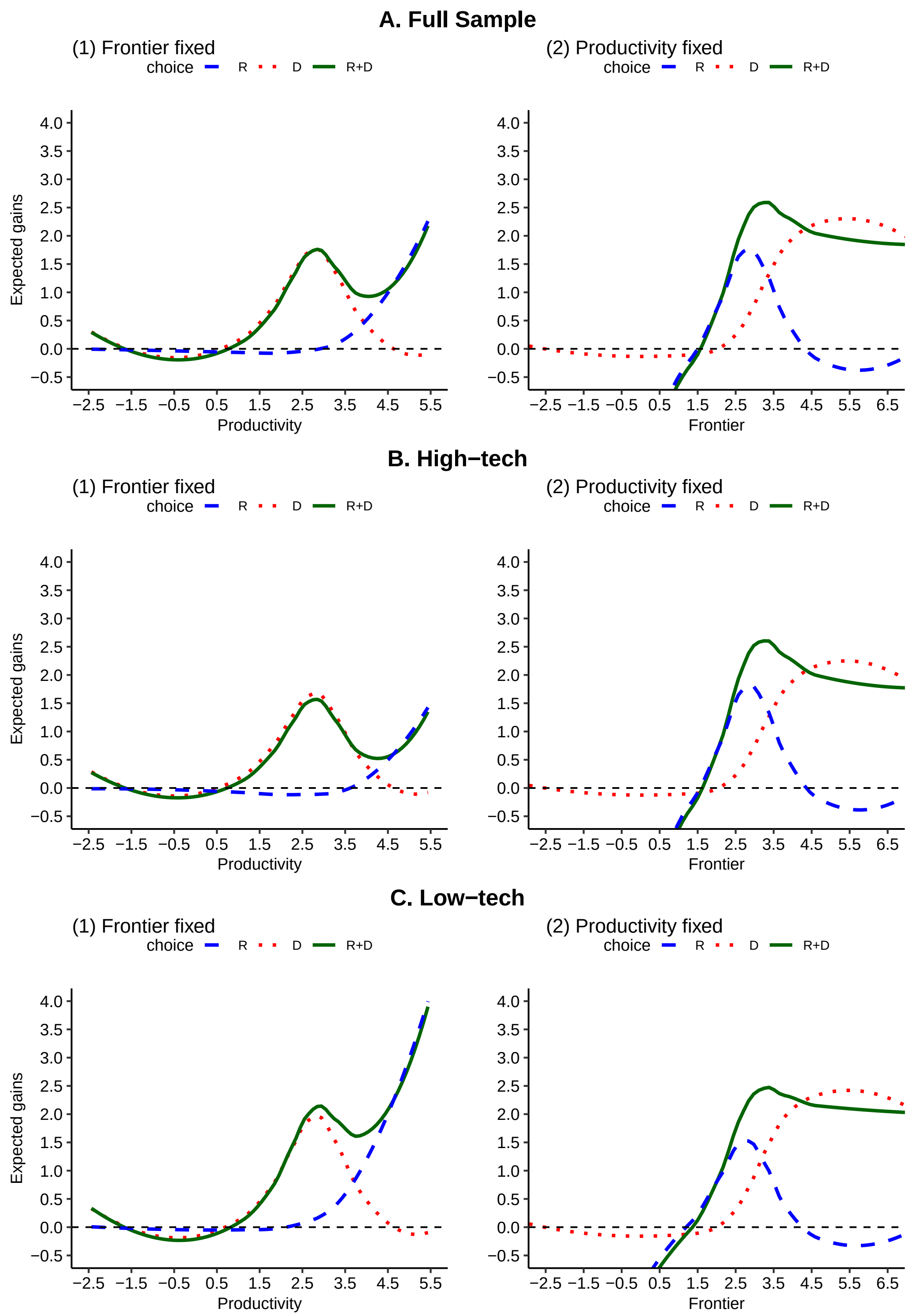
Comparing firms at the same technology frontier level, there is only a small subset of firms observed with relatively high productivity levels performing both research and development in the optimum. It is driven primarily by the fact that returns from research become positive only at relatively high productivity cut-off levels, when returns from development have already begun to diminish. In the high-tech sector the productivity cut-off level for research is much higher than in the low-tech sector. Similarly, due to higher fixed costs of research in the high-tech sector, there are negative returns from research at low productivity levels of a higher magnitude relative to the low-tech sector.

At extremely high productivity levels, it is only optimal to perform research. The explanation is straightforward since those firms have achieved productivity levels close to the end of the interval where productivity is observed in the data. The only way to improve productivity for them is to try to shift the frontier. Firms at low productivity levels do not perform R&D because they cannot cover the fixed costs.

Comparing firms at the same productivity level, there is again a relatively small subsample of firms observed performing both research and development. Intuitively, firms at low frontier levels start first on research and then proceed to development activities. It does not make sense for them to start with development because the expected improvement in productivity will be relatively small, hence, expected additional profit flows will also be insignificant. It is optimal to expand the frontier first, then to search for updated productivity levels with increased chances of success.

[21] See, for example, results in Arqué-Castells and Mohnen (2015) using the same dataset but slightly different methodology.

Figure 4: *Choice-dependent Dynamic Gains from R&D Activities* (ΔEV)



Notes: Expected gains are expressed in million euros (against the baseline of no R&D). Productivity ($\tilde{\omega}_{it}$) and frontier (τ_{it}) are on the log scale as per discretisation. Panels on the left reflect expected dynamic gains from different R&D choices depending on current productivity levels (given the frontier is fixed at the mean). Panels on the right reflect expected dynamic gains from different R&D choices depending on current frontier levels (given the productivity is fixed at the mean).

At higher frontier levels, returns from research start to diminish because the observed maximum is approached, while returns from development seem to converge at a certain average level.

Following up on the discussion in Section 3 and Section 6.4, it is particularly relevant to focus on firms persistently performing development without investing into research. Here those are the firms where the distance between $\tilde{\omega}_{it}$ and τ_{it} is the largest. It takes extra long time for productivity in these firms to reach its frontier. It is an interesting phenomenon worth focusing on in future studies. Potentially, there is a discrepancy between research projects and development activities within such firms. Additional qualitative variables (e.g., differentiating R and D management practices) could provide an opportunity to uncover specific reasons behind this issue.

Furthermore, as suggested by the theoretical framework, at the upper bound of the technology distribution we should observe firms stopping their R&D projects. The findings suggest that this is not yet the case for most firms. It implies that at some point in future both the returns from research at high productivity levels and returns from development at high frontier levels should begin to diminish. Alternatively, a shift in the technology search distribution should be modelled. In certain cases it might be necessary to test these hypotheses, which, however, requires longer panels, so that global technological changes are properly tracked and observed.

All in all, the analysis shows that there are several very specific groups of firms that will be choosing one of the four modes of investing in R&D projects depending on the combination of $\tilde{\omega}_{it}$ and τ_{it} levels. The group performing both research and development in the optimum is relatively small, primarily due to high fixed costs of research. Hence, if the goal is to increase private investments in research, incentives should be very specific and targeted.

7 Counterfactual analysis

Up until now the major focus of the paper was on separating R from D and estimating fixed costs associated with these activities. In this section my goal is to provide policy relevant outcomes related to a simulated decline in fixed costs of R and D. I focus on two variables to evaluate industry-level changes due to lower fixed costs: productivity and share of firms.

Productivity is calculated in levels as in the rest of the paper. Changes are measured at the firm level, then accumulated and averaged at an industry level. Share of firms accounts for firms performing any R&D activity in a period (only R, only D, or both). This is due to fixed costs of one activity affecting incentives of investing into another activity as well (see Propositions 1-4). In order to perform simulations, I keep firms in their original industry-size-capital stock groups and assume that a firm stays within its original group during each iteration. The first set of outcomes is estimated at a 5-year horizon, and the second set of outcomes is estimated at a 10-year horizon. Results are summarised in Table 8. The first simulation is for the case when fixed costs of development decrease by 10% ($\gamma^{\delta} \downarrow$) and fixed cost of research remain unchanged ($\overline{\gamma}^{\rho}$). The second simulation is for the case when fixed costs of development remain unchanged ($\overline{\gamma}^{\delta}$) and fixed cost of research decrease by 10% ($\gamma^{\rho} \downarrow$). The third simulation is for the case when fixed costs of research and fixed costs of development decrease by 10% each ($\gamma^\delta \downarrow$ and $\gamma^\rho \downarrow$). Such a setting makes it easier to identify synergy effects between research and development if any. Different time spans are used to differentiate between short- and long-term shifts in the industry. The parameters of the technology search distribution, hence, transition probabilities are assumed to be unchanged. In a similar fashion, after updating simulated states, a firm possesses exactly the same information about the technology search distribution as before the simulation period.

Table 8: *Responses to a 10% Decrease in Fixed Costs*

A. Changes in 5 years

	Productivity			Share of firms		
Sample	$\gamma^\delta \downarrow, \overline{\gamma}^\rho$	$\overline{\gamma}^\delta, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \overline{\gamma}^\rho$	$\overline{\gamma}^\delta, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \gamma^\rho \downarrow$
Full	0.002	0.016	0.023	0.045	0.097	0.102
High-tech	0.002	0.016	0.019	0.029	0.085	0.081
Chemicals and pharmaceuticals	0.002	0.018	0.020	0.044	0.089	0.088
Metals and minerals	0.003	0.018	0.022	0.044	0.096	0.091
Computers and electronics	0.001	0.011	0.014	0.003	0.073	0.070
Machinery	0.001	0.019	0.021	0.018	0.092	0.100
Low-tech	0.013	0.022	0.028	0.118	0.110	0.121

B. Changes in 10 years

	Productivity			Share of firms		
Sample	$\gamma^\delta \downarrow, \overline{\gamma}^\rho$	$\overline{\gamma}^\delta, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \overline{\gamma}^\rho$	$\overline{\gamma}^\delta, \gamma^\rho \downarrow$	$\gamma^\delta \downarrow, \gamma^\rho \downarrow$
Full	0.004	0.021	0.027	0.061	0.111	0.118
High-tech	0.003	0.022	0.026	0.042	0.103	0.110
Chemicals and pharmaceuticals	0.002	0.020	0.027	0.057	0.092	0.099
Metals and minerals	0.004	0.025	0.026	0.065	0.100	0.105
Computers and electronics	0.003	0.018	0.019	0.022	0.098	0.098
Machinery	0.003	0.022	0.025	0.028	0.111	0.116
Low-tech	0.015	0.023	0.028	0.115	0.115	0.120

Notes: Simulated outcomes due to a 10% decrease in fixed costs of R (γ^ρ), D (γ^δ), or both. Panel A shows changes after 5 years, while Panel B focuses on changes after 10 years. All numbers reflect percentage changes. Share of firms is calculated as a share of firms performing either R, or D, or both. New optimal choices are estimated for each firm and evaluated in accordance with the model. Random shocks are simulated at least 100 times, then final estimates are averaged. Technology search distribution and its parameters are assumed to be fixed over time.

On a shorter time horizon, a 10% decrease in fixed costs of development leads to a 4.5 pp. increase in total share of innovative firms and 0.2% increase in productivity on average. At the same time, a 10% decrease in fixed costs of research leads to 9.7 pp. more innovative firms and 1.6% productivity growth on average. If fixed costs decline by 10% each at once, then total share of innovative firms increases by 10.2 pp. with productivity growing by 2.3%. The effects are larger in the low-tech sector (with less-productive and smaller firms as well as lower absolute values of fixed costs) relative to the high-tech sector. Namely, in the third scenario ($\gamma^\delta \downarrow, \gamma^\rho \downarrow$), there are 12.1 pp. more innovative firms and 2.8% higher productivity in the low-tech sector vs. 8.1 pp. more innovative firms and 1.9% higher productivity in the high-tech sector. Within the high-tech sector there is practically no effect on productivity after a decline in fixed costs of development ($\gamma^\delta \downarrow, \overline{\gamma}^\rho$), even though the share of innovative firms is growing. It suggests that for an average firm in the high-tech sector it is optimal to expand the technology frontier first rather than perform development on a relatively narrow technology search interval. Overall, a decline in fixed costs of research has a stronger effect on productivity. It is partially due to the fact that it motivates firms to perform not only research, but also development (as a complementary activity), and do it at earlier stages (exploiting the expanded knowledge base potential).

On a longer time horizon, the effects of the fixed costs reduction are quite similar. The key difference is that there seems to be a stronger delay in the high-tech sector, while in the low-tech sector there is no postponed growth in productivity or total share of innovative firms. For instance, in the full sample, a 10% decrease in fixed costs of development leads to a 6.1 pp. increase in total share of innovative firms and 0.4% increase in productivity on average. At the same time, a 10% decrease in fixed costs of research leads to 11.1 pp. more innovative firms and 2.1% productivity growth on average. If fixed costs decline by 10% each at once, then total share of innovative firms increases by 11.8 pp. with productivity growing by 2.7%. The change in total share of innovative firms is the most significant in the high-tech sector on the 10-year horizon compared to the 5-year horizon. It implies that firms in the high-tech sector tend to distribute R&D investment choices over longer periods of time. In the low-tech sector it does not seem to be the case. However, it is important to note that positive effects in the low-tech sector after 10 years do not disappear either. Thus, a 10% decline in fixed costs of R&D opens a lot of new technological opportunities, such that firms are not able to exhaust them completely even after 10 years.

The reported findings suggest that there are indeed synergy effects between research and development. Almost in all industries and on all time horizons, the best case scenario is the one where both types of fixed costs fall. At the same time, it can be concluded that the greatest part of this positive effect is invoked by a reduction in fixed costs of research. Development activities play mostly a complementary role here.

Finally, it is possible to perform counterfactual analysis with a reduction in both types of fixed costs distributed across several time periods. The conclusions are almost identical in that case. The only fact worth noting is that firms might not utilise the benefits of the fixed costs reduction if it is happening too fast, because of the high research capacity or relatively low realised productivity.

8 Conclusion

Research and development activities are very different from each other in their nature. The former is concerned with the discovery of new ideas, while the latter aims to implement them into the production process. In this paper I estimate separate contributions of both activities to the productivity process at the firm level. The findings show that research plays the most significant role in the long run. Further, I provide dynamic estimates of fixed costs associated with research and development as well as expected gains from these activities. It is evident that research is almost ten times more expensive than development in terms of fixed costs on average. It does not require as many resources to implement an idea as to find a good one. Previous studies did not account for that variation, thus, underestimating total expenses associated with R&D and thresholds for entering R&D activities. Given the increase of interest to the design of public subsidies for R&D investment, current study provides one of the first evidences in support of locally targeted policies specific to the nature of a given R&D activity. Counterfactual estimates show that it is only required to reduce fixed costs of research to invoke significant positive changes in research as well as development choices. In turn, it has strong effects on productivity and total share of innovative firms at the industry level. Avenues for future research include studying potentially more complicated dynamic relationships between research and development that are currently not accounted for in the model as well as applications on datasets with a longer time span. Moreover, cross-country comparisons could provide some additional insights about parameters affecting the innovation process. Last but not least, more specific data on R&D processes within the group of small firms could be of benefit. Current study utilises the dataset with a better representation of large firms, thus potentially inflating the point estimates of R&D fixed costs applicable to industry as a whole.

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A Appendix

A.1 Properties of the value function

First, suppose that a firm does not perform R&D at all:

$$V(\tilde{\omega}_{it}, \tau_{it}) = \pi(\tilde{\omega}_{it}) + \lambda V(\tilde{\omega}_{it}, \tau_{it}) \tag{20}$$

The following set of derivatives can be retrieved:

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} = \lambda \frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} \tag{21}$$

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it}} = \frac{\pi'(\tilde{\omega}_{it})}{1-\lambda} \tag{22}$$

$$\frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} = \lambda \frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} \tag{23}$$

Next, suppose that a firm performs only development:

$$V(\tilde{\omega}_{it}, \tau_{it}) = \pi(\tilde{\omega}_{it}) - \gamma^{\delta} + \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} V(\tilde{\omega}_{it+1}, \tau_{it}) dF(\tilde{\omega}_{it+1}) + \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tilde{\omega}_{it}) \tag{24}$$

Derivatives:

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} = \frac{\lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} \frac{\partial V(\tilde{\omega}_{it+1}, \tau_{it})}{\partial \tau_{it}} dF(\tilde{\omega}_{it+1})}{1 - \lambda F(\tilde{\omega}_{it})} \tag{25}$$

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it}} = \frac{\pi'(\tilde{\omega}_{it})}{1 - \lambda F(\tilde{\omega}_{it})} \tag{26}$$

$$\frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} = 0 \tag{27}$$

Suppose now that a firm performs only research:

$$V(\tilde{\omega}_{it}, \tau_{it}) = \pi(\tilde{\omega}_{it}) - \gamma^{\rho} + \lambda \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it}, \tau_{it+1}) dF(\tau_{it+1}) + \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tau_{it}) \tag{28}$$

Derivatives:

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} = \lambda \frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} F(\tau_{it}) \tag{29}$$

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it}} = \frac{\pi'(\tilde{\omega}_{it}) + \lambda \int_{\tau_{it}}^{\infty} \frac{\partial V(\tilde{\omega}_{it}, \tau_{it+1})}{\partial \tilde{\omega}_{it}} dF(\tau_{it+1})}{1 - \lambda F(\tilde{\omega}_{it})} \tag{30}$$

$$\frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} = \lambda \frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} F(\tau_{it}) \tag{31}$$

Finally, suppose that a firm performs both research and development:

$$\begin{aligned}
V(\tilde{\omega}_{it}, \tau_{it}) = \pi(\tilde{\omega}_{it}) - \gamma^{\rho} - \gamma^{\delta} &+ \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it+1}, \tau_{it+1}) dF(\tau_{it+1}) dF(\tilde{\omega}_{it+1}) \\
&+ \lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} V(\tilde{\omega}_{it+1}, \tau_{it}) dF(\tilde{\omega}_{it+1}) F(\tau_{it}) \\
&+ \lambda \int_{\tau_{it}}^{\infty} V(\tilde{\omega}_{it}, \tau_{it+1}) dF(\tau_{it+1}) F(\tilde{\omega}_{it}) \\
&+ \lambda V(\tilde{\omega}_{it}, \tau_{it}) F(\tilde{\omega}_{it}) F(\tau_{it})
\end{aligned} \tag{32}$$

Derivatives:

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tau_{it}} = \frac{\lambda \int_{\tilde{\omega}_{it}}^{\tau_{it}} \frac{\partial V(\tilde{\omega}_{it+1}, \tau_{it})}{\partial \tau_{it}} dF(\tilde{\omega}_{it+1}) F(\tau_{it})}{1 - \lambda F(\tilde{\omega}_{it}) F(\tau_{it})} \tag{33}$$

$$\frac{\partial V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it}} = \frac{\pi'(\tilde{\omega}_{it}) + \lambda \int_{\tau_{it}}^{\infty} \frac{\partial V(\tilde{\omega}_{it}, \tau_{it+1})}{\partial \tilde{\omega}_{it}} dF(\tau_{it+1}) F(\tilde{\omega}_{it})}{1 - \lambda F(\tilde{\omega}_{it}) F(\tau_{it})} \tag{34}$$

$$\frac{\partial^2 V(\tilde{\omega}_{it}, \tau_{it})}{\partial \tilde{\omega}_{it} \partial \tau_{it}} = 0 \tag{35}$$

A.2 Estimates of η derived from the ESEE dataset

Table A1: *Demand Elasticity Parameters, by Industry*

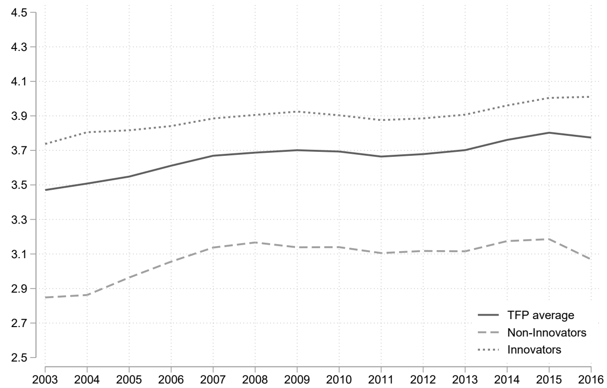
Sample	$1 + 1/\eta$	η
Full	0.821***	-5.601
	(0.015)	
High-tech	0.781***	-5.852
	(0.011)	
Chemicals and pharmaceuticals	0.761***	-4.180
	(0.015)	
Metals and minerals	0.795***	-4.887
	(0.011)	
Computers and electronics	0.824***	-5.698
	(0.023)	
Machinery	0.803***	-5.067
	(0.015)	
Low-tech	0.829***	-5.852
	(0.017)	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

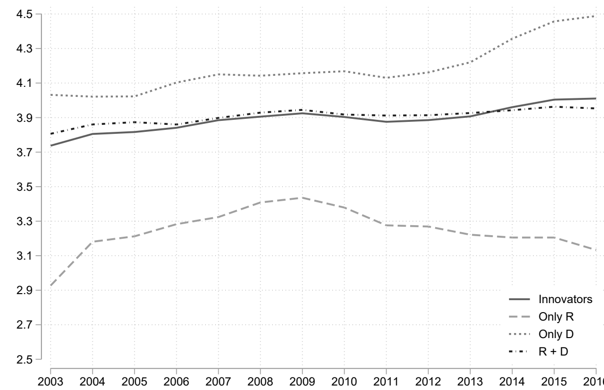
The ESEE (Encuesta Sobre Estrategias Empresariales) dataset is provided by the SEPI foundation in Madrid. It is an annual survey covering almost two thousand Spanish manufacturing firms each year. The survey aims to achieve a good level of representation for different types of firms. Large firms (more than 200 employees) are selected based on the exhaustiveness criteria. Smaller firms (10-200 employees) are selected through a stratified, proportional and systematic sampling with a random seed. The detailed description of the dataset is available at the SEPI webpage: `https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp`. The ESEE dataset uses industry classification comparable to the one in PITEC. Furthermore, the ESEE dataset contains all the necessary variables required for the construction of total variable costs as well as the information on firm sales (turnover).

A.3 Evolution of productivity in the Spanish manufacturing sector

Figure A1: *Dynamics of the Firm-level Productivity Measures*



(a) Weighted average productivity, innovators vs. others



(b) Weighted average productivity, innovators by type

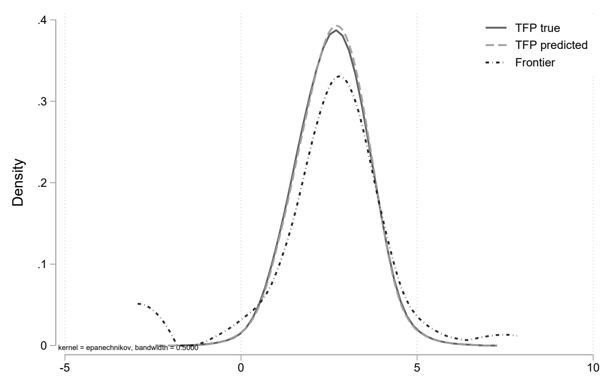
Notes: Productivity measures are reported in logs. Productivity measures in panels (a) and (b) are weighted by total turnover. Innovators are firms performing R&D over more than a half of their life in a sample. For example, a firm active during 14 years in the sample should perform R&D in at least 8 periods to be considered innovative. Similarly, groups of firms doing only research, only development or always predominantly both are constructed.

Figures A1a and A1b depict the evolution of productivity within the whole sample as well as within the groups of innovators and non-innovators. I calculate average productivity measures in every year using firm sales as weights. Over the years average productivity grew by about 36% with innovators showing the growth of 31% and non-innovators growing by 25%. Productivity of innovators is also consistently at a higher level relative to non-innovators. Within the group of innovators it is always firms performing predominantly development that demonstrate higher productivity levels and higher growth rates (58%). Firms performing predominantly research are consistently at lower levels of productivity but, at the same time, show second highest productivity growth rates within the group of innovators (23%). Finally, firms performing both research and development are in second place with respect to productivity levels but they grow, however, at slower rates (16%).

A.4 Numerical estimation of the technology search distribution parameters

Given the observed values of $\tilde{\omega}_{it}$, a grid for τ_{i0} is defined on the interval $[-2.94; 7.76]$. The grid for parameters of the technology search distribution has been defined as follows: interval $[-2.03; 4.02]$ with 0.05 increments for μ_s, and interval $[0.10; 2.09]$ with 0.01 increments for σ_s. As a result, I get the following optimal parameter values of the search distribution – $\mathcal{N}(-0.28, 0.31^2)$. Low mean implies that firms are more likely to search in the right tail of the distribution and probability of doing it successfully is rather small. Low standard deviation means that development becomes more risky at higher productivity levels. Overall, the model explains about 94% of variation in productivity dynamics. Figure A2 presents the comparison of distributions over true productivity ($\tilde{\omega}_{it}$), predicted productivity ($\hat{\omega}_{it}$) and estimated frontier (τ_{it}).

Figure A2: *Comparison of Distributions over* $\tilde{\omega}_{it}$, $\hat{\omega}_{it}$ *and* τ_{it}



Notes: TFP true is $\tilde{\omega}_{it}$ estimated from the first stage. TFP predicted is $\hat{\omega}_{it}$ estimated from the search model. Frontier is τ_{it} estimated from the search model. Search distribution parameters – $\mathcal{N}(-0.28, 0.31^2)$.

As it can be observed, the model approximates the empirical distribution of productivity measures very well. The spike to the left of the frontier productivity level distribution is due to low-productive firms assigned minimal $\tau_{i0} = -2.94$ if they never perform research. The derived distribution for τ_{it} in the sample is characterised by the mean of $\mu = 2.809$ with standard deviation of $\sigma = 1.284$ (excluding observations with $\tau_{i0} = \tau_{it} = -2.94$). The mean for $\tilde{\omega}_{it}$ is lower and equals to $\mu = 2.587$ with standard deviation of $\sigma = 0.899$. Hence, on average, firms seem to perform close to their individual frontiers. Empirical mean and standard deviation of the frontier distribution differ from the search distribution parameters because the empirical distribution represents realised levels of τ_{it} due to research and initial values of $\tilde{\omega}_{it}$.

A.5 Estimates of fixed costs in high-tech industries

Table A2: *Fixed Costs Estimation (million EUR), High-tech Industries*

A. Chemicals and pharmaceuticals				
	FC	Std. Err.	t-stat.	p-val.
Development	0.216	0.061	3.517	0.000
Research	3.005	0.298	10.067	0.000
R&D	3.218	0.296	10.884	0.000
B. Metals and minerals				
	FC	Std. Err.	t-stat.	p-val.
Development	0.253	0.057	4.413	0.000
Research	1.496	0.141	10.591	0.000
R&D	1.747	0.144	12.158	0.000
C. Computers and electronics				
	FC	Std. Err.	t-stat.	p-val.
Development	0.113	0.052	2.166	0.030
Research	5.084	0.515	9.864	0.000
R&D	5.194	0.512	10.141	0.000
D. Machinery				
	FC	Std. Err.	t-stat.	p-val.
Development	0.336	0.058	5.793	0.000
Research	5.084	0.564	9.021	0.000
R&D	5.417	0.558	9.707	0.000

Notes: Maximum likelihood estimation, where fixed costs parameters are evaluated up to a constant. All parameter values are estimated against the baseline of not performing R&D at all. Therefore, the last line 'R&D' should give the sum of separate research and development fixed costs.

A.6 Robustness

Table A3: *Fixed Costs of R&D (million EUR)*

Sample	FC	Std. Err.	t-stat.	p-val.
Full	0.487	0.043	11.326	0.000
High-tech	0.850	0.110	7.727	0.000
Chemicals and pharmaceuticals	0.754	0.098	7.694	0.000
Metals and minerals	0.332	0.028	11.857	0.000
Computers and electronics	1.205	0.130	9.269	0.000
Machinery	0.960	0.102	9.412	0.000
Low-tech	0.357	0.022	16.227	0.000

Notes: Maximum likelihood estimation without separating between R and D (traditional approach), where fixed costs parameters are evaluated up to a constant. All parameter values are estimated against the baseline of not performing R&D at all.