[The Impact of Green Innovation on Firm Value in the Biotech Sector in Europe: A Path to Efficient and Sustainable Growth]

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Name: **NGUYEN THUY DUONG** | *d.nguyenthuyduong@students.uu.nl*

Honors Bachelor's in ***Economics & Business Economics***

Dedicated Minor in ***Applied Data Science for Economics***

Student number: **6827209**

Supervisors:

Prof. Dr. WOUTER BOTZEN | *wouter.botzen@vu.nl*

PhD. Brian Colgan | *b.p.colgan@uu.nl*

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Statement of Originality

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Abstract

The economy is transiting towards sustainable development, stimulating more and more enterprises to incorporate environmental concerns into corporate development strategy. Technology development and innovation – the key drivers of economic growth and productivity – empower such a unification. A substantial attention, however, is paid to the effects of eco-transformation in heavily polluting or non-high-tech industries. This paper, instead, focuses on the biotechnology sector and seeks to shed light on the impact of green innovation on business development. This analysis deploys patent data as a measure for business green growth in alternative to the traditional metrics, such as R&D investment and publications, to investigate the impact of green innovation on the value of publicly listed biotechnology enterprises in Europe. This analysis detects no negative consequences of green innovation on a firm's value and evidences its contribution to the success of young biotech enterprises in the near future.

Keywords: green (eco) innovation, firm value, sustainability, patent data.

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I. Introduction

Global environmental challenges should be perceived as opportunities rather than obstacles purely. They in fact contribute to the emergence and expansion of new socially conscious economies, one of which is industrial biotechnology, or so-called white biotechnology (OECD, 2011). This bio-based economy offers a range of options for competitive industrial performance in selected sectors and creates motive for economic growth (OECD, 2011), while at the same time channels an efficient allocation of the natural resources to sustain the planet and human well-being (Leal, 2017). From this positive stance, environmental concerns constitute a stimulus for continuous innovation, which might lead firms to discover new market opportunities and enhance economic performance (Hofmann, 2020).

Unfortunately, green innovation (GI) implementation is confronting at least three barriers. The biggest issue is that the economic returns generated from eco-conscious investments have still been unspecified (Duque-Grisales, 2020), causing many enterprises to choose to delay or even abandon the investment plans. This occurs because most of previous studies do not directly examine the influence of GI on firm value and primarily target those operating in carbon-intensive or non-high-tech industries. In these sectors, a higher chance is that the costs involved could overweight the benefits of green investments (Yao (2019); Xie, Wang & Zhao 2022). Secondly, as these analyses are mainly conducted within a short time frame, they might have failed to capture the long-term effects of the eco-friendly technological development. Finally, sustainable investments can affect young and long-established firms differently, which triggers more inconsistencies in research findings. OECD (2013) states that new firms are more likely to participate in more radical innovation than their long-standing incumbents. This is supported by Kloosterman's findings (2018) that firm age has a certain effect on the rate of green innovation – longer established firms tend to be less engaged in the transformation compared to younger companies. Therefore, it is essential to take age gap between firms into consideration when inspecting the role of GI on performance of businesses. Receiving signals from these conflicting and asymmetric views, enterprises might consequently envisage eco-transition as a threat to business development rather than an opportunity for expansion.

The objectives of this research, therefore, are to investigate if green innovation is constructive to the business value and to examine if its effects vary between different groups of firms.

The analysis can make a considerable scientific contribution. Firstly, it examines the statement that eco-conscious transition can be harmful to business in the short run, but potentially generates economic gains in the long run. Secondly, it lays a ground for further research by suggesting a new estimator of innovation using patent data. It highlights the importance and advantages of patent data relative to other alternatives, such as R&D expenditures or the number of scientific publications, in quantitative research.

The analysis also serves the interests of different parties in the society, including customers, businesses, and governments. Since nowadays' customers are moving their preference towards healthier and more eco-conscious consumption (Forbes, 2021; IBM, 2020), they seek products and brands that align with their values (EU Parliament, 2020). GI level, therefore, can be an appropriate indicator for Corporate Social Responsibility (CSR) that matches consumers to their expected firms' values. Simultaneously, the results of this paper are particularly useful for biotech managers in considering investing in eco-friendly technology. Indeed, they confirm that GI constructs a stronger economic stance for the investors in the near future, especially for younger biotechnology entities. The paper eventually provides an opinion on the current controversy on how we define a transformative industry for the 21st century and suggests appropriate policies for policymakers to accelerate the process of enterprise transformation.

The remaining of the paper is organized as follows. The next section provides an explanation of the theoretical framework and hypothesis development. Section 3 provides background information on the key concepts of green innovation (GI), biotechnology, and patent data. Sections 4 and 5 elaborate on data description and descriptive statistics. The empirical approaches are explained in Section 6, while the results are thoroughly elucidated in Section 7. The last part provides a brief conclusion and discusses the external validity of the research.

II. Literature review and hypothesis development

Insufficient research has been carried out to investigate the role of GI on financial performance. Existing studies mainly link GI to Corporate Social Responsibility (CSR) or the generic concept of sustainable development, to assess business financial achievement. Examples are research by Simon, A. (2002), Sueyoshi & Goto (2009), Kaur & Singh (2020), Kapoor & Sandhu (2010). Few studies that directly examine relationship between GI and firm performance, however, provide conflicting inferences.

Duque-Grisales (2020) recognizes certain impacts of innovation initiatives on the firm, which, unfortunately, do not guarantee higher financial performance. Conversely, Rizki and Hartanti (2021) conclude that GI positively influence firm value as they contribute to sustaining corporations' competitive advantages as well as sustainable development. Recent works by Xie, Wang & Zhao (2022) counteract both findings and suggest that environmentally related innovation are harmful to the businesses in short-term but can eventually generate profitability. Their works have so far ignored the argument by Kloosterman (2018) that longer established firms tend to be less engaged in the transformation compared to younger companies. His conclusion is in line with the 2013 OECD's implications that new firms are more likely to participate in more radical innovation than their long-standing incumbents. Therefore, it is essential to regard to age gap between firms when assessing the role of GI on business economic performance.

These studies typically employ the Pooled OLS regression, which possibly includes omission variable bias (OVB) that can weaken their causal inferences. Fixed Effects Regression (FER) and Random Effects Regression (RER) are alternatives to handle this problem (Dieleman & Templin (2014); Frondel & Vance (2010)). However, the FER is favored since it is proved to efficiently address unobservable heterogeneity in panel data (Arnold (2019); Dranove (2012)) employed in this analysis.

Compiling all perspectives, this research proposes four research sub-questions to clarify the potential effects of eco-conscious movements on a firm's economic performance: *(1)* Does green innovation (GI) influence the firm value? (2) Are the effects of GI on firm value negative or positive, if any? (*3*) Are these effects sustained, or short-term? *(4)* Do they vary by subgroups of ages? This leads to the following three hypotheses:

Hypothesis 1: Green innovation (GI) has a negative impact on firm value in the short run.

Hypothesis 2: In the long run, GI can generate favorable outcomes to businesses.

Hypothesis 3: GI affects the economic performance of younger and older firms differently.

The first two hypotheses separate the mixed effects of GI on a firm's value mentioned by Xie, Wang & Zhao (2022), Rizki and Hartanti (2021), Duque-Grisales (2020), Sueyoshi & Goto (2009), while the last one is based on the argument that firm age has a certain effect on the rate of GI (OECD's (2013), Kloosterman's (2018)). The hypotheses are examined using FE model. Since the analysis focuses on the European biotechnology sector, its findings are applicable to this sample.

III. Background

1. Green Innovation

Definitions

The conceptualization of GI has evolved from resource-oriented definitions to a more comprehensive framework that encompasses industrial relationships between firm's and the stakeholders' green requirements and demands (Leal, 2017). The traditional focus of GI was on mitigating the adverse impacts of production and consumption activities on the environment (Miedzinski, et. all, 2020), thus as Leal, 2017 explained: "*comprise all type of innovations that contribute to the creation of key products, services, or processes to reduce the harm, impact, and deterioration of the environment at the same time that optimizes the use of natural resources*." Nowadays, GI has gone beyond the limited concept of marginal environmental concern (Wahidatul & Bambang, 2021) and presented itself as a critical indicator of the long-term sustainability and as a useful tool for businesses to improve financial performance and competitiveness (Hofmann, 2020; Antoine & Misato, 2018). From an academic stance, this paper incorporates both approaches and interprets GI as sustainable technologies or non-technological methods which simultaneously serve commercial purposes, benefit the society, and contribute to minimizing environmental impacts.

Patents reflecting green innovation

Patents are a strong indicator of the innovation power of the company. Patents can appropriately capture the proprietary and competitive dimension of technological change (Kürtössy, 2004) and thus can be equally understood as innovation. Nonetheless, neither all innovations nor patents are sustainable. Innovations can exist either in the forms of green technologies or production methods (Chiara & Iannone, 2020) or non-green inventions that essentially benefit the public or businesses but not necessarily serve sustainable goals. The same goes for patents.

However, this research assumes that all patents granted to biotechnology firms are sustainable. This assumption is based on a fact that patent-holding entities in the bio-based industry are strongly linked to sustainable production and consumption, as explicitly demonstrated in their definitions[1]. The rising

[1] *2. Biotechnology*, Section II: *Background*, and Appendix A.

concern about eco-efficiency has even reinforced this relation by creating an engine for bio-businesses to achieve commercial success via launching more new sustainable technologies on to the markets. Hence, such a postulation is reasonable within this research.

Relationship with sustainability and firm performance

The close relationship between eco-transition, business value, and industrial sustainability have not only been incorporated in their definitions but also validated in numerous research and publications. The OECD (2012) states that eco-innovation is a key piece towards a greener economy: it enables industry to create new business values through a combination of technological and non-technological changes that can yield substantial environmental improvements. At firm-level, it can improve efficiency of resource allocation, corporate reputation (Xie, Wang, Zhao, 2022; Miedzinski, et. all, 2020), and contribute to stronger business competitiveness and better financial performance (Antoine & Misato, 2018). One of the driving engines for firms to environmentally innovate can be the increasing customer green demand (Cai and Li, 2018). Since customers increasingly prefer healthier and lower-carbon consumption (Forbes, 2021; IBM, 2020), they tend to seek products and brands that align with their values (EU Parliament, 2020). This trend incentivizes business to increase eco-investments to meet customers' expectations and sustain their long-term development.

Unfortunately, it bears emphasizing that not all enterprises are ready to execute the investment plans due to the expected negative economic returns from GI investments. Although negative economic returns are mostly visible in heavily polluted industries, they can still intervene investment decisions of biotech companies. This research, therefore, concentrates on eco-conscious innovation in the biotech industry.

2. Biotechnology

Definitions

The definition of biotechnology varies across industries due to its diversity in applications and cultural backgrounds (Simon, 2002). In general, the term is defined via two approaches, namely "traditional biotechnology" and the "modern biotechnology" (Hofmann, 2020; Delgoda, 2017).

Coined by the Hungarian engineer Karl Erkey in 1919 (Delgoda, 2017), biotechnology was narrowly interpreted as the utilization of tools and techniques to identify, analyze, and genetically modify microorganisms to create new products or transform foods for human use (Kumar, 2015; NTNU, 2019; BIO, 2019)[2]. Since biotechnology applications are benefiting a much wider range of industries (OECD 2011), the academia has developed a modern view to interpret the term.

The new approach appraises biotechnology as a multidisciplinary and interdisciplinary field (Delgoda, 2017) that encompasses both scientific interests and commercial purposes. This is reflected in the 2020 definition by the European Commission: **"***Biotechnology and life sciences contribute to the modernization of European industry. They are used in a variety of industrial sectors such as healthcare and pharmaceuticals, animal health, textiles, chemicals, plastic, paper, fuel, food, and feed processing. Taking advantage of biotechnology helps the EU economy grow and provides new jobs, while also supporting sustainable development, public health, and environmental protection*." For the purpose of this paper, emphasis is placed on the commercial side of biotechnology, which is typically referred to as white or industrial biotechnology (OECD, 2011)**.**

Biotechnology Industry, Environmental Protection, and its Contributions to the European Economy

Industrial biotechnology is flourishing and increasingly crucial to our life. Repeatedly seen as a key technology of the 21st century (Simon, 2002), it has become a central pillar of innovation in Europe and a key driver in the transition towards a more sustainable and competitive bioeconomy (Hofmann, 2020). It supplements the European Union's economy growth by boosting GDP, generating new employment opportunities, and strengthening market competitiveness of the region (Hofmann, 2020; Aguilar, Bochereau, & Matthiessen, 2009). Its applications for industrial purposes also play an essential role in climate change mitigation, particularly in terms of renewable energy management and sustainable production (OECD 2011).

Despite its transformative contributions, industrial biotechnology has suffered a lack of investments at all levels (OECD 2011). These facts incentivize this analysis to particularly study the significance of eco-based technology to companies within the industry as well as to the future landscape of the European economy.

[2] Appendix A.

3. Patent data

Patent data as a measure of green innovation

Dozens of metrics researchers can use to conceptualize GI, but the most common are R&D spending and scientific publication count (Ivan & Mauro, OECD, 2015). This paper instead suggests employing patent data as an indicator of GI due to its flexibility and reliability. A comparison of different methodologies is included in Table A, which is extracted from an analysis by Ivan and Mauro (2015) published on OECD Environmental Working papers. It emphasizes the method's ability to capture the long-run effects of GI, which is a fundamental limitation of other methodologies.

Table A: *Alternative measures of innovation and their key values* (Ivan & Mauro, OECD, 2015)

Stage of innovation cycle	Measures	Pros and cons
Technology development	R&D expenditures and personnel	(+) ease of communication (–) input measure of innovation (–) difficult to identify "environmental" activities (–) data availability: only OECD countries and some sectors
	Scientific publications	(+) geographical and temporal coverage (±) possible to identify some "environmental" aspects
	Patented inventions	(+) measures innovation by definition (+) measures (intermediate) outputs of innovation (+) granularity, possible to identify specific "environmental" aspects (+) global coverage, long time series (–) captures only technological innovation (–) timeliness
Technology diffusion	Patenting activity	
	International trade	(–) difficult to identify "environmental" commodities (–) most of traded goods are not innovative products
Technology adoption	Licensing surveys	(+) measure of value of innovation (royalties) (–) cost, confidentiality
	Sales and market penetration	(+) proxy for improvements in environmental endpoints (–) availability, confidentiality
Non-technological innovations	Innovation surveys	(+) can measure organisational and managerial innovations (–) availability, cost, comparability

Definitions & practical applications

Patent data covers applications and grants classified by field of technology (OECD, 1993). It contains information which can be vital to a broad variety of professions, ranging from technical developers and researchers to legal advisers and business strategists, and therefore are widely used in the framework of output indicators, especially when it comes to those of science and technology (S&T) activities (Eurostat, 2000).

In practice, patent data is increasingly stipulated as an effective metric for technology innovation because it can reflect copious amount of information on a firm's innovation output level (Popp, 2019; Kürtössy, 2004), whereas the return of R&D investment has high uncertainty (Popp, 2019; as cited in Xie, Wang, Zhao, 2022).

Three common ways to measure GI using patent data are green patent count (the number of patents granted to a firm), green patent ratio (green patent counts over the total patents granted), and rate of change in patent count (natural log of patent counts) (Ivan & Mauro, OECD, 2015). This paper adopts the last method for several reasons. Firstly, the logarithmic scale can handle data skewness by considering the existence of abnormally high or low values (outliers), while patent count cannot. Secondly, it is computationally efficient and can be directly extracted from patent count (Table 1).

IV. Data description

1. Data source

The administrative dataset is secondary panel data of the 53 publicly traded biotechnology firms from 11 countries in Europe from 2006 to 2019[3]. It is merged from two segregated datasets, with one containing patent information and another reporting financial performance of the businesses. The research countries are Sweden, Switzerland, England, France, Denmark, Germany, Austria, Netherlands, Finland, Norway, and Italy.

2. Data description

Patent data (*patent*) contains the annual number of patents granted (*patent_counts*) and the number of patent applications of each business (*patent_apps*) downloaded from Lens.org. This is an online platform developed by the social enterprise Cambia, which serves as a public resource to researchers and scholars. From this dataset, patent count data is extracted and named as *patent_counts.* Financial data (*fin_data*) demonstrates firm-specific characteristics such as firm value, leverage ratio, size. This information is systematically collected and freely available on FactSet Research Systems Inc (FactSet), an American financial data and software company in the United States.

The complete merged dataset of *patent_counts* and *fin_data* is named "*data*" in R and originally contains 720 observations and 17 columns. Data explanatory analysis is performed to detect missing values and outliers. Since the proportions of missing observations is relatively trivial (5.6%) and there are two abnormal values, they are dropped out to assure the quality of the data. The dataset then shrinks to 646 observations, which is still sufficient for performing the regression.

New variables, including $Green\_inn$, $Size$, Age, $Location$, are either extracted from or computed by available variables. Information of each variable is carefully explained in Table 1.

[3] Purposely, this is to exclude the potential effects of the Covid pandemic.

TABLE 1: ***Data Description***

Statistics	Variables	Description	Mathematics
Firm_value	Firm value	Tobin's q	Equity Market Value/ Equity Book Value
Count	Patent count	Number of patents granted	
Green_inn	Green innovation	Indicated by % change in number of patents	Ln (1 + patent counts)
Age	Firm age	The log value of operating years since the firm's establishment	Log (Research period – Establishment year)
Sales	Annual sales	The current operating income	
Sale_growth	Annual sales growth	The rate of increase in annual sales	Current operating income - Previous year's operating income)/(Previous year's operating income
Total_asset	Total assets	Total amount of assets owned by the company	
Total_debt	Total debt	Total amount of liabilities owned by the company	
Leverage	Leverage ratio	Indicator of financial capability of the firms	Total Debt/Total Assets
Tshare_equity	Total shareholders' equity	The shareholders' claim on assets after all debts owed are paid	Total Assets - Total Debt
ROA	Return on Asset	Indicator of profitability of the firm in relation to assets	Net profit/Total assets
ROE	Return on Equity	Indicator of profitability of the firm in relation to equity	Net income/ Total shareholders' equity
Size	Firm size	The log value of total asset	Log (Total Asset)
Location	Country	Country of establishment: Sweden, Switzerland, England, France, Denmark, Germany, Autria, Netherlands, Finland, Norway, Italy	SE, CH, GB, FR, DK, DE, AU, NL, FI, NO, IT
Year	Year	Research periods	2006, 2007, ..., 2019

Note: All values, except for sales growth, are reported in thousand euros. Sales growth is reported in percentage.

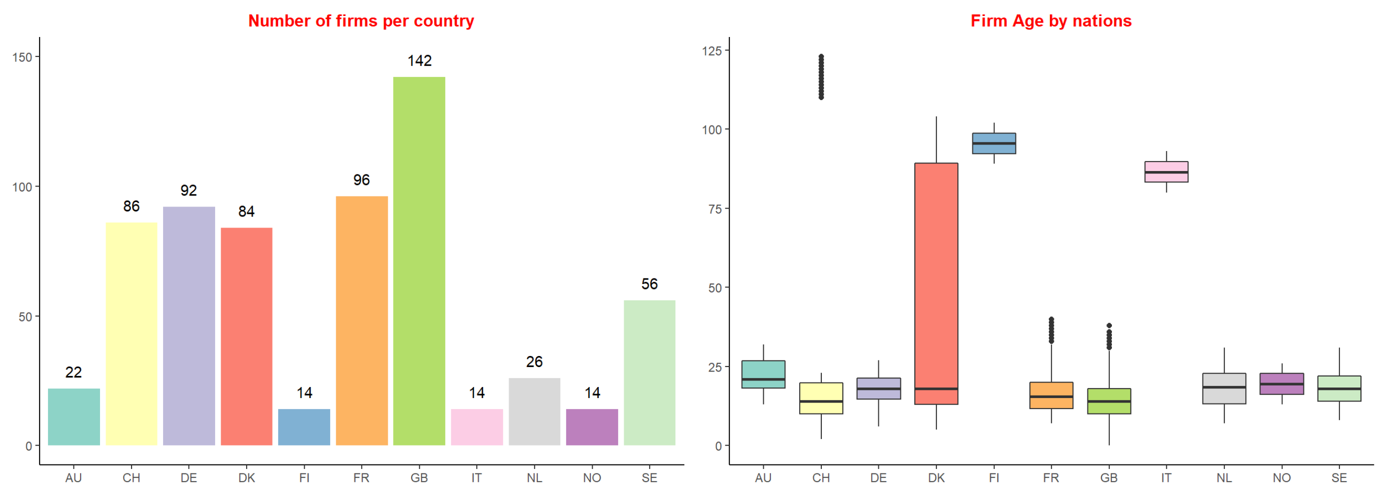
V. Data descriptive

Before regression can take over, an important step of understanding data and checking the underlying quality data needs to be performed. This section serves these purposes. The first sub-section provides a univariate analysis, including the statistical features and visual distribution of individual variables. The second part elaborates on the correlations between key covariates.

1. Univariate analysis

Firms have significantly different financial features. They grow at different rates and make unequal profits, as evidenced by the variations in sales volumes and profitability ratios in Table 2. Several companies had noticeably high sales at certain years, corresponding to high rates of sales growth in the year after[4]. Conversely, some businesses incurred losses and had low growth rates and negative ROA, ROE. Additionally, Table 2 demonstrates large differences between the means and medians, which indicate outliers and support that the log should be taken.

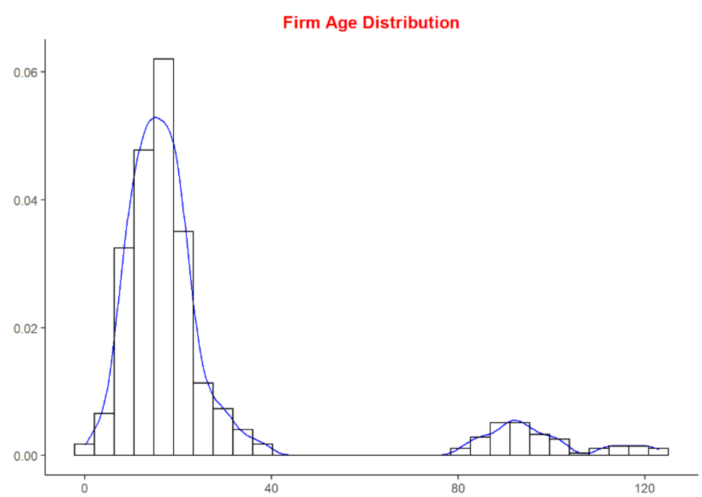
Figure 1: *Firm observations and Firm Age*



[4] Medivir's sales increased approximately 296% between 2013 and 2014 (Appendix C).

Figure 1 indicates a higher frequency appearance of firms from France, UK, and Germany[5]. Observably, firms can be segregated into two groups: The younger group consists of 576 observations aged between 0 and 40, while the older group has 70 units aged between 80 and 130 (Figure 2). The sample sizes also explain why total assets of the younger are substantially larger than that of the older. Outliers exist for Switzerland (CH) because Roche (ROG-CH) is the only long-standing firm in this country[6]. Noticeably, long-established corporates are neither substantially different in sizes nor firm values as their corresponding standard errors are low (Table 2).

<u>Figure 2</u>: *Age group of firms*



[5] The author recognizes that most bio-based companies in other countries, such as Italy, Norway, and Finland, are not publicly listed.
[6] Appendix C.

TABLE 2: ***Administrative Data Statistical Summary***

	Observations	Mean	St. deviation	Median	Min	Max
Year	646	2012.52	4.01	2013.00	2006.00	2019.00
Firm_value	646	65.02	22.76	68.90	-5.91	99.15
Count	646	531.16	1076.05	40.00	0.00	5616.00
Green_inn	646	4.17	2.19	3.71	0.00	8.63
Age	646	25.04	26.18	17.00	0.00	123.00
Sales	646	11392.30	18847.57	2483.57	0.00	194033.24
Sales_growth	646	348.92	4372.79	7.85	-100.00	94150.00
Total_assets	646	48203.12	73635.93	29205.41	14.92	625685.97
Total_debt	646	5886.85	17178.46	85.82	0.00	183618.00
Leverage	646	10.51	15.21	2.74	0.00	77.58
Tshare_equity	646	31255.40	53897.21	14832.46	-657.77	470117.00
ROA	646	-17.61	28.46	-14.40	-142.57	71.20
ROE	646	-27.82	59.60	-21.09	-415.39	290.15
Size	646	9.32	2.34	10.28	2.70	13.35

Note: The table reports statistics of all available variables using the full sample.

Table 3 reports that long-established corporates have undertaken greater changes in innovation levels ($\mu_{GI\_old} = 5.467$) and have positive profitability ratios – ROA and ROE. Conversely, younger enterprises, who tend to have lower and less equivalently distributed investments in GI ($\mu_{GI\_young} = 4.011$; $sd_{GI\_young} = 2.182$), incur losses ($\mu_{ROA} = -21.184$, $\mu_{ROE} = -34.235$). However, given the large difference in sample sizes, any findings should be interpreted with care.

The number of patents granted varies remarkably among firms, ranging from 0 to as high as 5,616 patents per year (Table 3). This indeed supports using the log change in patent counts to account for data skewness and reduce biases. Nevertheless, log transformation might not eliminate all biases. Therefore, a robustness check will be conducted in Section VI: *Empirical Approach* to inquire if the regression outcomes change dramatically when excluding outliers.

TABLE 3: ***Descriptive Statistics***

	All	Young firms	Old firms
Dependent variable			
Firm value	65.017 (22.755)	66.215 (23.24)	55.159 (15.126)
Explanatory variable			
Patent count	531.158 (1076.049)	484.849 (1037.999)	912.214 (1296.059)
Green innovation	4.169 (2.195)	4.011 (2.182)	5.467 (1.85)
Firm-specific features			
Firm age	25.037 (26.176)	16.28 (6.651)	97.1 (11.31)
Annual sales	11392.295 (18847.57)	11732.683 (19177.124)	8591.388 (15717.086)
Annual sales growth	348.92 (4372.788)	390.935 (4629.551)	3.196 (13.267)
Total assets	48203.119 (73635.934)	52517.503 (76452.13)	12701.902 (23335.27)
Total debt	5886.846 (17178.461)	6176.251 (17988.907)	3505.457 (7444.013)
Leverage ratio	10.511 (15.21)	9.662 (15.368)	17.5 (11.778)
Total Shareholders' Equity	31255.396 (53897.214)	34515.071 (56144.725)	4432.931 (8211.853)
Return on Asset	-17.608 (28.457)	-21.184 (27.964)	11.819 (8.233)
Return on Equity	-27.821 (59.596)	-34.235 (59.567)	24.959 (21.513)
Firm size	9.32 (2.34)	9.508 (2.336)	7.767 (1.723)
Number of observations	646	576	70

Note: Table columns report means and standard deviations (shown in parentheses) of young and old firm samples compared to the full sample.

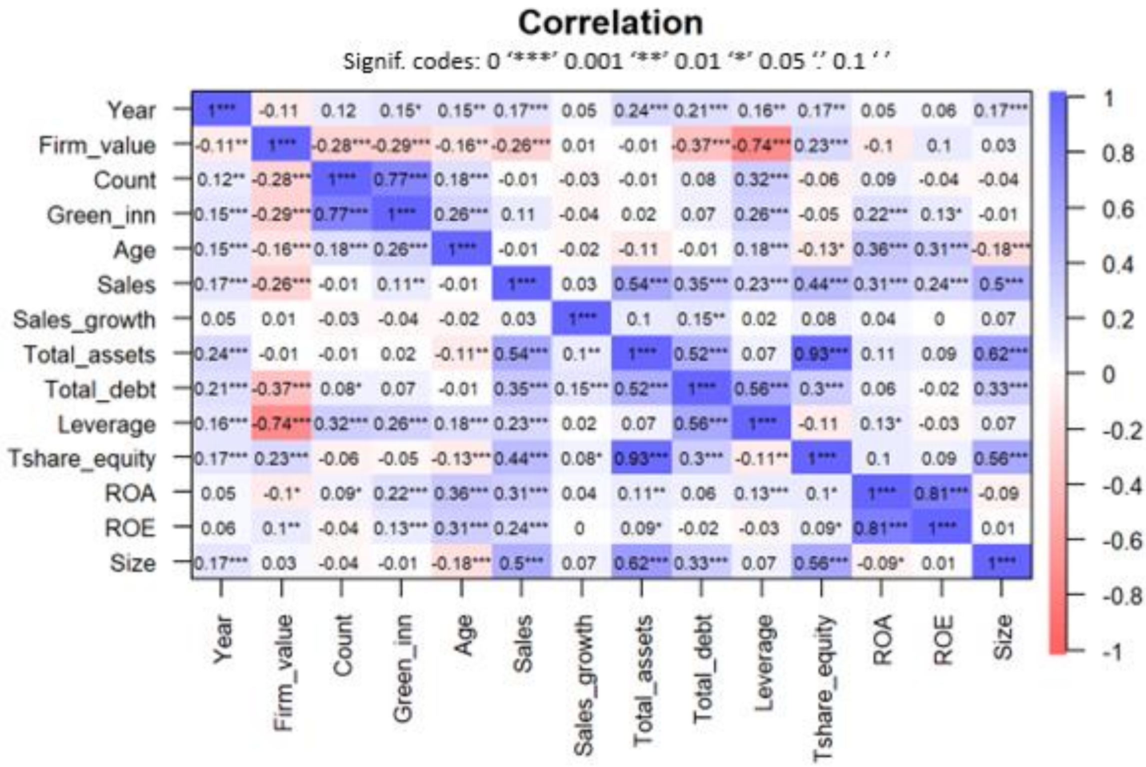
2. Multivariate analysis

Variable Correlations

Significant correlations are highlighted in the Figure 3 and ranking correlations figures[7]. A firm's value is largely associated with its leverage ratio ($\rho = -0.74$). GI is inversely correlated to firm value ($\rho = -0.29$), but its correlations with business profitability indicators, including ROA, ROE, leverage ratios are positive, respectively 0.22, 0.13, 0.26.

[7] Figure A: *Ranking correlations* (Appendix B)

<u>Figure 3</u>: *Correlation matrix*



VI. Empirical Approach

This section starts by discussing internal validity of the research and formulation of the regression equations. Regressions are performed, firstly, on the short-run models, and secondly on the long-run models using one-year and two-year lagged and leading values. This step is to statistically test the first two hypotheses regarding the immediate and future effects of GI. Similar procedures are applied to two age samples to determine the responsiveness of young and older companies to GI. In this phase, deviations of the coefficients on financial features and standard errors between subgroup models are examined to draw conclusions for the third hypothesis. Section VI closes with robustness check methods regarding effectiveness of log transformation and FER in handling different types of biases. Key findings are interpreted in Section VII. *Results*.

1. Model specification

Based on the panel data of 53 firms in the European biotechnology sector between 2006 and 2019, the analysis employs the FER to examine GI's impact on biotech firms' value. It is a natural extension of the basic estimation metric (Dranove, 2012) commonly employed in panel data to control for any individual-level attributes that are constant over time (Library of Statistical Techniques (LOST)).

1.1. Internal validity

Omission variables bias

Simply regressing the explanatory variable on the outcome variable cannot guarantee causal inferences due to high possibility of OVB. The bias can originate from observable heterogeneities among firms, i.e., sizes, growth rates, and profitability, or unobservable factors, i.e., management quality, human resources' ability. While the prior can be eliminated by directly adding the excluded variables into the equation, the latter is difficult or even impossible to quantify. Panel data analysis using FE is typically an efficient solution to the second issue.

Regression method

The regressions conducted in this analysis are "two-ways effects" models, in which $Firm\_id$ and $Year$ variables respectively indicate unit-level effects and yearly effects.

This method is favorably applied to panel data due to its fundamental advantages. Firstly, it can efficiently control for time-consistent observable and unobservable attributes (Arnold, 2019; Dranove, 2012), or in this case, between-firm differences. FER allows observations to have different intercepts (Arnold, 2019) within each group of observations[8], thus any effects of time-invariant firm-specific features are mathematically cancelled out. It is also computationally convenient and highly interpretable (Arnold, 2019) since the equations and clustered standard errors can be easily estimated with packages available in R[9].

This analysis chooses a general significance level of 10% and interprets any variable whose coefficient-standard error ratio is at least 2 as being significant.

1.2. Model development

The general model includes a dependent variable ($Firm\_value_{i,t}$) denoting value of the listed biotechnology enterprises, and a main explanatory variable, green innovation ($Green\_inn_{i,t}$), which is translated into the percentage change in number of patents granted to individual firms. $Controls_{i,t}$ are a set of control variables indicating firm-level characteristics, including location, firm age, sales growth, leverage ratio, ROA, ROE, firm size. $Year_t$ is year-specific effects covariate. $\epsilon_{i,\,t}$ reflects all other unobservable exogenous factors.

General model

$$Firm\_value_{i,t} = \beta_{0i} + \beta_{1i}Green\_inn_{i,t} + (\sum \beta_{i,t}Controls) + \epsilon_{i,\,t} \tag{1}$$

From the general model, two types of models are formulated. The baseline model encompasses a dependent variable and an explanatory variable while extended models also include control variables that account for firm heterogeneities and year-specific effects. Three extended equations are estimated using the Pooled OLS regression and compared. As equation (3) is proved to have the strongest explanatory power[10], it is adopted as the main extended model for further analysis.

Baseline model

$$Firm\_value_{i,t} = \beta_{0i} + \beta_{1i}Green\_inn_{i,t} + \epsilon_{i,\,t} \tag{2}$$

[8] A set of observations of an individual firm across year, i.e., Rocher observations from 2006 to 2019.
[9] Appendix C.
[10] Appendix C.

Extended model

$$Firm\_value_{i,t} = \beta_{0i} + \beta_{1i}Green\_inn_{i,t} + \beta_{2i}Location_{i,t} + \beta_{3i}Age_{i,t} + \beta_{5i}Sales\_growth_{i,t} + \beta_{6i}Leverage_{i,t} + \beta_{7i}Year_{i,t} + \beta_{8i}ROA_{i,t} + \beta_{4i}Size_{i,t} + \epsilon_{i,t} \qquad (3)$$

The estimates computed with equations (2) and (3) are interpreted as the short-run effects of GI. The long-run effects are measured using similar equations, but with one and two-year lags on $Green\_inn$ or one and two leading years on $Firm\_value$[11]. These lag-lead models solve the third sub-question concerning if GI's impact is sustained.

2. Variable construction

2.1. Dependent variable

Firm value is the outcome variable, which is constructed by Tobin's q or Q ratio that has been suggested in numerous studies. Defined as the "value of capital relative to is replacement cost" (Precha Thavikulwat, 2004), Q ratio can incorporate proper adjustments for market risks and distortions due to taxes and accounting conventions (Wernerfelt & Montgomery, 1988). Tobin's q is calculated as the capital market value of the firm divided by the replacement value of its assets.

$$Tobin's\ q = \frac{Total\ Asset\ Value\ of\ the\ Firm}{Total\ Market\ Value\ of\ the\ Firm} = \frac{Equity\ Book\ Value}{Equity\ Market\ Value}$$

2.2. Explanatory variable

GI is the fundamental explanatory parameter proxied by the log change in patent count of a firm from one period to another, *log(Count)*. Since patent count varies significantly among firms, using it as an indicator of green innovation might lead to bias. This analysis, therefore, prefers the log change in patent counts to adjust such differences and avoid biases.

[11] See Appendix C.

2.3. Control variables

To alleviate observable heterogeneity problems, six covariates capturing firm-specific patterns are added into the baseline model, as shown in equation (3). Lastly, a year covariate is included to control for time-specific effects.

3. Robustness checks

Two robustness checks are performed in this research. The first test inspects whether log transformation can efficiently handle data skewness. This is achieved by comparing the results produced with the original data and the cleaned data[12] on both full and subgroup samples. If the estimates are largely different, there exists bias that cannot be solved with log transformation, which also weakens the causal inferences. The second check looks at the effectiveness of FER in handling the data's unobserved heterogeneities by applying the Hausman test[13] to determine whether FER can outperform RER[14].

[12] Original dataset excluding observations with over 4,000 patents (Appendix C).
[13] Appendix A.
[14] Appendix C.

VII. Results

1. Short run effects

Estimates of equations (2) and (3) using the Pooled OLS estimator support the first hypothesis that GI negatively affects firm value. Table 5 reports a decrease of 3% in firm value per 1% increase in patent count ($s.e. = 0.391$). However, these naïve OLS regressions explicitly contain upward bias[15] as GI estimates (2) increase dramatically when controlling for other factors. Additionally, the standard errors are relatively similar, implying that increases in the estimates are attributed to explanatory power of the control variables rather than random effects. These results, consequently, are unreliable.

TABLE 5: ***Pooled OLS Regression***

	Coefficients	Standard errors	Significance
Model specifications			
GI	-3.036	0.391	***
GI + Location + Age + Sales_growth + Leverage + Year + ROA + ROE + Size	-1.348	0.307	***
GI + Location + Age + Sales_growth + Leverage + Year + ROA + Size	-1.347	0.312	***
GI + Location + Age + Sales_growth + Leverage + Year + ROE + Size	-1.416	0.309	***
Observations	646	646	

Note: The table reports the coefficients and stardard errors estimated with the Pooled OLS using the full sample. A variable is considered significant if the ratio between its coefficient and its standard error is equal to or greater than 2.

Table 6 and Table 7 denote FE estimates on equations (2) and (3) using the full sample and separate results for two firm subgroups. They show that unlike the OLS, FER confirms GI's positive influences on business value. These results are also in favor of the second hypothesis regarding the long-run effects of GI. They indicate that it might take at least a year for the effects to be observable, if there is any.

Table 6 suggests the impact of sustainable investments is neither instantaneous nor negative for any companies. Regardless of firm heterogeneities, 1% increase in GI level can considerably add up 5.6% value to the implemented firms (column 1). Surprisingly, per 1% increase in GI, a young bio-tech company can experience an average 5.68% increase in value in the same year. This indeed infers those effects are skewed towards the younger enterprises.

However, turning to the extended models, no effect is detected regardless of firm age: members in both groups are not influenced by their investment decisions (Table 6). This finding supports that in the short run, sustainable innovation does not destroy business profitability. Therefore, hypothesis 1 can be reasonably rejected.

[15] Appendix C.

TABLE 6: ***Short-run Effects of Green Innovation***

	Full sample	Young	Old
Baseline			
GI	5.619 (1.71371)	5.685 (1.78421)	2.107 (2.68575)
Extended			
GI + Controls	1.126 (1.30123)	1.124 (1.33059)	0.403 (2.77463)
Observations	646	576	70

Note: The table reports the Fixed Effects estimates in the same year of GI investment decisions. Robust standard errors are reported in parentheses. A variable is considered significant if the ratio between its coefficient and its standard error is equal to or greater than 2.

2. Long run effects

Looking from a longer time span, future value of a firm can be attributed to today's green investment decisions. Biotech entities choosing to eco-consciously innovate can achieve fruitful outcomes. This can be seen from the positive estimates of baseline models on the full sample, reported in columns 1 – 4 of Table 7. For instance, the FE estimates in columns 1 and 2 are significantly positive at 4.613 and 4.709 ($s.e. = 1.7229$; $s.e. = 1.9057$) for 1 and 2 lagged years respectively.

Separate analysis by age ranges, demonstrated in columns 5 – 12, Table 7, is in favor of hypothesis 3. They show sharp differences in effects for short and long-standing corporates. While positive outcomes are applicable to younger enterprises under certain circumstances, there are no significant estimates for the older group. For example, the largest impact on younger members is captured after 2 years of innovation in the baseline model (Columns 6 and 8). A young biotechnology entity can enhance its value by as much as 4.93% ($s.e. = 1.9776$). Conversely, economic value of longer-existing firms is unlikely to depend on their GI levels, but on other financial criteria, such as leverage ratio and size[16].

TABLE 7: ***Long-run effects of Green Innovation***

	Full sample				Young				Old			
	Lag		Lead		Lag		Lead		Lag		Lead	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Baseline												
GI	4.613 (1.7279)	4.709 (1.9057)	4.613 (1.7279)	4.709 (1.9057)	4.772 (1.7981)	4.934 (1.9776)	4.772 (1.7981)	4.934 (1.9776)	1.815 (2.3061)	0.512 (1.3377)	1.815 (2.3061)	0.512 (1.3377)
Extended												
GI + Controls	1.874 (-5e-05)	2.23 (-5e-05)	3.433 (3e-05)	4.763 (1e-05)	1.943 (-5e-05)	2.264 (-5e-05)	3.608 (3e-05)	4.985 (1e-05)	0.294 (-0.03218)	1.53 (-0.11658)	-0.688 (0.08322)	-2.486 (0.14893)
Observations	582	530	582	530	517	470	517	470	65	60	65	60

Note: The table reports the Fixed Effects estimates using (1) or (2) years of lagged or leading values of variables of interest. Robust standard errors are reported in parentheses. A variable is considered significant if the ratio between its coefficient and its standard error is equal to or greater than 2.

Nonetheless, ambiguous effects on subgroup regressions exist, as shown with inconsistent estimates produced with lag and lead equations in Row 2, Table 7. Regarding the young sample, estimates using

[16] Appendix C

lagged years become insignificant when taking firm-specific patterns into account, whereas those in lead models stay significant. Although in all cases, no effects on long-standing firms are recorded, it bears stressing the small sample size of the old group can affect this interpretation's certainty.

In conclusion, what has been inferred so far counteracts the first hypothesis and confirms the last two. Accordingly, eco-innovation can eventually create marginal value for biotechnology firms, particularly for the younger.

3. Robustness checks

Table 8 investigates if there remain biases that cannot be solved by log transformation. It suggests taking natural logarithm of patent count can efficiently address outliers in the dataset since estimates and robust standard errors are relatively similar between models using original and trimmed data.

TABLE 9: ***Fixed Effects and Random Effects Comparison***

	Full sample		Young		Old	
	Fixed	Random	Fixed	Random	Fixed	Random
Baseline						
GI	5.619 (1.714)	-1.273 (1.044)	5.685 (1.784)	-1.42 (1.21)	2.107 (2.686)	2.457 (0.139)
Extended						
GI + Controls	1.126 (-4e-05)	-0.69 (0.788)	1.124 (-4e-05)	-1.064 (0.895)	0.403 (-0.007)	0.403 (3.263)
Observations	646	646	576	576	70	70

Note: The table reports the Fixed Effects and Random Effects estimates. Robust standard errors are reported in parentheses. A variable is considered significant if the ratio between its coefficient and its standard error is equal to or greater than 2.

Table 9 denoting equations (2) and (3) computed with FER and RER emphasizes several opposite results. Except for regressions on the old group, all RE coefficients are negative, but insignificant, which is against those estimated with the FER. Most surprisingly, FE model confirms that in the short-run, long-establishing bio-based corporations are unaffected by GI, whereas the RER suggests positive effects. For instance, the first row of Table 9 shows a significantly estimate of GI at 2.4572 ($s.e. = 0.1385$), meaning that 1% increase in GI's level can leverage the financial performance of a long-standing firm by approximately 2.45%.

Both estimators reflect no significant estimates in the extended models regardless of firm age (row 2, Table 9). They also provide consistent estimated coefficients on the control variables, as shown in Appendix C.

TABLE 9: ***Fixed Effects and Random Effects Comparison***

	Full sample		Young		Old	
	Fixed	Random	Fixed	Random	Fixed	Random
Baseline						
GI	5.619	-1.273	5.685	-1.42	2.107	2.457
	(1.714)	(1.044)	(1.784)	(1.21)	(2.686)	(0.139)
Extended						
GI + Controls	1.126	-0.69	1.124	-1.064	0.403	0.403
	(-4e-05)	(0.788)	(-4e-05)	(0.895)	(-0.007)	(3.263)
Observations	646	646	576	576	70	70

Note: The table reports the Fixed Effects and Random Effects estimates. Robust standard errors are reported in parentheses. A variable is considered significant if the ratio between its coefficient and its standard error is equal to or greater than 2.

All the Hausman tests [17], however, are in favor of the alternative that FER should be preferred to the RER, which gives confidence on the modeling approach and results of this analysis.

In short, the robustness checks guarantee the reliability of results discussed in Section VI and support that FER is a proper estimator in assessing the influence of GI on firm value.

[17] Figure B. *Examples of the Hausman test* and Appendix C.

VIII. Conclusions & Discussions

1. Conclusions

This research deploys patent data from 2006 and 2019 and Fixed Effects Regression (FER) to investigates the influence of green innovation (GI) on the value of 53 biotech companies operating in Europe. This is achieved by answering four sub-research questions. Regarding the first question, this analysis confirms that GI has a certain influence on business value. The second concern is solved as this impact is possibly positive. Answers for the third and fourth concerns are that GI's effects are sustained, and they vary between firms of different age groups.

Academically, this research has bridged the gap among existing studies by verifying the potential contribution of GI to business performance and discovering the differentials in young-old biotech firms' responsiveness to GI. Opposed to existing opinion that GI is destructive to a firm's value in the short term, the analysis detects no significant negative effects. Additionally, it assesses GI's effects in the long-run and conditionally on firms' age, which are lacked in previous studies. By separately regressing lag-lead equations on samples for young and old enterprises, it reveals several positive influence and significantly different subgroup effects. While the lag regression indicates significant results in some baseline models only, the lead demonstrates certainly positive effects on younger corporates. Both models consent older entities do not benefit from GI.

These causal inferences are reinforced by two robustness checks. The first certifies that the natural logarithm of patent count is an appropriate proxy of GI as it can efficiently address data outliers. The second highlights the advantages of the FER in addressing biases in patent data compared to typically applied method, namely the Pooled OLS and RER.

In conclusion, the paper finds promising outcomes that encourage businesses, particularly young enterprises in the European biotechnology sector, to undertake sustainable transition.

2. Discussions

This analysis has significant implications for managers and policy makers. It suggests managers to regard eco-based innovation as an investment that enhances business competitiveness and meets customers' green expectations. Financially, businesses are unharmed from allocating some resources towards GI.

Incorporating GI into corporate strategies can even be beneficial since it helps companies build stronger bonds with customers, particularly those who are increasingly eco-conscious.

From a political perspective, the results of this study encourage policymakers to stimulate business sustainable transformations. Green technology promoting programs prioritizing new bio-based companies should be constructed. Policymakers can incentivize these entities to become leaders in GI initiatives by offering them proper incentives, such as tax reduction or low-interest allowances. Simultaneously, government should create long-term financial instruments to booster financial flexibility of corporations. For instance, governments can systematically reflect the contribution of patent data and R&D innovation spending to green transformations and critically determine which is most suited and cost-effective to support business change-driven eco-innovation. This will benefit both young and long-standing enterprises and thus the society and economy as a whole.

The research, however, faces several limitations. It is strongly based on the sample of firms operating within the European biotechnology sector. Therefore, its findings are only limited to the scope of the analysis applicable to sample. This follows that they should not be considered representative outcomes for enterprises from other sectors or continents, which might encompass diverged socioeconomic features. Moreover, since the sample of older companies is relatively small, foregoing inferences might not be relevant for all long-standing biotech companies in Europe. Lastly, this research assumes that all granted patents are sustainable, thus patent count is a perfect proxy of GI, which is not necessarily the case.

These limitations, however, signal space for future research. Two questions to be answered are whether the payoffs of this sort of innovation vary among industries and whether some effects are found on a larger sample of older companies. Researchers can also employ alternatives, including R&D spending or publication counts, as measures of firm-level GI, to replicate this work. By doing this, they can form a more complete view on how effective other metrics are in relative to patent data.

APPENDICES

LIST OF ACRONYMS

BIO: Biotechnology Innovation Organization

CSR: Corporate Social Responsibility

EU: Europe

FE: Fixed Effects

FER: Fixed Effects Regression

GI: Green innovation

NUST: Norwegian University of Science and Technology

RE: Random Effects

RER: Random Effects Regression

ROA: Return on Assets

R&D: Research & Development

ROE: Return on Equity

S&T: Science and Technology

OECD: Organization for Economic Co-operation and Development

APPENDIX A – Additional Literature & Definitions

Definitions of Biotechnology

Traditional approach

1. Biotechnology is technology that utilizes biological systems, living organisms or parts of this to develop or create different products (Norwegian University of Science and Technology (NUST), 2019).
2. At its simplest, biotechnology is technology based on biology - biotechnology harnesses cellular and biomolecular processes to develop technologies and products that help improve our lives and the health of our planet. (Biotechnology Innovation Organization (BIO), 2019)

Modern approach

1. Biotechnology is the application of science and technology to living organisms, as well as parts, products, and models thereof, to alter living or non-living materials for the production of knowledge, goods and services. (OECD, 2007)
2. Biotechnology and life sciences contribute to the modernization of European industry. They are used in a variety of industrial sectors such as healthcare and pharmaceuticals, animal health, textiles, chemicals, plastic, paper, fuel, food, and feed processing. Taking advantage of biotechnology helps the EU economy grow and provides new jobs, while also supporting sustainable development, public health, and environmental protection. (EU Commission, 2020).
3. Biotechnology is the manipulation (as through genetic engineering) of living organisms or their components to produce useful usually commercial products (such as pest resistant crops, new bacterial strains, or novel pharmaceuticals) (Merriam Webster, 2019)

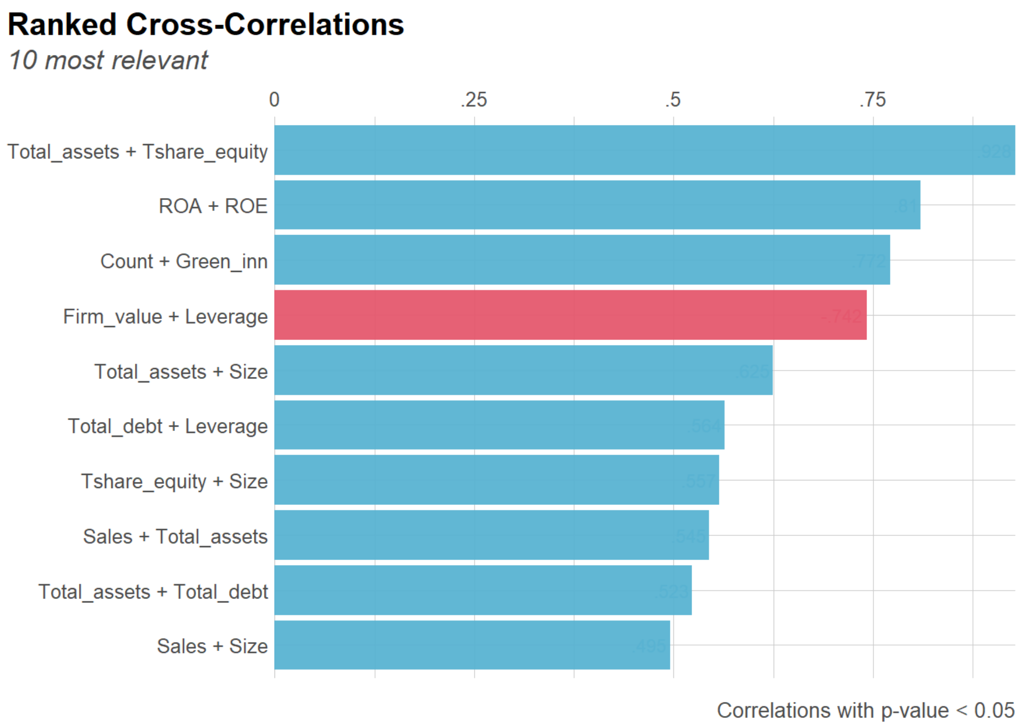
The Hausman Test

The Hausman Test, also known as the Hausman Specification Test or Durbin-Wu-Hausman Test, investigates endogenous regressors in a regression model. It is typically applied in panel data to detect model misspecifications (Fielding, 2004). According to Frondel & Vance (2010), the Hausman Test is particularly suggested to examine the appropriateness of the economic modeling of panel data, namely Fixed and Random Effects estimators.

The test is performed in R using the command $phtest()$ on two hypotheses. The null hypothesis states that the preferred model is the Random Effects against the alternative hypothesis that the Fixed Effects is more appropriate. The alternative hypothesis is supported if the p-value of is smaller than 0.5 and rejected otherwise. Further explanations are provided in Appendix C.

APPENDIX B – Additional Tables & Figures

Figure A: *Ranking Correlations* (Appendix C)



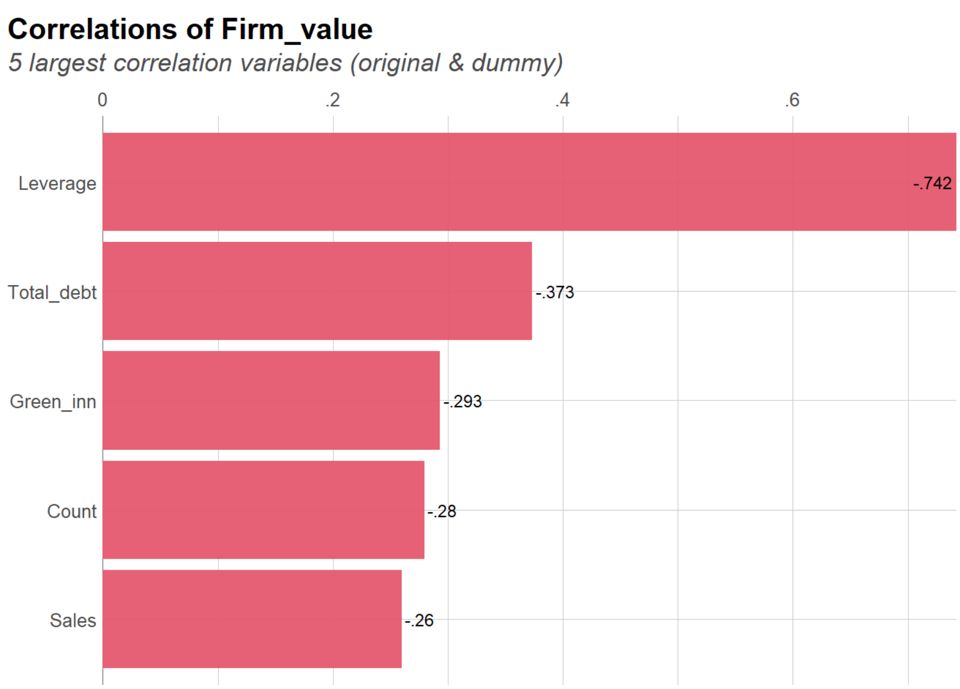


Figure B: *Examples of the Hausman test* (Appendix C)

```
# Compare baseline models in different samples
phtest(rand_base, fix_base)
```

```
##
##  Hausman Test
##
## data:  Firm_value ~ Green_inn
## chisq = 26.53, df = 1, p-value = 2.594e-07
## alternative hypothesis: one model is inconsistent
```

```
# Compare extended models in different samples
phtest(fix_ext, rand_ext)
```

```
##
##  Hausman Test
##
## data:  Firm_value ~ Green_inn + Location + Age + Sales_growth + 
Leverage +  ...
## chisq = 17.253, df = 5, p-value = 0.004044
## alternative hypothesis: one model is inconsistent
```

```
phtest(rand_ybase, young_base)
```

```
##
##  Hausman Test
##
## data:  Firm_value ~ Green_inn
## chisq = 24.812, df = 1, p-value = 6.32e-07
## alternative hypothesis: one model is inconsistent
```

```
phtest(rand_obase, old_base)
```

```
##
##  Hausman Test
##
## data:  Firm_value ~ Green_inn
## chisq = 0.0070949, df = 1, p-value = 0.9329
## alternative hypothesis: one model is inconsistent
```

APPENDIX C – R Codes & Interpretations

See R HTML file

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