# From Research to Returns: A Firm-Level Analysis of R&D and Productivity in the Human Health Industry

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**Abstract:** In the rapidly evolving human health industry, the role of research and development (R&D) is pivotal. This study aims to investigate the relationship between R&D and labor productivity in the pharmaceutical, biotechnology, and medical device industries, collectively referred to as the human health industry. Utilizing a comprehensive dataset of 1,106 publicly traded firms with 5,457 observations from various countries between 2011 and 2018 available on the Medtrack proprietary database, we employ econometric techniques, including quantile regressions and dynamic panel estimation using the Generalized Method of Moments. Our findings reveal a positive and statistically significant relationship between R&D and productivity across the sample. Notably, this relationship is more pronounced in large firms based in Asia than in smaller firms in other regions. However, no significant differences in the intensity of this relationship were observed among the industries analyzed. Furthermore, our analysis indicates that R&D spending has an increasing marginal effect on productivity, suggesting that more productive companies experience a greater impact from R&D investment. The study offers robust results on the variable impacts of R&D investments on productivity, providing important insights for stakeholders and suggesting avenues for future research in driving innovation and growth in the human health industry.

**Keywords:** Research and Development; Productivity; Pharmaceutical industry; Biotechnology industry; Medical devices industry

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## 1. Introduction

The economics of innovation and technology has held a longstanding interest in the human health industry, which includes the pharmaceutical, biotechnology, and medical device sectors (Dosi et al., 2023; Hopkins et al., 2007; Jain, 2023; Malerba & Orsenigo, 2015; Morlacchi & Nelson, 2011; Nishimura et al., 2019; Saviotti et al., 2005; Toole, 2012; Xiao, 2022). This interest is largely due to these industries' strategic significance, economic potential, and the pivotal role of technological innovation in their firm's growth strategy (Mazzucato & Dosi, 2006; Mazzucato & Roy, 2019). The recent coronavirus disease 2019 (COVID-19) pandemic has further highlighted these industries' importance and innovative capacity (Abi Younes et al., 2021; Agarwal & Gaule, 2022; Sampat & Shadlen, 2021).

Extensive research has explored the relationship between research and development (R&D) spending and productivity in various industries, including the human health industry (Hall & Bagchi-Sen, 2002; O'Mahony & Vecchi, 2009; Soltanisehat et al., 2019). These studies have generally found a positive relationship between R&D expenditure and productivity, highlighting the crucial role of innovation in driving economic growth and competitiveness (Hall & Bagchi-Sen, 2002; Soltanisehat et al., 2019). However, the magnitude and nature of this relationship can vary significantly across industries, firm sizes, and geographical regions, warranting further investigation.

In light of these previous findings, our research question is: How does R&D spending affect productivity in the human health industry, and do these effects differ across firm size and geographical regions? To address this question, we analyze a proprietary database from Medtrack containing information on more than a thousand publicly traded companies operating in the pharmaceutical, biotechnology, and medical device industries, collectively referred to in this paper as the human health industry. Medtrack, a proprietary database of Pharma Intelligence, is a subsidiary of Informa UK Group that offers reliable information on pharmaceutical and biopharmaceutical companies, their products, and their collaborations (Diestre et al., 2015; Shin et al., 2018). Although proprietary, its comprehensive data on a wide range of companies make it a popular choice for studies in the human health industry (Baglieri et al., 2015; Fernald et al., 2015; Jeon et al., 2016; Shin et al., 2018). Drawing upon previous works (Crepon et al., 1998; Griliches, 1979), we employ econometric techniques, including quantile regressions and dynamic panel estimation using the Generalized Method of Moments, to assess nuances in different percentiles of R&D spending and productivity and account for innovation's endogenous and cumulative effects.

Our study contributes to the existing body of literature by offering an overview of the innovative dynamics within the human health industry. Furthermore, our study investigates variations in R&D spending and productivity across different continents and firm sizes, yielding valuable

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insights for stakeholders such as policymakers, industry leaders, and researchers. Through this research, we aspire to deepen the comprehension of the intricate relationship between R&D expenditure and productivity in the human health industry. The insights gained from our findings may assist decision-makers in devising effective strategies and policies that promote innovation and stimulate growth within this industry. Ultimately, this enhanced understanding can inform the academic literature and future research endeavors, guiding the direction of innovation policies and fostering industry development in the human health industry.

## 2. Innovation, productivity, and the human health industry

The empirical analysis of the causal relationship between innovation and productivity at the firm level can be traced back to the groundbreaking work of Zvi Griliches, who concentrated on an econometric approach to estimating a firm's production function. In a seminal paper, Griliches reviewed several studies on the subject and established the methodological foundation for his approach (Griliches, 1979), influencing most subsequent research (Heckman, 2006). Griliches introduced the concept of a firm's stock of knowledge, which, like capital and labor, would function as a production input. R&D investment primarily served as a proxy variable for this knowledge stock. By doing so, Griliches aimed to shift the focus from more qualitative case study analyses to a broader quantitative approach to assessing the impact of R&D on productivity (Griliches, 1979).

More recently, with the increased availability of microdata from innovation surveys conducted by research institutes based on the Oslo Manual (OCDE, 2005), there has been considerable growth in the number of studies that apply Griliches' concepts more comprehensively (Heckman, 2006). The most frequently cited and replicated model in this context is the CDM Model (the acronym of the three authors' names, Crépon, Duguet, and Mairesse) (Lööf et al., 2017). It is characterized by inserting the hypothesis that innovation is an intermediary process between the decision and intensity of investing in R&D and the resulting productivity, in addition to seeking a more robust econometric model (Crepon et al., 1998).

Since then, estimations of the relationship between R&D and productivity have been applied to numerous databases of firms in various economies of developed countries (Griffith et al., 2006; Hall et al., 2008) and developing countries (Albis Salas et al., 2023; Audretsch & Belitski, 2020; Crespi & Zuniga, 2012; Ndicu et al., 2023; Taveira et al., 2019; Tetteh, 2024). From an econometric perspective, some authors have deepened the analysis using panel data and estimation techniques to overcome the endogeneity problem of the relationship between R&D and productivity (Baum et al., 2017; Doraszelski & Jaumandreu, 2013).

This empirical relationship has been the subject of some meta-analysis studies, including the literature review by Mohnen and Hall (2013) and the most comprehensive and statistical analysis of Ugur et al. (2016). Among other findings, Mohnen and Hall (2013) highlight consistent evidence from studies of a positive and statistically significant relationship between innovative effort (R&D) and the generation of innovations. However, the relationship between innovation (especially process innovation) and productivity is less consensual and more ambiguous among the reviewed studies. On the other hand, Ugur et al. (2016) statistically analyze 1,253 estimations from 65 studies and find that, in general, the elasticity of R&D expenditure on firm productivity is positive. However, the authors draw attention to some relevant heterogeneities across studies, especially regarding scale effects in the R&D-productivity relationship, as there is evidence that returns to R&D may vary based on firms' different existing levels of R&D and productivity.

However, few studies (Frantzen, 2003; Gong & Wang, 2022; Moretti et al., 2023; Wakelin, 2001) evaluate the relationship between R&D and productivity in specific sectors or economic activities, in which comparisons are more related to groups of countries, firm size, and technological intensity of the companies. This is due to restrictions on the size of the samples at the firm level of the publications analyzed, which covered manufacturing companies from distinct industries. In some cases, such as in the human health industry, increasing innovation rates attract particular interest in innovation dynamics and have promoted greater attention from innovation scholars. In these industries, the ratio of R&D spending to sales revenue, rising from 3.7% in the 1950s to over 20% from the 1980s onwards, together with increasingly large in-house R&D departments, have also been accompanied by the growing internationalization of leading companies in the US and Europe, and more recently also in Asia (Malerba & Orsenigo, 2015). However, despite substantial investments, the pharmaceutical industry is currently facing challenges in R&D productivity, indicating that increasing R&D expenditure does not always translate into proportional productivity gains (Dosi et al., 2023; Schuhmacher et al., 2023).

While the pharmaceutical, biotechnology, and medical devices industries have unique competitive dynamics and business strategies, they share fundamental similarities in their approach to research and innovation. The pharmaceutical industry, for instance, is characterized by its high level of research intensity and innovation efforts (Danzon, 2006; Malerba & Orsenigo, 2015; Pammolli et al., 2020; Toole, 2012) and by large public funding of basic research (Dosi et al., 2023). Similarly, the biotechnology sector also thrives on a culture of innovation and is known for its knowledge-intensive nature (Coriat et al., 2002; Jain, 2023; Niosi, 2011, 2017; Pisano, 2010). Meanwhile, the medical devices industry stands out for its heavy investment in new products (Brown et al., 2008; Morlacchi & Nelson, 2011), the presence of numerous small companies (Donzé & Imer, 2020) and the challenges involved in formulating effective industrial policies for the sector (Kale & Wield, 2019; Srinivas & Kale, 2023).

In the case of the pharmaceutical industry, its birth takes place as a segment of the chemical industry in large German and Swiss companies such as Bayer, Hoechst, Ciba, and Sandoz at the end of the 19th century. New entrants from the United Kingdom (UK) and France also entered this market, and the first North American companies followed them in the first decades of the 20th century. However, the reality of high investment in R&D that is known today in these companies only became a reality starting in the 1940s - until then, few new drugs were introduced to the market, and the investments were more dedicated to marketing. The increase in investments in science after World War II, with the systematization of processes dedicated to innovation and a substantial increase in public and private investment in research, became the new paradigm afterward (Malerba & Orsenigo, 2015).

The transformation of the pharmaceutical industry was continuous and, from the 1970s onwards, resulted in the emergence of the biotechnology industry (Gittelman, 2006; McKelvey et al., 2004; Pisano, 2010). Whereas the traditional pharmaceutical industry was based on the random discovery of new chemical components and combinations that could be marketed as drugs (Radaelli, 2008), the biotechnology industry combined new knowledge in microbiology and created applications of biological manipulations to meet medical demands (Gittelman, 2016; McKelvey et al., 2004). In addition to representing a radical technological advance, the biotechnology industry has opened up opportunities for new companies to enter the healthcare market - historically dominated by scale-intensive oligopolistic companies. To some extent, this has also meant a new form of organization of companies, with greater proximity to academia and commercial strengthening of science (Pisano, 2010).

At the same time, the trend of higher R&D investments also increased for the medical devices industry from World War II onwards. Although it is an industry less studied because it has somewhat lower levels of investment in research, the innovative and competitive dynamics resemble the other two industries (Donzé & Imer, 2020; Jakovljevic et al., 2021; Xiao, 2022). This industry includes various products, and definitions may vary: some authors exclude imaging and information technology equipment, while others exclude ophthalmic products. There is no widely accepted industry definition, although most authors treat this industry as containing all the medical equipment needed to provide health services, excluding pharmaceutical and biotechnology products (Donzé & Imer, 2020).

## 3. Method

The relationship between R&D and productivity was examined using two types of econometric estimation: quantile regressions and dynamic panel data models. Quantile regressions are a common approach in the literature, as they estimate the median of the dependent variable (productivity) conditional on the values of the explanatory variables (R&D). In this case, the estimation minimizes the sum of absolute residuals instead of the sum of squared residuals, as in Ordinary Least Squares (OLS) regressions (Cameron & Trivedi, 2005). Given the high dispersion in terms of firm sizes and values of R&D and productivity in the sample, quantile regressions provide valuable information by generating approximate estimates of the median for any percentile of the dependent variable (productivity). The Generalized Method of Moments (GMM) estimates dynamic panel models in various specifications (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Detailed descriptions of these models can be found in other studies (Batalgi, 2008; Cameron & Trivedi, 2005).

Panel models that employ fixed effects and are estimated by Ordinary Least Squares (OLS), commonly called static panels, necessitate that time-varying regressors are exogenous, meaning they are not correlated with the error term (omitted variables). However, numerous economic issues involve endogenous relationships. For instance, the association between the explanatory variable of innovation (proxied by R&D spending) and the dependent variable of productivity is characterized by omitted variables influencing productivity, which may correlate with innovation. This results in an endogeneity problem in econometric estimations. In this scenario, causality may be bidirectional, implying that increased innovation efforts can boost productivity, while firms with higher productivity levels may exhibit a greater propensity to invest in innovation. Employing instrumental variables, that is, variables correlated with R&D spending but not with the error term, could address this issue. Nonetheless, obtaining valid instrumental variables can be challenging in practice.

Addressing endogeneity issues in panel data can be achieved through dynamic models, estimated using the Generalized Method of Moments (GMM). These dynamic panel models enable the treatment of lagged explanatory and dependent variables (periods t-1, t-2, and so on) as endogenous, using them as instruments. Unlike static panel models, this methodology provides unbiased estimators, including lagged dependent variables, resulting in biased estimated coefficients. From the Economics point of view, employing lagged variables allows for a more accurate understanding of dynamic relationships between variables, which often exhibit strong correlations with their past values. Given that the variable of interest (R&D expenditure) is endogenous in relation to the dependent variable productivity, dynamic panel models are justified due to their ability to yield consistent and asymptotically efficient estimates of the relevant parameters.

In this study, we employ the first-difference GMM (GMM difference) method proposed by Arellano and Bond (1991) and the GMM system method introduced by Arellano and Bover (1995) and Blundell e Bond (1998). To assess the consistency of both the GMM difference and GMM system estimators, as well as the validity of the instruments used, we apply Hansen's test, Hansen's difference test, and the no second-order autocorrelation test (AR(2)) as described by Roodman (2009). The GMM dynamic panel models employed in this paper were estimated using Stata software, utilizing the "xtabond2" command developed by Roodman (2009).

### 3.1. Database and Estimated Models

To estimate the relationship between R&D and productivity, we utilized the Medtrack (2019) company-level database, which compiles extensive information on firms across various human health sectors in numerous countries. We selected companies that had, at the very least, information on R&D expenditures, sales revenues, and the number of employees. Our sample consists of publicly traded firms operating in the pharmaceutical, biotechnology, and medical devices sectors, originating from 31 countries across North America, Europe, Asia, and Oceania. The analyzed sample comprises an unbalanced panel featuring data from 1,106 companies between 2011 and 2018 (eight periods), resulting in 5,457 observations. All monetary variables are presented in US dollars and deflated using the Consumer Price Index (CPI), as calculated and provided by the US Bureau of Labor Statistics (2020). The estimated model representing the relationship between R&D and productivity at the firm level, as determined by the dynamic panel technique, is depicted in Equation 3:

$$\mathrm{Product}_{i,t} = \alpha + \beta_1 \mathrm{Product}_{it-1} + \beta_2 \mathrm{RD\_Work}_{it} + \beta_3 \mathit{Work}_{it} + \beta_4 \mathrm{Country}_i + \beta_5 \mathrm{Time}_i + \mu_{it} \quad (3)$$

Where:

$i = 1, 2, ..., 1.106$ companies;

$t = 1, 2, ..., 8$ periods between 2011 and 2018;

$\alpha$: constant;

$\beta_i$: coefficients;

$\mathrm{Product}_{i,t}$: labor productivity of firm i at time t, calculated as sales revenue divided by the number of employees;

$\mathrm{Produtc}_{i,t-1}$: labor productivity of firm i in time *t*–1 ;

$\mathrm{RD\_Work}_{it}$: R&D spending per employee in firm *i* at time *t*;

$\mathrm{Work}_{it}$: number of employees of the company *i* at time *t*;

$\mathit{Country}_i$: set of nationality dummies of firm *i* ;

$\mathrm{Time}_i$: set of annual dummies;

$\mu_{it}$: error term.

For quantile regressions, which are not dynamic models, the lagged productivity variable ($\mathrm{Produtc}_{i,t-1}$:) is omitted. In dynamic panel models, all variables are treated as endogenous, with their lags used as instruments. To conduct a sensitivity analysis for the estimation, we also examine the dynamic panel model using a balanced sample consisting of 346 firms that are present throughout all eight periods, amounting to 2,768 observations.

**3.2 Limitations**

A limitation of this study is the potential selection bias within the sample of companies. Despite the considerable number of observations for the analyzed activity groups, the sample contains significantly more companies in North America than in other regions, which may lead to greater heterogeneity of company types in this location than in other regions. In Asia, for instance, the sample is predominantly composed of large companies, making it challenging to determine whether the significant impact of R&D spending on productivity is specific to the region or the size of the companies. A more comprehensive analysis of the health industry companies' profiles in Asian countries could help ascertain whether the sample accurately represents the population. Another limitation is the database's limited information on other control variables, which could enhance the models' robustness.

## 4. Descriptive Statistics

To further detail the database, Table 1 presents the mean values of the variables by five levels of percentiles. In general, the data indicate a high dispersion of the variables. The table shows, for instance, that while companies in the 10th percentile in terms of sales revenue presented an average value of only US$ 1.05 million, companies in the 90th percentile presented an average value of US$ 8,255.73 million.

**Table 1** - Descriptive statistics by percentiles (2011-2018)

| | **10%** | **25%** | **50%** | **75%** | **90%** |
|---|---|---|---|---|---|
| Sales revenue[1] | 1.05 | 10.11 | 122.50 | 1,169,75 | 8,255.73 |
| R&D spending[1] | 1.45 | 4.60 | 21.86 | 95.97 | 623.24 |
| Number of employees | 26 | 68 | 338 | 2,700 | 11,954 |
| Labor productivity[1] | 0.03 | 0.12 | 0.26 | 0.51 | 1.36 |
| R&D spending per employee[1] | 0.01 | 0.02 | 0.05 | 0.18 | 0.56 |

Note: [1] in million US$ at 2011 prices

Table 2 presents some descriptive statistics (means and standard deviations) of the sample variables by continent. The table shows that sales revenue and R&D spending are much higher in Asia than in the other continents. For example, while the average R&D expenditure of the Asian firms in the sample was $4.13 million, for North American firms, it was only $0.23 million. However, the standard deviation was much higher in Asia, indicating a great inequality among the companies regarding the magnitude of the investments made. This influences the higher average labor productivity values of Asian countries in relation to the other regions. As for company size, using the number of employees as a proxy, Table 2 shows that European companies are more than twice as large as the general average, reaching 12,152 workers on average.

**Table 2** - Descriptive Statistics of Enterprises by Continent (2011-2018)

Averages and standard deviations in parentheses

| | North America | Asia | Europe | Oceania | Overall |
|---|---|---|---|---|---|
| Sales revenue[1] | 2.29 | 162.35 | 7.76 | 0.30 | 41.86 |
| | (10.46) | (1,327.53) | (34.43) | (1.05) | (655.48) |
| R&D spending[1] | 0.23 | 4.13 | 0.70 | 0.03 | 1.25 |
| | (0.96) | (20.32) | (3.32) | (0.09) | (10.24) |
| Number of employees | 4,936 | 4,981 | 12,152 | 859 | 6,192 |
| | (16,762) | (9,150) | (42,084) | (2,727) | (22,625) |
| Labor productivity[2] | 0.37 | 23.53 | 0.92 | 0.22 | 6.06 |
| | (3.18) | (154.81) | (2.92) | (0.26) | (76.66) |
| R&D spending per employee[2] | 0.14 | 2.13 | 0.30 | 0.14 | 0.65 |
| | (0.39) | (9.05) | (0.72) | (0.20) | (4.54) |
| Number of observations | 3,001 | 1,316 | 1,014 | 126 | 5,457 |

Note: [1] in millions of US$ at 2011 prices

[2] in thousand US$ at 2011 prices

Table 3 presents some descriptive statistics (means and standard deviations) of the sample variables by company size. The table shows that the larger the company's size (from up to 49 employees to above 1,000 employees), the higher its average values in sales revenue, R&D spending, and labor productivity. For example, R&D spending for firms in the sample with up to 49 employees averaged $0.03 million, well below the average spending of $3.33 million for firms in the sample with more than 1,000 employees. However, when R&D per worker is calculated, it is found that the smallest firms invest proportionally more: the smallest firms in the sample spend, on average, US$ 1.2 thousand on R&D per worker, while the largest firms spend only US$ 0.32 thousand per worker. In science-based sectors, the data shows the strong role of investment in innovation also made by small companies.

**Table 3** - Descriptive Statistics by Company Size (2011-2018)

Means and standard deviations in parentheses

| | 1-49 | 50-249 | 250-999 | 1000- | Total |
|---|---|---|---|---|---|
| Sales revenue[1] | 0.02 | 0.18 | 3.13 | 115.85 | 41.86 |
| | (0.11) | (1.77) | (36.05) | (1,094.78) | (655.48) |
| R&D spending[1] | 0.03 | 0.06 | 0.23 | 3.33 | 1.25 |
| | (0.20) | (0.31) | (2.20) | (16.89) | (10.24) |
| Number of employees | 25 | 117 | 526 | 17,008 | 6,192 |
| | (13) | (53) | (200) | (35,434) | (22,625) |
| Labor productivity[2] | 1.16 | 1.44 | 8.09 | 11.08 | 6.06 |
| | (13.26) | (10.14) | (111.46) | (99.07) | (76.66) |
| R&D spending per employee[2] | 1.20 | 0.76 | 0.55 | 0.32 | 0.65 |
| | (6.12) | (4.37) | (6.29) | (1.58) | (4.54) |
| Number of observations | 1,060 | 1,443 | 1,012 | 1,942 | 5,457 |

Note: [1] in millions of US$ at 2011 prices

[2] in thousand US$ at 2011 prices.

Figure 1 presents a cross-referencing of the sample data by region and company size. We observe that the region that concentrates the largest companies (in terms of the number of employees) is Asia, in which about 57% of the companies have more than a thousand employees, while Oceania concentrates the largest relative quantity of small companies with less than 50 employees (53%). The data in North America is more equally distributed regarding company size, reflecting a more balanced distribution in the total sample.

**Figure 1** - Descriptive Statistics by Region and Company Size (2011-2018) Quantities of observations and percentages

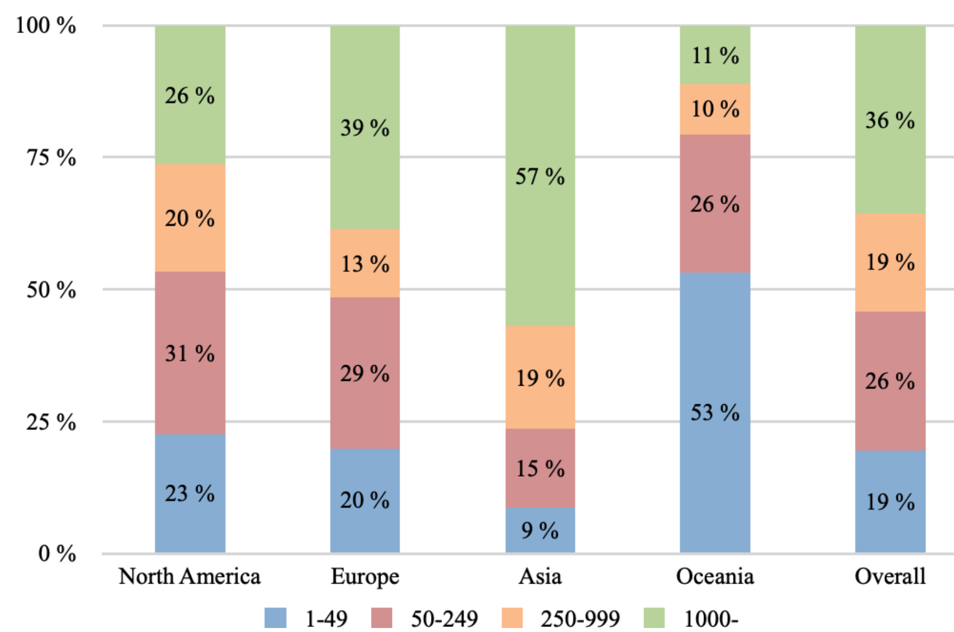



Figure 2 presents a diagram of the proportional number of observations by type of economic activity. One can observe that a large set of diversified companies operate in more than one activity. For example, of the total 3,352 observations in the pharmaceutical industry, 2,176 do biotechnology activities, and 620 operate in the medical devices sector. The diagram indicates that more firms in the pharmaceutical industry also operate in the biotechnology sector (1,862 observations) than alone (870 observations). On the other hand, the medical devices sector has a much more distinctive characteristic, being less integrated with the other sectors and having a greater share in the sample in isolation (1,398 observations). Only 314 observations are present in the three highlighted activities.

**Figure 2** - Diagram of the Number of Observations by Type of Economic Activities

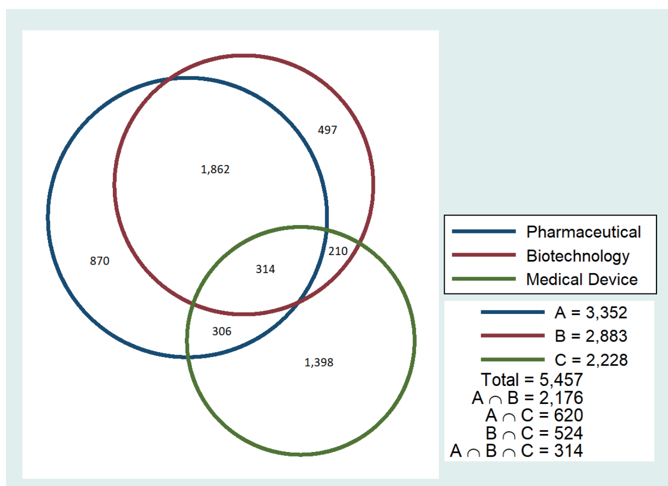


Table 4 presents some descriptive statistics of the sample by type of economic activity. We considered companies that participate in the three industrial branches highlighted, regardless of whether they also participate in others. The table shows a predominance of values in the pharmaceutical industry compared to the other sectors, whether in sales revenues and R&D spending or firm size and productivity. The biotechnology branch stands out for having smaller companies (an average of 3,798 employees, almost half compared to the other two activities) and high R&D spending per worker, similar to the values of the pharmaceutical industry. On the other hand, the medical devices sector has larger companies (an average of 6,192 employees), which is more similar to the size profile of companies in the pharmaceutical sector. However, R&D expenditures, in absolute values and per worker, and labor productivity values are much lower compared to the other two industries.

**Table 4** - Descriptive Statistics by Economic Activity (2011-2018)

Means and standard deviations in parentheses

| | **Pharmaceutical** | **Biotechnology** | **Medical Device** | **Overall** |
|---|---|---|---|---|
| Sales revenue[1] | 65.76 | 23.00 | 5.89 | 41.86 |
| | (835.12) | (264.77) | (50.68) | (655.48) |
| R&D spending[1] | 1.90 | 1.01 | 0.33 | 1.25 |
| | (12.95) | (7.48) | (2.29) | (10.24) |
| Number of employees | 7,192 | 3,798 | 6,353 | 6,192 |
| | (21,872) | (21,266) | (21,175) | (22,625) |
| Labor productivity[2] | 9.18 | 5.71 | 1,02 | 6.06 |
| | (97.40) | (75.48) | (6.04) | (76.66) |
| R&D spending per employee[2] | 0.94 | 0.92 | 0.15 | 0.65 |
| | (5.64) | (5.91) | (1.23) | (4.54) |
| Number of observations | 3,352 | 2,883 | 2,228 | 5,457 |

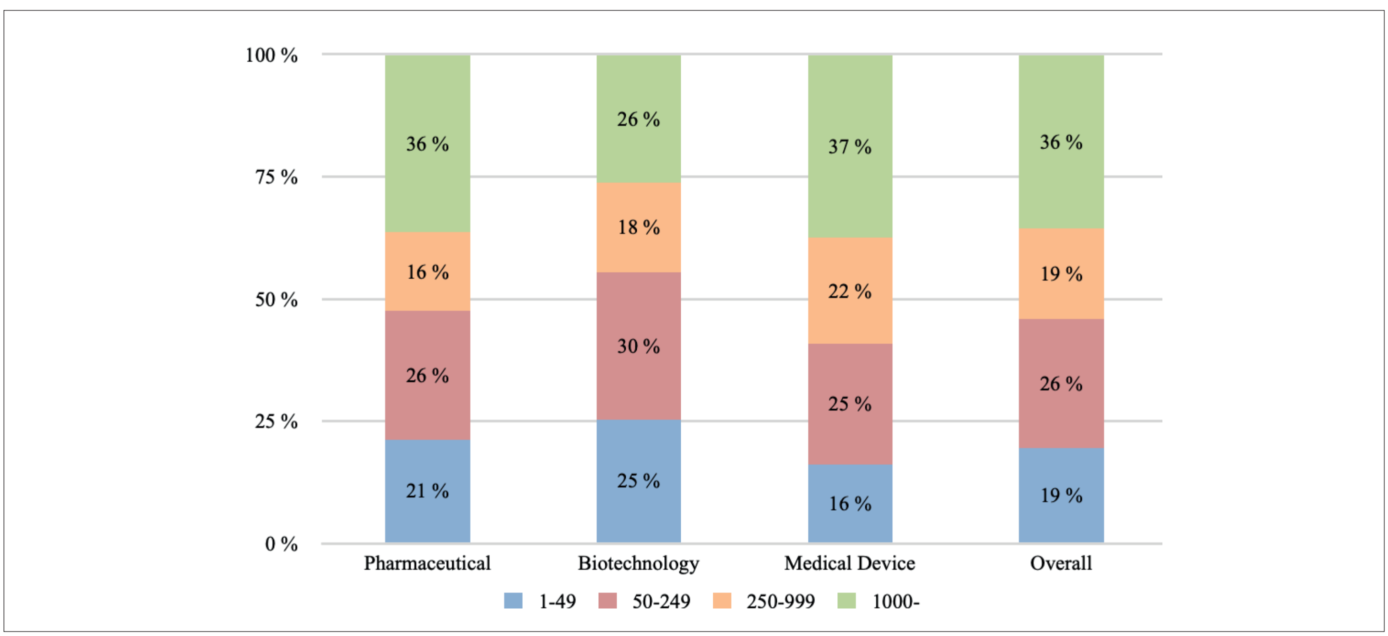
Note: [1] in millions of US$ at 2011 prices

[2] in thousand US$ at 2011 prices.

Figure 3 cross-referenced sample data by economic activity and company size. As also presented in Table 3, one observes the greater predominance of smaller companies in the biotechnology activity than in the other sectors, which large companies dominate. However, there are no major discrepancies in the shares between the four firm size categories in the three sectors analyzed, which shows great diversity in the sample.

**Figure 3** - Descriptive statistics by economic activity and company size (2011-2018)

Quantities of observations and percentages

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Finally, Table 5 presents the correlation between the variables of the companies in the sample. One notices a moderate correlation (0.477) between the variables R&D per worker and labor productivity. The correlations presented, however, do not consider the causal effects of the variables and problems of endogeneity. It also does not account for all correlations, cross effects between them, or controls for other factors. The next section seeks to present these nuances through an analysis of the model specified by Equation 3, estimated both by the GMM dynamic panel methodology and by the quantile regression methodology, seeking to analyze the differences in the dispersion of the sample companies.

**Table 5** – Correlation between variables (2011-2018)

| | Sales revenue | R&D spending | Number of employees | Labor productivity | R&D spending per employee |
|---|---|---|---|---|---|
| Sales revenue | 1.000 | | | | |
| R&D spending | 0.655 | 1.000 | | | |
| Number of employees | 0.032 | 0.103 | 1.000 | | |
| Labor productivity | 0.758 | 0.503 | 0.002 | 1.000 | |
| R&D spending per employee | 0.126 | 0.217 | -0.027 | 0.477 | 1.000 |

## 5. Results

Table 6 presents the estimation results between R&D per worker and labor productivity using quantile regressions. The first column of the table presents the linear regression by traditional OLS, while the other columns present the regressions at the 10th, 25th, 50th, 75th, and 90th percentiles. The results show that the relationship between R&D per worker and labor productivity is positive and statistically significant at 1% for all models. All variables are logarithms, so the results are interpreted through elasticity effects. For example, for the OLS model, a 1% increase in R&D expenditure per worker in firms increases labor productivity by 0.25%. Quantile regressions show that the higher the firm's labor productivity, the greater the effect of R&D per worker. While the impact of the innovation effort variable is 0.07% for the least productive firms (10th percentile), for the most productive firms (90th percentile), the impact reaches 0.38%.

Table 6 also shows a positive and statistically significant relationship at 1% between firm size (number of employees) and labor productivity in all columns. For example, by the OLS model, a 1% increase in the number of employees increases productivity by 0.28%. On the other hand, the quantile regressions show that the relationship between the two variables is now one of decreasing marginal effects, i.e., firm size is less and less important as the firm grows. While the impact of the number of employees is 0.42% for the smallest firms (10th percentile), for the largest (90th percentile), it is only 0.12%.

**Table 6** - Results of Quantile Regressions

(Var. Dependent: (ln) Labor Productivity)

| | OLS | p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|
| ln (R&D_Work) | 0.255*** | 0.078*** | 0.125*** | 0.183*** | 0.357*** | 0.387*** |
| | (0.015) | (0.019) | (0.010) | (0.008) | (0.010) | (0.008) |
| ln (Work) | 0.285*** | 0.425*** | 0.273*** | 0.169*** | 0.148*** | 0.128*** |
| | (0.008) | (0.017) | (0.007) | (0.005) | (0.006) | (0.005) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Countries dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$ | 0.437 | 0.252 | 0.223 | 0.229 | 0.320 | 0.470 |

Note: The symbols *, **, and *** indicate p-values less than 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses. Constant not reported.

The quantile regressions of the relationship between R&D per worker and labor productivity in Table 6 are represented graphically in Figure 4. While the dashed lines represent the OLS estimation and its confidence intervals, the continuous line indicates the coefficients of the quantile regression for values of R&D per worker in percentiles of labor productivity. The shaded area represents the 95% confidence interval for the quantile regression coefficients. The figure shows the increasing marginal effects between R&D and productivity observed in Table 6.

**Figure 4** - Results of Quantile Regressions: Relationship between R&D Spending per Employee and Labor Productivity

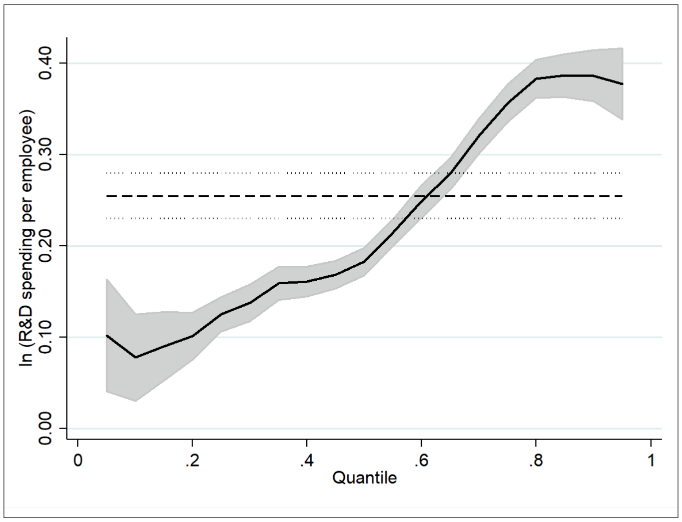


Table 7 presents the estimation results using the dynamic panel GMM system. In this case, we add the lagged labor productivity explanatory variable. The table also shows the model estimation for different groups of firms according to their location (North America, Europe, and Asia)[1] and firm size (up to 49 employees, from 50 to 249, from 250 to 999, and above 1,000). The bottom part of the table shows the p-values of the AR autocorrelation test (2) and the validity of the instruments (Hansen's Test and Hansen's Difference Test). For most of the models, the p-values were high, above 10%; therefore, the null hypothesis of the absence of second-order serial correlation is accepted, confirming the consistency of the estimates, and the null hypothesis that the set of instruments is valid and uncorrelated with the error term is accepted, eliminating endogeneity bias. Only the model with US firms rejected the null hypothesis in Hansen's test. Table A in the Supplementary Material presents the models estimated via dynamic panel GMM difference. The results, in general, were quite similar to those of Table 7, accepting the null hypotheses of the tests for all sets of samples. We preferred to analyze the system estimations due to the lower number of lost observations that this technique can provide compared to estimation by differences.

Table 7 shows that, except for the samples of North American and European firms, the relationship between R&D per worker and labor productivity is positive and statistically significant at 1%. In the total sample, a 1% increase in R&D expenditure per worker increases productivity by 0.88%, a much higher magnitude than that observed in the quantile regressions (Table 6). Thus, the impact of R&D spending on productivity is even more relevant in a more robust estimation technique. This relationship is even stronger in Asian firms compared to European and North American ones and in larger firms compared to smaller ones. For example, a 1% increase in R&D spending per worker increases labor productivity by 0.93% in Asian firms. The relationship between R&D and productivity was not statistically significant in North America and Europe, although the coefficients were positive. Table 7 also shows the effects of employee number and lagged labor productivity. The estimations show that a 1% increase in the number of employees increases productivity by 0.45%. However, in the continents' sample subgroups, this relationship is only shown to be statistically significant in Asian firms.

**Table 7** - Results of the GMM Dynamic Panel System Estimation by Continent and Size

Dependent variable: Labor productivity

| | Overall | North America | Europe | Asia | 0-49 | 50-249 | 250-999 | 1000- |
|---|---|---|---|---|---|---|---|---|
| | 0.673*** | 0.729*** | 0.498*** | 0.198* | 0.624*** | 0.689*** | 0.576*** | 0.004 |
| | (0.080) | (0.078) | (0.138) | (0.116) | (0.110) | (0.101) | (0.173) | (0.069) |
| R&D_Work | 0.886*** | 0.093 | 0.265 | 0.930*** | 0.390*** | 0.780*** | 0.849*** | 0.939*** |
| | (0.034) | (0.064) | (0.196) | (0.043) | (0.106) | (0.109) | (0.071) | (0.029) |
| Work | 0.459*** | 0.012 | 0.009 | 0.689*** | 0.235 | 0.298 | 0.765*** | -0.037 |
| | (0.082) | (0.097) | (0.216) | (0.162) | (0.214) | (0.432) | (0.279) | (0.110) |
| AR (2) | 0..915 | 0.765 | 0.529 | 0.737 | 0.989 | 0.821 | 0.142 | 0.579 |
| Hansen | 0.183 | 0.026 | 0.973 | 0.645 | 0.629 | 0.860 | 0.685 | 0.949 |
| Dif Hansen | 0.219 | 0.018 | 0.582 | 0.698 | 0.082 | 0.433 | 0.053 | 0.358 |
| No. inst. | 168 | 41 | 110 | 69 | 97 | 112 | 110 | 142 |
| No. obs. | 4,228 | 2,372 | 808 | 954 | 720 | 1,134 | 810 | 1,564 |
| No. groups | 938 | 491 | 162 | 260 | 241 | 337 | 228 | 350 |

Note: The symbols *, **, and *** indicate p-values less than 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses. The p-values of AR test statistics (2), Hansen's test, and Hansen's difference test for the GMM instruments are reported. Dependent and explanatory variables are in logarithms (ln). Time dummies and the constant were estimated in the models and are not reported. The estimated models were run from the "xtabond2" command of Stata 14 software, developed by Roodman (2009), and control for excess instruments ("collapse" command), have adjustments for small samples ("small" command) and orthogonal variances ("orthogonal" command). One-stage GMM system estimation.

[1] The values for Oceania were not measured due to the low number of observations.

Table 8 presents the results of the estimations by dynamic panel GMM system in subsamples of economic activities. Table B in the Supplementary Material presents the models estimated via dynamic panel GMM difference. The table also presents, in its last four columns, estimates with balanced data in order to test the robustness of the results. The results were positive and statistically significant for all subsamples of sectors. It was not possible to identify significant differences regarding the magnitude of the impact of R&D expenditure on productivity in the different models, in which the coefficients were very similar to the total sample in all sets. The results for the balanced data were slightly higher than those presented in the unbalanced data, highlighting the robustness of the findings.

**Table 8** - Results of the GMM Dynamic Panel System Estimation by Economic Activity

Dependent variable: Labor productivity

| | Unbalanced Panel | | | | Balanced Panel | | | |
|---|---|---|---|---|---|---|---|---|
| | **Overall** | **Pharma** | **Biotech** | **Device** | **Overall** | **Pharma** | **Biotech** | **Device** |
| | 0.673*** | 0.617*** | 0.730*** | 0.804*** | 0.588*** | 0.448*** | 0.774*** | 0.977*** |
| | (0.080) | (0.093) | (0.094) | (0.116) | (0.133) | (0.152) | (0.154) | (0.213) |
| R&D_Work | 0.886*** | 0.867*** | 0.863*** | 0.875*** | 0.957*** | 0.944*** | 0.905*** | 0.948*** |
| | (0.034) | (0.044) | (0.057) | (0.078) | (0.034) | (0.043) | (0.055) | (0.099) |
| Work | 0.459*** | 0.456*** | 0.455*** | 0.705*** | 0.744*** | 0.762*** | 0.611* | 1.210** |
| | (0.082) | (0.100) | (0.135) | (0.233) | (0.282) | (0.293) | (0.362) | (0.533) |
| AR (2) | 0.915 | 0.810 | 0.791 | 0.520 | 0.612 | 0.385 | 0.754 | 0.289 |
| Hansen | 0.183 | 0.501 | 0.547 | 0.045 | 0.931 | 1.000 | 0.914 | 0.213 |
| Dif Hansen | 0.219 | 0.054 | 0.045 | 0.967 | 0.314 | 0.082 | 0.049 | 0.152 |
| No. inst. | 168 | 168 | 143 | 29 | 137 | 137 | 107 | 29 |
| No. obs. | 4,228 | 2,548 | 2,182 | 1,783 | 2,422 | 1,365 | 1,127 | 1,127 |
| No. groups | 938 | 594 | 514 | 351 | 346 | 195 | 161 | 161 |

Note: The symbols *, **, and *** indicate p-values less than 10%, 5%, and 1%, respectively. Robust standard errors are in parentheses. The p-values of AR test statistics (2), Hansen's test, and Hansen's difference test for the GMM instruments are reported. Dependent and explanatory variables are in logarithms (ln). Time dummies and the constant were estimated in the models and are not reported. The estimated models were run from the "xtabond2" command of Stata 14 software, developed by Roodman (2009), and control for excess instruments ("collapse" command), have adjustments for small samples ("small" command) and orthogonal variances ("orthogonal" command). One-stage GMM system estimation.

## 6. Discussion

Our results show a strong and positive relationship between R&D expenditure and labor productivity in the human health industry, aligning with existing literature emphasizing the importance of R&D investments in driving productivity growth and innovation (Crepon et al., 1998; Griffith et al., 2006; Griliches, 2007; Mohnen & Hall, 2013). The findings contribute to this body of knowledge by also highlighting the increasing marginal effects of R&D investment on labor productivity, particularly for more productive and larger firms. This observation suggests that the returns to R&D investments may not be constant across all firms and could be influenced by various factors.

The findings indicate that Asian firms experience a stronger relationship between R&D and productivity than North American and European firms. This shows that, at least for the pharmaceutical, biotechnology, and medical device industries in the sample, spending on innovative efforts by the largest companies and those headquartered in Asia generated greater positive results in terms of productivity than in the smallest companies and those headquartered in other regions. The differences in the impact of R&D on productivity across regions might be attributed to varying institutional frameworks, technological infrastructure, and levels of investment in human capital (Belderbos et al., 2015; Prenzel et al., 2018; Sterlacchini & Venturini, 2014).

The Asian continent has several prominent countries in the international human health industry. Japan has the longest tradition in this industry, but unlike other national industries (notably automobiles and electronics), the protectionist policies in place until the 1990s were not enough to position Japanese companies in the top echelon of global companies. Japanese pharmaceutical companies, for example, invest less in R&D, launch fewer drugs, and sell less than their competitors (Umemura, 2013). On the other hand, India and China have stood out in recent years for using the pharmaceutical and biotechnology industry as one of their vectors of industrial development. These countries have invested heavily in generic drugs (and, after, in biosimilars) and together account for more than half of the world's exports of activated pharmaceutical ingredients (API) (Dorocki, 2014).

Nonetheless, it is crucial to consider that the sample's Asian companies account for a relatively larger proportion of firms with over 1,000 employees. Consequently, the high impact of R&D on productivity for these companies may be more closely associated with size rather than location. The relationship between past and current productivity was positive across all models but lacked statistical significance in Asian firms and those with more than 1,000 employees. While the effects of the previous year's productivity appear highly significant for current productivity in all subsets of firms has been discussed in previous studies (Bond & Guceri, 2017), for our sample, they seem to exert less influence on larger and Asian firms. Additionally, R&D spending per worker seems to be the key variable driving productivity growth for these firms – which also aligns with previous studies (Heshmati & Kim, 2011).

Additionally, the positive and statistically significant relationship between firm size (number of employees) and labor productivity aligns with other findings in the literature for both manufacturing and non-manufacturing industries (Diaz & Sanchez, 2008; Leung et al., 2008; Van Biesebroeck, 2005). The impact of the number of employees is bigger for the smallest firms, which shows that firm size is a relevant factor for productivity growth, most likely due to greater economies of scale. However, there is a limit to the companies' continuous benefit of scale effects. The increasing marginal effects between R&D and productivity for the companies that are among the 20% most productive are still positive, statistically significant, and relatively high but decrease as the company increases its efficiency. Therefore, there are also decreasing marginal effects of R&D spending on productivity at the top of the most efficient companies in the sample.

The results show a persistent positive and statistically significant relationship between R&D spending per worker and labor productivity in the different estimation methods and sample sets. It was not possible to perceive differences in the magnitude of the impact of R&D on productivity between the pharmaceutical, biotechnology, and medical devices sectors. The intensities of the impacts were more diversified in the analysis by region (stronger in Asia) and in the analysis by company size (stronger in large companies).

## 7. Final remarks

This study comprehensively analyzes the relationship between R&D investments and labor productivity in the human health industry. Our findings demonstrate a strong and positive link between R&D expenditure and labor productivity, with increasing marginal effects as firm productivity and size grow. Moreover, we observe regional disparities in the R&D-productivity relationship, with a more pronounced impact for Asian firms than their North American and European counterparts. The results align with existing literature on the critical role of R&D investments in driving innovation, growth, and productivity in various industries (Bond & Guceri, 2017; Heshmati & Kim, 2011; Smith et al., 2004). The observed heterogeneity in the R&D-productivity relationship across firms, regions, and sectors evidences the complexity of the innovation process.

Our study contributes to the literature by employing a dynamic panel GMM system estimation, which addresses potential endogeneity issues and offers more robust results. The findings also have practical implications for policymakers and industry stakeholders. The stronger effect of R&D in larger and more productive firms suggests that policies should focus on scaling up innovation efforts, particularly in high-growth firms. At the same time, support for smaller firms and firms in regions with less established innovation ecosystems is necessary to ensure broader productivity gains across the sector. This approach can help reduce regional disparities in the R&D-productivity relationship.

Future research could take a more in-depth look into regional differences and explore the role of human capital and institutional factors in enhancing the impact of R&D on productivity in the human health industry. For regional differences, a more comprehensive analysis of the size of human health firms in Asia is needed. This requires examining the relationship between R&D and productivity using other firm-level databases in representative countries of this industry in Asia, such as China, India, and Japan. A sample of more heterogeneous Asian companies in terms of size could help mitigate the limitation of this study regarding potential selection bias.

As the human health industry continues to evolve and face global challenges, sustained investment in R&D remains essential for fostering innovation and maintaining competitiveness. Understanding the varying effects of R&D spending across different firm sizes and regions is crucial for shaping effective innovation strategies.

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