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Pension Fund Investment and Firm Innovation*

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Abstract

We use a unique database on domestic pension fund investment to analyze the relationship between pension fund investment and innovation within Danish firms. We find a significant positive association between pension fund investment and various measures of innovation, including green technologies for climate change mitigation and adaptation. However, this relationship is much weaker in highly competitive industries, suggesting that pension funds encourage innovation by monitoring and holding managers accountable. Our analysis also shows that pension funds foster innovation by providing stable long-term capital. Overall, our study highlights the important role of pension funds in driving firm innovation, particularly by reducing managerial slack and by supplying stable, long-term capital.

Keywords: Pension Fund Investment, Innovation, R&D.
JEL code: J24, J60, L20.

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1 Introduction

Seminal works by Solow (1956), further supported by Romer (1994), established the pivotal role of innovation for sustainable economic growth. However, financing innovative projects poses a significant challenge due to the need for enduring and stable commitments from financiers. Moreover, managers may adopt inefficient "empire building" strategies that discourage risk-taking activities, such as innovation (Baumol, 1959). Additionally, innovation is characterized by high uncertainty, lengthy lead times, and the need for cumulative efforts (Arrow, 1962; Mazzucato & Semieniuk, 2017). These uncertainties require investors to be willing to take significant risks, while the long-term nature of innovation and its cumulative effects require steady, long-term capital provision.

There are two primary ways in which pension funds can help firms overcome the challenges associated with financing innovation. First, pension funds typically have a longer investment horizon compared to other investors, who often have short-term return objectives and frequently move in and out of stocks. Research has shown that pension funds tend to adopt a particularly long investment horizon compared to other institutional investors (Cella et al., 2013; Cremers & Pareek, 2016; Döring et al., 2021; Harford et al., 2018). This longer-term investment approach allows pension funds to stay invested for a longer period instead of reacting to short-term shocks, thus providing stable and patient capital to firms pursuing innovative projects, especially in green innovations, which are known to carry higher levels of risk and uncertainty (D'Orazio & Valente, 2019).

Second, pension funds can represent an effective instrument to combat managers' tendency to support short-sighted and inefficient strategies. By providing a sizable amount of capital to the firm, pension funds can exercise greater influence on firms' management and governance, promoting more long-term and sustainable strategies, including innovation. They can help to align the interests of the investors and the management of the firm and provide the necessary incentives to pursue innovative projects with a long time horizon. The relationship between the firm and the investor, and their ability to manage the misalignment of incentives between them, may influence the amount and shape of innovation generated (de Bettignies & Ries, 2023). In summary, pension funds can offer a critical source of stable, long-term capital to firms pursuing innovation while also providing governance mechanisms to promote long-term and sustainable strategies.

This study provides the first analysis of the role of pension funds' investments in Danish firms' innovation in general and in the area of green technologies specifically. Environmental, social and governance (ESG) issues have become increasingly relevant for the investment industry and pension funds in particular OECD (2021). Pension funds can integrate ESG factors into their portfolios for various reasons, such as enhancing risk-adjusted returns, pursuing non-financial objectives, or expressing the preferences of their members (Edmans & Kacperczyk, 2022; Lachance & Stroehle, 2021).[1] While prior literature has analysed the effects of institutional ownership on ESG scores (Dyck et al., 2019, see e.g.), this paper is the first to focus on green patenting.

In recent decades, pension funds have emerged as major owners of private companies in capital markets worldwide, and Denmark is no exception to this trend. At the end of 2021 global assets in funded and private pension plans reached 60 trillion USD for the first time (OECD, 2023). In Denmark, these assets amounted to over 230 percent of GDP, the highest ratio among all countries included in comparable OECD statistics (OECD, 2023). Most of these assets were managed by pension funds. The amount of equity of Danish non-financial corporations held by the domestic pension fund and insurance sectors increased from 213.6 to 316.8 billion DKK from 2017 to 2021, representing a growth of over 48%.[2] This trend highlights the increasing significance of pension funds as major investors in the Danish economy, emphasizing their potential role in promoting innovation and sustainable growth. In particular, ESG investing has emerged as a key issue for pension funds, and Danish funds are leading the way in this regard. One example of Danish leadership in this area is ATP, Denmark's largest pension fund, which announced an increase in its climate investment targets in October 2021, demonstrating its commitment to ESG principles. This growing trend is not limited to Denmark alone; the United States has also witnessed substantial growth in ESG investments by institutional investors.[3] Against this backdrop, this study contributes to the ongoing discussions about pension funds and the climate transition by examining the extent to which pension fund investments specifically support innovation in green technologies.

The identification and estimation of the relationship between pension fund investment and firms' innovation have been plagued by a lack of sufficiently rich data at both the investor and firm levels. In this study, we address this challenge by merging the Danish matched employer-employee dataset with newly collected data on pension funds' investments spanning the period 2003-2019. Unlike previous studies in this field (see e.g. Aghion et al.,

[1]The academic literature on the financial implications of ESG investing is still evolving and inconclusive. Some studies suggest that ESG performance is positively related to stock returns, firm value, and profitability, while others find mixed or negative effects (Hammond et al., 2023; Lachance & Stroehle, 2021).

[2]Authors' calculations based on National Accounts Statistics published by the Danish Central Bank (Danmarks Nationalbank, 2022).

[3]According to the 2020 report by the U.S. SIF Foundation, the total assets managed by U.S. institutional investors incorporating ESG principles reached a remarkable 6.2 trillion dollars as of 2020, marking substantial growth over the past 15 years. Notably, pension funds account for more than half of these assets, comprising 54% of the total. As highlighted by Stéphanie Lachance, managing director of Responsible Investment at the Public Sector Pension Investment Board (PSP Investments) Canada: "Pension funds are ideally positioned to embrace ESG principles, as the long-term investment time horizon inherent to pension funds and their diversified portfolio structures are key factors enabling the integration of ESG considerations".

2013), our analysis includes both publicly listed and unlisted companies, and we study three different measures of innovation. First, we rely on patent applications and their citations recorded for Danish firms at the European Patent Office (PATSTAT) to proxy for innovation (Bloom, Draca, & Van Reenen, 2016). Second, we define a patent application as "green" if it involves climate change mitigation technologies, using either the Cooperative Patent Classification (CPC) or the International Patent Classification (IPC) (Li et al., 2021). Third, we examine the share of R&D workers within a firm as an additional proxy for the intensive margin of innovation. We identify R&D workers using individual occupational codes and the classification of knowledge-intensive jobs suggested by Bernard et al. (2017). Consistent with previous research on innovation (Blundell et al., 1999), we focus our analysis on the sample of firms that operate in the manufacturing sector only. Nevertheless, we conduct a refinement analysis that encompasses all industries.

To address concerns of potential selection bias, we employ an event study analysis to test for the presence of pre-trends. Furthermore, we complement our main analysis with additional findings that shed light on two primary mechanisms through which pension funds contribute to improved innovation. These mechanisms involve disciplining underperforming managers and providing long-term capital to firms. These additional results allow us to rule out that the main findings are only due to selection and to establish a comprehensive understanding of how pension funds facilitate innovation within companies.

Our results show that pension funds' investments relate positively with firms' innovation in a static specification, in which we control for a number of observed confounding factors and unobserved heterogeneity with the method developed by Blundell et al. (1999). Specifically, firms where pension funds invest have on average a 7 percentage points higher probability of having at least one patent application and a nearly twice as large number of patent applications (weighted by citations) relative to the other companies, controlling for unobserved heterogeneity and a whole host of observed characteristics, such as firms' productivity and capital intensity. Interestingly, pension funds' investments are shown to be correlated with firms' innovation in green technologies, with firms, where pension funds invest, featuring on average a 1 percentage point larger probability of having at least one green patent application compared to other firms in the sample. Finally, we also show that firms with a pension fund investment have on average a 5 percentage points larger share of R&D workers than otherwise similar firms. The main results include both direct investments by domestic pension funds and indirect investments, which means that the funds invest in the firm through another corporate entity. In a refinement, we only focus on direct investments, and the results show slightly larger magnitudes, albeit with less precise estimates due to the lower frequency of direct investments in our sample. We augment our main findings with several supplementary analyses.

First, we complement our static analysis with a dynamic event study approach, which is based on the method proposed by Sun and Abraham (2021) and demonstrates that before a pension fund investment, there are no discernible differences in trends regarding innovation between firms that pension funds invest in and other firms. This finding refutes the possibility that pension funds selectively invest in more innovative firms, which could bias the results of the static models (see, e.g., Aghion et al., 2013; Fons-Rosen et al., 2021; Garel, 2017; Lerner et al., 2011; Levine & Warusawitharana, 2021). In other words, we observe no significant differences in innovation outcomes between firms that receive pension fund investment and those that do not prior to the investment.

Second, we show that product market competition weakens the association between pension funds and firm-level innovation, suggesting that pension fund investment is more beneficial for firms' innovation when competition is weak. This result supports the hypothesis that pension funds reduce managerial slack, motivating managers to exert more effort. In highly competitive environments, market forces naturally discipline "lazy managers," leading to their termination without requiring extensive monitoring (Bertrand & Mullainathan, 2003). Our findings contrast with those of Aghion et al. (2013), who find that competition strengthens the impact of ownership by institutional investors on innovation. This difference in results may be partly explained by three key differences between our study and theirs. First, we examine a large and representative sample of publicly listed and unlisted manufacturing firms, while Aghion et al. (2013) only analyze publicly listed firms. Second, we study a more recent sample period and a European country, whereas their study focused on the US. Third, we focus solely on pension fund ownership, while their study analyses the ownership of the broader institutional investor space. Additionally, other studies have revisited the findings of Aghion et al. (2013). For instance, using the same dataset, Schain and Stiebale (2021) find that the relationship between competition and institutional investment does not hold when they account for heterogeneity in external finance dependency and financial constraints at the firm level. Similarly, Samila et al. (2021) find that high levels of competition do not promote innovation through institutional ownership, in contrast with Aghion et al. (2013). The importance of this channel is also confirmed by additional analysis in which we show that larger amount of pension fund investment affect to a larger extent firm-level innovation presumably because in those cases pension funds can exercise greater influence on firms' management and governance.

Third, we show that the duration of investment plays a significant role in fostering innovation. This suggests that pension funds facilitate investment in innovation not only by disciplining managers but also by providing long-term capital stability.

Finally, we explore the influence exerted by additional investors within the financial sector and examine their impact on the coefficient associated with our pension fund investment variable. Since pension funds can invest in a company either alongside or independently, concurrently with other investors, such as private equity, insurance companies or a foreign investor, it is possible that the positive effects discussed above are not solely driven by pension fund investments. Our analysis addresses this concern. When incorporating the presence of other investors in three alternate specifications, our focal variable of interest, which captures pension fund investments, not only remains positive but it also sustains statistical significance. Moreover, the observed magnitudes closely align with those documented in the baseline analysis. This examination effectively supports the hypothesis that the positive effects identified earlier are contingent on pension fund investments.

This study makes several contributions to the existing literature. First, due to a lack of detailed data on pension fund asset allocation, we know relatively little about how they affect the companies they invest in. A few studies have analyzed only the effect of other investor types, notably private equity (PE) and venture capital (VC) funds (see e.g. Chemmanur et al., 2011; Davis et al., 2014). These studies suggest that PE and VC funds have a positive impact on the performance of the firms, in which they invest. They also show that this positive effect goes beyond the mere provision of capital. The mechanisms highlighted are among others: the hiring of better managers, improved company oversight, and easier access to third-party financing for the firm as a consequence of being associated with a given investor (Chemmanur et al., 2011). Our study is the first one to undertake a similar analysis for pension funds. There are critical differences between pension funds and VC and PE funds. PE and VC funds are more likely to take an active part in the functioning of the target firm to raise its value, while pension funds tend to invest in mature companies with a longer investment horizon. Although pension funds may not take an active role in improving the value of the firm, their long-term investment horizon could enable firms to invest in innovative projects with long-term objectives. Furthermore, large pension funds have recently increasingly made use of their voting power as shareholders, particularly regarding ESG issues. They also exert pressure on their external asset managers to take ESG into account.

Second, despite the growing importance of institutional investors in financial markets, there have been relatively few studies that specifically examine their impact on firm-level innovation (Aghion et al., 2013; Bena et al., 2017; Samila et al., 2021; Schain & Stiebale, 2021). These studies offer mixed results. For example, Aghion et al. (2013) find that publicly listed US firms with a higher share of institutional ownership tend to apply for more patents. However, more recent studies using similar datasets arrive at more ambiguous conclusions (Samila et al., 2021; Schain & Stiebale, 2021). Analyzing a dataset of publicly listed firms in 30 countries, Bena et al. (2017) find that only foreign institutional investors have a positive effect on corporate innovation. On the related topic of R&D spending, Bushee (1998) finds that firms with a higher share of institutional ownership reduce R&D investment less after a decline in earnings, with this effect stemming from ownership by investors with a long investment horizon. Our paper differs from previous studies by focusing on a sample that includes both listed and unlisted companies, with a specific focus on the effect of pension funds on firm-level innovation. We also contribute to the understanding of whether pension funds induce firms to invest in "green" innovation, specifically patent applications within climate change mitigation and adaptation technologies. The role of institutional investors in the ESG investment area has received increased attention in recent years, with Dyck et al. (2019) finding that ownership by institutional investors has a positive impact on the environmental and social performance of their portfolio firms. Interestingly, Dyck et al. (2019) also find a positive effect of pension funds specifically when separating the institutional investors by investor type. Additionally, institutional investors are increasingly incorporating climate risk in their investment process (Krueger et al., 2020). However, very few studies have focused on the impact of pension funds (e.g. Alda, 2019). Overall, this study aims to fill a gap in the literature by examining the impact of pension funds on firm-level innovation, with a particular focus on the potential for these investors to promote green innovation. In doing so, we contribute to a better understanding of the role of institutional investors in driving innovation and promoting sustainable growth.

The paper is organized as follows. Section 2 describes the data. Section 3 lays out the empirical strategy, whereas section 4 presents the main results. Sections 5 and 6 offer some mechanisms and refinements. Section 7 concludes.

2 Data

This study draws on data from multiple sources, including two registers at Denmark Statistics - the Integrated Database for Labor Market Research (IDA) and the Firm Statistics Register (FIRM). In addition, we integrate these registers with a newly collected database on Danish pension funds' domestic investments from Experian, as well as a register of patent applications by Danish firms (PATSTAT). To ensure the quality of our analysis, we limit our sample to private firms operating in the manufacturing industry and included in the first two registers between 2003 and 2019. In the following sections, we describe in more detail the data processing procedures for each database.

The Integrated Database for Labor Market Research (IDA) is a register maintained by Denmark Statistics. It is a longitudinal employer-employee database that contains information on gender, place of work, education, labor market status, and occupation of individuals aged 15-74 from 1980 to 2019. The information is updated once a year in week 48. We only use information on individuals' main occupation from 2003 to 2019. This information is used to measure various workforce characteristics at the firm level, such as the share of R&D workers and of workers with tertiary education.

Our second database is the Firm Statistics Register (FIRM), which provides comprehensive data on a sample of private-sector firms from 2003 to 2019. FIRM contains information on firms' annual sales and capital stock[4] and the 4-digit level classification of the Danish Industrial Activities. To ensure the accuracy of our analysis, we exclude observations with missing values for any of the financial items used as control variables, as well as those with negative equity values.

The third data source consists of all domestic investments made by Danish pension funds. We construct information on pension fund investment from shareholder data of all limited liability Danish firms obtained through the data provider Experian. Our panel dataset consists of ownership relationships between two domestic firms in a given year as the unit of observation.[5] We construct the ownership structure of each firm in the sample and determine its ultimate owner. For example, if firm A owns 100% of firm B, and firm B owns 100% of firm C, then firm A is deemed the ultimate owner of firm C. We distinguish between ultimate owners and intermediary owners, like firm B in our example, which may be a legal entity established with the sole purpose of owning firm C. We iterate through all ownership layers until all owners in the dataset are either ultimate owners or firms owned at less than 80% by other firms.[6] As a result, we obtain a panel dataset where each observation identifies a relationship between two firms in a given year, or an owner-owned-year combination. To identify pension fund ownership, we manually check the business registration number (Danish "CVR" number) of each domestic pension fund group using the Danish Business Register (Virk, 2022). We consider a firm as having received pension fund investment if any of these CVR numbers belong to the ultimate owners of the firm. Importantly, the Experian ownership data covers all incorporated Danish firms, allowing us to analyze both publicly listed and private firms, an important contribution to the literature, as previous studies have primarily focused on listed firms (Aghion et al., 2013; Alvarez et al., 2018; Jara et al., 2019; Samila et al., 2021; Schain & Stiebale, 2021, e.g.). While the main datasets do not include information on debt financing, this limitation is unlikely to significantly impact our analysis since equity is the primary source of funding for Danish non-financial companies. In fact, national accounts data from 2019 shows that equity accounts for 59.5% of total liabilities, while loans account for 30.1%. These facts are supported by a refinement of our analysis, that includes a proxy for debt financing as a control variable, using a supplementary dataset

[4]We calculate the real version of all monetary values by using industry-specific deflators at the DB07 36-industry grouping level based on national accounts data.

[5]This data does not encompass ownership by foreign firms or individuals. However, in a refinement, we also include a control for foreign ownership without distinguishing the type of investor.

[6]A detailed description of this dataset can be found in Appendix A.

available for a subsample of firms.

We collect patent filings by Danish firms at the European Patent Office (EPO) from the PATSTAT databse. We record the number of patent applications for each Danish firm as well as the forward citations to each patent, a proxy for the importance of a patent, from 1970 through 2022. We use the data from 1970 to 2002 as a pre-sample information to proxy for firms' unobserved propensity to patent (Blundell et al., 1999 and Lach and Schankerman, 2008). To address right-censoring issues, we exclude the data from 2020 to 2022. To link the firm-level data with PATSTAT, we match on the name and address of the headquarters using the Danish Business Register (Virk, 2022), as in Bloom, Draca, and Van Reenen (2016). Accurate name and address matching poses challenges due to inconsistent names, incomplete or missing information, and multiple entries for the same entity. To enhance matching precision, we employ four criteria: perfect match, alphanumeric match, Jaro-Winkler distance, and Levenshtein distance. The Jaro-Winkler distance assesses string similarity based on shared tokens, while the Levenshtein distance measures the number of changes required to transform one name into another. Only matches exceeding a specific threshold are deemed valid. For a detailed methodology explanation, see Tarasconi and Menon (2017).

After merging the Experian, PATSTAT, and Danish Business Register data on a server controlled by Statistics Denmark, where data is anonymized, we combine them with the IDA and FIRM registers.

2.1 Descriptive Statistics

The first panel of Table 1 displays descriptive statistics of the main outcome variables used in the empirical analysis. We measure the extensive and intensive margins of innovation respectively as the probability of having at least one patent application and the number of patent applications. The intensive measure is weighted by the number of citations, which ensures that only patent applications of higher quality are considered as innovations. In a refinement, we also use the negative hyperbolic sine function of the number of patent applications, weighted by citations. In addition, we extend the analysis to patent applications related to climate change mitigation and adaptation technologies using either the ICP or the CPC classifications. Specifically, a patent application is defined as green, if its Cooperative Patent Classification (CPC) is either in category *Y02* or *Y04S*. Category *Y02* covers selected technologies, which control, reduce or prevent anthropogenic emissions of greenhouse gases, in the framework of the Kyoto Protocol and the Paris Agreement. It also includes technologies that allow adapting to the adverse effects of climate change. Category *Y04S* refers to systems integrating technologies related to power network operation, communication, or information technologies for improving the electrical power generation, transmission, distribution, or usage, i.e., smart grids.[7] We also classify a patent as green, if its International Patent Classification (IPC) is under the categories that refer to climate change mitigation and adaptation technologies.[8] The averages for the extensive and intensive margins (green) are approximately 1 (0.2) percent and 0.084 (0.013), respectively. This means that on average, we record patenting in 1% of firm-year observations. The averages for the extensive margin are low because many firm-year observations have no patent applications. However, in the sample in which we condition on having at least a patent application over the sample period, the average number of patent applications weighted by future citations is 1.5 (0.24 for green applications). In our final sample, around 849 (200) firms record at least one patent (green) application over the sample period and a large fraction of these innovative firms operate in the following industries: i) computer, electronic and optical products (34 percent); ii) manufacture of machinery and equipment (28 percent); iii) basic pharmaceutical products (11 percent); iv) chemical products (6.8 percent); v) rubber and plastic products (5.9 percent). Additional descriptive statistics by 2-digit industries are reported in table C.2 in the Appendix.

Using patents as a measure of innovation, like any other innovation indicator, has advantages and disadvantages. On the positive side, patent applications (i) are a direct outcome of the innovation process and (ii) can be documented. However, it is important to note that not all inventions are patentable, and firms may have different propensities to apply for patents, which may lead to some limitations in relying solely on patent applications. Nevertheless, we consider patent applications a relatively objective and conservative measure of innovation, making them a plausible and suitable proxy for our purposes. To enhance the reliability of our analysis, we also use the share of R&D workers within a firm as an additional proxy for the intensive margin of innovation. To identify workers involved in R&D activities, we use the classification of knowledge-intensive occupations suggested by Bernard et al. (2017). Specifically, in the Danish registers workers' occupational affiliation is defined by the so-called DISCO code, which is the Danish version of the ISCO-88 classification (International Standard Classification of Occupations) before 2009 and of the ISCO-08 after 2009. The validity of the codes is considered high, particularly because they are monitored by employers and unions and form the basis of wage bargaining at the national level (Groes et al., 2015). For instance, such R&D workers are engaged in medical jobs, natural sciences, social

[7] The detailed description of CPC can be found at https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html#Y02.

[8] The categories included are: 6A (Treatment, disposal, combustion and recycling of waste; cleaning of air and water pollution), 6B (Energy conservation and energy efficiency), 6C (Biofuels), 6D (Fuel cells and hydrogen technology), 6E (Solar Energy), 6F (Hydro Energy), 6G (Waste energy, energy from waste heat, fuel from waste), 6H (Wind Energy), 6I (Geothermal energy, energy from natural heat), 6Z (Environment excluded in 6A), ZB (Automobiles), ZC (Other transport technologies).

sciences, programming, or in using the highest skills in their professional area.[9] By using multiple indicators of innovation, we aim to strengthen the robustness of our findings and provide a more comprehensive picture of the relationship between pension fund investments and innovation.

In the following panel of Table 1, we present the descriptive statistics for the main explanatory variables used in our empirical analysis. The first variable, PFI_{it}, is measured as a dummy variable indicating whether a pension fund invests in firm i at time t. We find that only around 1 (8) percent of observations feature a pension fund investment (conditionally on having at least one patent application). Among these selected firms, roughly 50 percent have filed at least one patent application. Additionally, 15 percent of these firms operate within industries characterized by high levels of competition, such as the manufacture of fabricated metal products and the repair and installation of machinery. The duration ($Duration_{it}$, i.e. the length of the pension fund investment in a given firm) and intensity ($Intensity_{it}$, i.e. the percentage of shares outstanding held by pension funds in a given firm) of the investment in a given firm are integrated into our analysis, with an average duration of 4 years and an average intensity of 4 percent respectively for the firms receiving pension fund investments. These figures suggest that pension funds' investments are on average of a considerable amount and have a long-term nature. Empirical evidence supports the notion that pension funds typically have a longer investment horizon than other institutional investors (Cella et al., 2013; Cremers & Pareek, 2016; Döring et al., 2021; Harford et al., 2018). Our data for Denmark confirms this trend. Using another sample extracted from the same dataset as ours, Beetsma et al. (2022) compare the length of the investment period of domestic pension funds with that of other firms in the domestic financial industry (investors) and find that pension funds have a longer holding period for domestic firms than other domestic investors. Pension funds also stand out with a higher frequency of holding periods exceeding 6 years.

The remaining sections of Table 1 present the descriptive statistics for the control variables used in our regression models, which include measures of firms' productivity and capital intensity, among other factors.

3 Empirical Strategy

This section presents the empirical strategy used to estimate the association between pension fund investment and firm-level innovation.

[9] Note that we use the following mapping to take into account the data break for the DISCO variable in 2009: https://www.dropbox.com/s/i2yvj3jbyx5ytfz/correspondence08_88.docx?dl=0

3.1 Event Study and Pre-trends

To determine if pension funds base their investment decisions on the firms' past patenting activity, we begin the empirical analysis with an event study approach. This method allows us to investigate the presence of dynamic effects preceding and following the investment event. However, we face a challenge in that the impact of pension fund investments varies not only among companies but also in terms of the timing of the investments, as not all firms receive investments at the same time. The econometric literature has highlighted that the standard event study specification may exhibit bias towards zero when there is treatment heterogeneity.[10] To address this issue, we estimate the following dynamic two-way fixed effects model using the approach developed by Sun and Abraham (2021), which accounts for heterogeneous treatment effects and incorporates never-treated units as controls (C):

$$Outcome_{it} = \alpha + \sum_{l=-K, l\neq -1}^{L} \beta_l \mathbb{1}\{F_i = t - l\} + X_{it}^{'}\Gamma + \lambda_t + \theta_i + \epsilon_{it} \tag{1}$$

where F_i is the period when firm i is initially benefits a pension fund investment. The variable $Outcome_{it}$ corresponds to one of the innovation outcomes discussed in the previous section. The outcome is regressed on firm and period fixed effects, as well as relative time indicators $\mathbb{1}\{F_i = t - l\}$ which take the value of one if firm i begins receiving a pension fund investment l years prior to t. For $l \geq 0$, β_l estimates the cumulative effect of $l + 1$ treatment periods. For $l \leq -2$, β_l denotes the vector of placebo coefficients that test the assumption of parallel trends. Unbiased estimation of post-event treatment effects relies on this assumption.

In the absence of treatment, the model assumes that treated and control firms would have maintained similar differences as observed in the baseline period. We test this assumption by comparing the outcome trends of firms that will and will not start receiving a pension fund treatment in $|l|$ periods. In other words, regression (1) interacts relative time indicators with the treatment event, excluding indicators for the comparison group, C. Additionally, a single lag or lead variable is excluded to account for the baseline difference between firms with and without the event occurrence. In our specification, the baseline omitted case is the period prior to the first pension fund investment, where l =-1. We augment the specification with control variables X_{it} measured in year t, which encompass a range of firm characteristics that could influence our firm-level outcomes, such as productivity (Bao & Chen, 2018) and the share of tertiary educated workers (Kaiser et al., 2015).

[10] For a comprehensive overview of this discussion, please refer to de Chaisemartin and D'Haultfoeuille (2022b).

3.2 Static Models

We then proceed the analysis by using the following static specification in order to examine the association between pension funds' investments and the extensive and intensive margins of innovation:

$$Outcome_{it} = \beta_1 Pension_{it} + X'_{it}\gamma_1 + \delta_i + \delta_t + \epsilon_{it} \tag{2}$$

where the dependent variable, $Outcome_{it}$, is one of the innovation outcomes of firm i in year t. Our main independent variable is a dummy variable $Pension_{it}$ taking value 1 if at least one domestic pension fund is a shareholder in firm i in year t, and is equal to 0 otherwise. We also present the results obtained using the investment intensity and duration instead of the dummy variable in additional refinements. Furthermore, we incorporate firms' unobserved time-invariant characteristics that influence the ability to innovate (δ_i). Following Blundell et al. (1999) and Lach and Schankerman (2008), we proxy for these time-invariant firm effects in two ways. First, we use the firm's number of patent applications in the pre-sample period (1978-2002) normalized by the total number of patent applications in the same period. Second, we proxy unobserved time-invariant heterogeneity with a dummy for having any patent applications in the pre-sample period. All patent applications in these calculations are weighted by citations. This "pre-sample mean scaling" relaxes the strict exogeneity assumption underlying the fixed-effect models.[11] We finally complete the specification with a vector of explanatory variables (X_{it}) and year fixed effects (δ_t). All of these additional control variables allow us to focus more carefully on the effects of pension funds' investments. We cluster the standard errors at the firm-level.

The linear specification may be problematic when we use the quality-adjusted number of patent applications because our dependent variable only takes on positive values, contains many zeros and its distribution is right-skewed, in which case outliers may influence the results. To address these issues, we use the following approaches. First, we estimate linear models using the inverse hyperbolic sine (IHS) function of citation-weighted patents to account for the large number of zeros and reduce the influence of outliers in the dependent variable. Second, we report Poisson Quasi-Maximum Likelihood (QML) estimates using the following log-link formulation of the conditional mean of our dependent variable:

$$E[Outcome_{it}|Pension_{it}, X'_{it}, \delta_i, \delta_t] = exp(\beta_2 Pension_{it} + X'_{it}\gamma_2 + \delta_i + \delta_t) \tag{3}$$

[11] Since we are limited by the low variation in patenting activity and pension fund investment occurrences, we primarily rely on the pre-sample mean scaling to account for firm-specific unobserved heterogeneity in the linear specifications. However, we also estimate fixed-effect Poisson models with the intensive margin of patenting as the dependent variable.

Because the Poisson distribution is in the linear exponential family, Poisson QML estimates have the advantage of being consistent, provided the mean is correctly specified, independently of the true underlying distribution (Gourieroux et al., 1984). To account for unobserved heterogeneity, we include the pre-sample mean scaling suggested by Blundell et al. (1999) in the Poisson QML model (3). Additionally, we report the QML estimates (Wooldridge, 1999) of the fixed-effect Poisson model developed by Hausman et al. (1984).

3.3 Matching Approach

Estimating the relationship between pension fund investment and innovation using either dynamic or static approaches poses a significant challenge due to pension funds only investing in a limited subset of firms. This may introduce bias in our findings as we compare this subset of firms with the rest of the sample. Furthermore, the "treated" firms that receive pension fund investment, may differ fundamentally from the control group in ways that cannot be captured by the available controls.

To address this challenge, we use propensity score estimation to create a matched control group for our analysis. To calculate the probability of a firm receiving pension fund investment, we begin by estimating a logit regression of the dummy variable PFI_{it} on the following firm variables lagged by one period: sales, fixed assets, number of employees, total assets, total liabilities, net income, sales growth, ratio of fixed to total assets, firm age, the share of workers with tertiary education and a dummy equal to one if the firm belongs to a business group listed on the domestic Stock Exchange. Propensity scores are calculated sector-year wise, and any firm with a propensity score below the 25th percentile of its respective sector-year cell in any year is dropped from the matched control sample.[12] While the specification for the propensity score is simple, estimating it separately for each sector-year reduces the risk of mis-specification. We report the descriptive statistics for the lag of the matching variables and the sample used to estimate the propensity score in appendix (see Appendix Table C.3).

In the following section, we present our results for both static and dynamic approaches for the entire sample, as well as a selected sample where we only keep firms in the matched control group with a high probability of receiving pension fund investment over the sample period.

[12] Sectors are defined based on NACE Rev.2 2-digit grouping. The 25th percentile is only calculated among firms that do not receive pension fund investment in any year. Only firms for which a propensity score can be computed in at least one year are kept. The inclusion of firms with missing propensity scores in all years from the matched control group does not alter our results.

4 Main Results

4.1 Results from the Event Study

To assess the evolution of the relationship between pension fund investment and firm innovation over time, we first use the event study approach described in Section 3.1. This allows us to visually inspect the pre-trends. However, traditional event study methods may not yield accurate estimates when the magnitude of the effect of treatment is correlated with the timing of treatment. To address this issue, we implement the method developed by Sun and Abraham (2021). Figure 1 presents our timing-based estimates which trace out the effect of pension fund investment on patenting as in equation (1), considering the firm's IHS of the number of patent applications weighted by citations in year t as the dependent variable and using both the entire sample (panel a) and the matched sample (panel b).[13] In both panels, the trend in patenting prior to pension fund investment is flat and about equal to zero, but begins rising in the year of pension fund investment. The effect of pension fund investment varies between 5 and 10 percent throughout the post-treatment window. The relatively flat pre-trend centered around zero, and the sharp upward break after pension fund investment, are consistent with the interpretation that we are detecting a causal effect of pension fund investment on patenting.[14]

[FIGURE 1 HERE]

We obtain similar results, when excluding cases of short-term investments by pension funds, defined as investments lasting only one year (see Appendix Figure B.2). Finally, to further strengthen the analysis and rule out that all the observed effects during the post-treatment period can be attributed to selection, we conducted two additional analysis. In the first test, we perform an event study using a simulated placebo event in the matched sample, from which we exclude the actual treated firms. To do this, we assign a hypothetical pension fund investment event to the year when the firms in the matched sample exceed the 75th percentile value of the propensity score. The purpose of this test is to examine whether the placebo event would trigger a similar increase in the intensive margin within the matched sample, as observed in the main analysis, where the actual event is used. The results from this analysis indicate that the placebo event does not lead to an increase in the intensive margin within the matched sample, contrasting the findings from the main analysis (refer to Appendix Figure B.3 for details). In the second test, we re-run our main event study

[13] We use the IHS transformation because it is a newer, widely accepted way of dealing with the zeros in the outcome variable relatively to the log(outcome+1) transformation. Results obtained with the plain level as a measure of intensive margin are available in Appendix Figure B.1.

[14] Qualitatively similar results, which are available on request from the authors, are obtained by using the approach suggested by de Chaisemartin and D'Haultfoeuille (2022a).

analysis by excluding the period after the event occurs, including the event year. The results of this placebo test shows that none of the coefficients estimated on the years leading up to the event are statistically significant, corroborating the hypothesis of no selection in terms of firms' innovation (refer to Appendix Figure B.4 for details).

In the next section, we present an empirical specification that accounts for the large number of zero in the intensive margins and control for the unobserved propensity to patent using the approach suggested in Blundell et al. (1999).

4.2 Results from the Static Models

We now focus on the static approach described in equation (2). In all specifications presented in this sub-section, the explanatory variable capturing pension fund investment PFI_{it} is a dummy variable taking on the value 1 if at least one domestic pension fund is among the shareholders of firm i at time t, and 0 otherwise. First, we explore whether pension funds' investments in a firm affect its propensity to apply for a patent (extensive margin of innovation) in a linear probability model. Column 1 of Table 2 shows a positive association between pension fund investments at time t and the probability to file for a patent application in the same year after controlling for firm characteristics, firm unobserved propensity to innovate and year fixed effects. The regression results show that pension fund investment at time t leads to a 7 percentage point increase in the likelihood of patenting.

In column 2, we examine the effect of pension fund investments on the quality-adjusted intensive margin of innovation, defined as the number of patent applications weighted by the number of forward citations. The results show that pension fund investments in a firm at time t are associated with an increase of about one quality-adjusted patent. The regression using the inverse hyperbolic sine transformation (IHS) of the number of patents (column 3 of Table 2) suggests that pension fund investments increase patenting by about 10 %.[15]

The Poisson model with standard firm fixed effects (column 4 of Table 2) and the Poisson model following la Blundell et al. (1999) (column 5) confirm the positive association between pension funds' investments and the firm's intensive margin of innovation. The fixed-effect Poisson QML estimates indicate that pension fund investments increases the expected count of patents by almost 100 percent on the logarithmic scale or equivalently by a factor of 2.5 (=exp(0.908)). Similarly, the Poisson QML estimates with presample mean scaling suggest an increase by a factor of 2.2 (=exp(0.803)).

We proceed to examine whether pension fund investments encourage firms to engage in

[15] Note that the IHS transformation allows to retain values of zero in the dependent variable. This implies that the estimated coefficient reflects a combination of both the extensive margin effect (how many firms change from zero to a positive number of patent applications), and the intensive margin effect (what the percent increase is from pension fund investment for those firms with positive number of patent applications).

green technology innovation using a linear probability model that controls for firms' characteristics, unobserved heterogeneity, and year fixed effects (column 6 of Table 2). The results indicate that firms that receive investments from pension funds are more likely to apply for a green patent by approximately 1 percentage point. The lower adjusted R^2 in comparison to the one reported in column 1 for the propensity to apply for a patent can be attributed to the relatively lower variation in green patenting within our sample. In the last column of Table 2, we use the share of R&D workers as an outcome variable. The estimated coefficient on our variable of interest is positive and significant, indicating that pension fund investments are associated with a 5 percentage point increase in the share of R&D workers in the firm.

[TABLE 2 HERE]

To ensure our main results are not influenced by selection issues, we repeat the regressions from Table 2 using the matched sample of firms with no pension fund investment, as outlined in the previous section. The results from the matched sample, presented in Table 3, are consistent with those using the full sample in Table 2, indicating a positive association between pension fund investments and firm-level innovation, regardless of the measurement method.

[TABLE 3 HERE]

5 Mechanisms

This section explores the two main mechanisms behind our main results, i.e. the role of pension funds in terms of governance and long term capital provision.

5.1 First Mechanism: The role of Management and Corporate Governance

Overall, our findings indicate a positive association between pension funds' investments and firms' innovation outcomes. However, the precise mechanism behind this relationship remains uncertain. The theoretical framework presented in Aghion et al. (2013) provides two possible hypotheses. One hypothesis suggests that pension funds can bridge the informational gap between managers and shareholders, thereby motivating managers to undertake innovative projects and investments. Under normal circumstances, managers may hesitate to engage in risky activities due to the fear that failure could tarnish their reputation and harm their careers. In extreme cases, they may even face termination. However, pension funds, given their significant stake in the company, possess a greater incentive to gather information about the managers. Consequently, they are less inclined to dismiss a manager who experiences mere misfortune and provide a form of "insurance" to those who innovate, thus alleviating career concerns. This hypothesis, referred to as the "career concern" hypothesis in Aghion et al. (2013), offers one explanation.

In addition to the "career concern" hypothesis, the theoretical framework in Aghion et al. (2013) suggests another potential mechanism known as the "lazy manager" hypothesis. According to this hypothesis, managers may exhibit a preference for stable and routine practices, but pension funds can motivate them to exert more effort and engage in innovative activities (Bertrand & Mullainathan, 2003). However, as Aghion et al. (2013) argue, if product market competition is intense, the need for pension funds to monitor managers diminishes. The threat of bankruptcy or takeover, inherent in fierce competition, already compels managers to work diligently and pursue innovation activities. Therefore, if the "career concern" hypothesis holds true, intense competition should reinforce the positive impact of pension funds on managers' incentives to engage in innovation.

To examine the relationship between pension fund investments and innovation under conditions of high product market competition, we estimate a regression model using specification (2) and introduce an interaction term between the variable $Pension_{it}$ and a dummy variable capturing high levels of competition in the NACE Rev.2 2-digit industry of firm i.[16]

We adopt two approaches to measure competition, the inverse Herfindahl index based on firms' sales at the 2-digit industry level and the inverse Lerner index based on gross margins. In the first approach, we define a dummy variable $High\ Competition$ that takes the value one if the firm operates in a sector where the inverse of the Herfindahl index based on sales is above the 75th percentile of the sector-specific distribution. In the second approach, the dummy variable $High\ Competition$ takes the value one if the firm operates in a sector where the inverse of the Lerner index is above the 75th percentile of the sector-specific distribution.

The results of these specifications, including the interaction terms, are displayed in Tables 4 and 5. The results of column 1 in both Table 4 and 5 indicate that pension fund investment roughly leads to a 7 percentage point increase in the likelihood of patenting in industries where competition is weak, and only a 2 percentage point increase in more competitive industries.

The results of the other models presented in Tables 4 and 5 convey comparable results. We find a negative interaction between product market competition and pension fund investments, both on the extensive and intensive dimensions of innovation. While the estimated coefficients for pension fund investment remain positive, they generally exhibit smaller mag-

[16] We exclude the non-interacted dummy variable $High\ Competition$ from the specification for three reasons i) we define competition as a time-invariant characteristic of the sector, (ii) firms rarely change sector and (iii) we control for time-invariant firm characteristics using the approach developed by Blundell et al. (1999) in columns 1,2,3,5,6 and 7 of Tables 4 and 5. We control for firm fixed effects in column 4 of Tables 4 and 5.

nitudes compared to the negative coefficients for the interaction term. Moreover, in almost all the estimated models the joint significance tests at the bottom of Tables 4 and 5 indicate that the null hypothesis that the sum of both coefficients is zero, cannot be rejected. This finding supports the hypothesis that pension funds are ineffective in fostering innovation in companies operating in competitive industries.

[TABLE 4 HERE]

[TABLE 5 HERE]

Nearly identical results are obtained when: i) using the 50th percentile of the Herfindahl index as a threshold for defining high-competition industries and ii) estimating the interaction specifications on the matched sample, as detailed in the appendix (see Appendix Tables C.12 and C.13).[17]

Our findings are consistent with the "lazy manager" hypothesis rather than the alternative "career concern" theory, as we observe that product market competition does not enhance the influence of pension funds on firms' innovation. Pension funds don't seem to exert a larger effect on firms operating in highly competitive industries, mainly because these industries consists of a highly selected group of firms driven by strong incentives to innovate, as suggested by neo-Schumpeterian theories (Bloom, Draca, & van Reenen, 2016). Interestingly, our results differ from the findings of Aghion et al. (2013), where competition strengthens the impact of institutional ownership on innovation. However, these different findings can partly be explained by the features of our data. First, we use a large and representative sample of manufacturing firms, including both listed and unlisted firms, while Aghion et al. (2013) only focuses on publicly listed firms, which are typically larger and more non-representative of the economy. Second, we examine a small European country and a more recent sample period than Aghion et al. (2013). Given the theoretical ambiguity in the relationships examined, it is possible that other studies may also reach different conclusions than Aghion et al. (2013) (see e.g. Samila et al., 2021; Schain & Stiebale, 2021).

The hypothesis that pension fund investments affect innovation through their influence on governance is supported by two additional sets of results, in which we show that the the monetary amount invested in a firm plays a significant role in innovation. In the first approach, we redefine the variable $Pension_{it}$ in equation (2) as the aggregate percentage of equity held by all domestic pension funds, instead of the dummy variable used previously. Additionally, we include a squared term to capture any possible non-linear relationship between pension fund investments and firm innovation. The refined results are reported in

[17] The results obtained with the Lerner index using a 50th threshold and the matched sample are very similar to the ones reported in the paper and are available upon request.

Table 7, which reaffirm that pension funds have a positive effect on firm-level innovation at both the extensive and intensive margins, as well as in relation to green technologies, although the coefficient for the latter is not precisely estimated. Furthermore, there is suggestive evidence for a positive and concave relationship between firm innovation and the pension fund investment intensity variable.

[TABLE 7 HERE]

In the second approach, we explore the relationship between pension fund investment and firm innovation, focusing specifically on cases where the monetary amount of investment is large. In Table 8, we use a dummy variable that equals one if the combined ownership by Danish pension funds in a given firm amounts to at least 5% of its total equity. This approach allows us to exclude cases where the investment by pension funds represents a negligible source of capital for the firm and focus on cases where pension funds exhibit larger commitments. Importantly, the positive and statistically significant coefficients of the pension fund investment variable persist when we limit the analysis to sizeable pension fund investments.

[TABLE 8 HERE]

5.2 Second Mechanism: Investment Duration

In the introduction we mention that pension fund investment may also promote innovation at the firm-level by securing long-term funding. We now explore explicitly this hypothesis by estimating the potential impact of a pension fund investment's duration. Specifically, we measure the duration of investment as the consecutive number of years during which at least one pension fund has invested in the firm, and analyze the relationship between this duration and innovation outcomes. The findings obtained with the duration variable are reported in Table 6 and reveal a positive association between investment duration and innovation activities. This result aligns with the hypothesis that the duration of investment plays a significant role in fostering innovation. Therefore, pension funds facilitate investment in innovation not only by disciplining managers (as discussed in section 5.1) but also by providing long-term capital stability. Our results also hint at a concave relationship, as the positive link between duration and both the extensive and intensive margins of innovation diminishes with each additional year of investment.[18]

[TABLE 6 HERE]

[18] Similar results, available upon request, are obtained when defining the duration variable based on investments for which the percentage of shares outstanding held by pension funds is at least 5 percent.

6 Additional Analysis

This section tests the validity of the main findings as follows. First, we explore the effect of pension fund on energy efficiency as a way of further testing the impact of pension fund investment on green innovation at the firm-level. Second, we look at the role of other investors and debt financing, and we finally conclude with a few robustness checks where we estimate the main effects by focusing on specific sub-samples of firms.

6.1 Energy efficiency

In the main analysis, we find that pension fund investment promotes firms' green innovation. This type of innovation often entails new technologies that allow companies to improve their energy efficiency. We therefore explore whether indeed pension fund investments associate with a firm's energy efficiency relatively to its peers in a given industry. First, we define the firm's energy efficiency ratio by normalizing a firm's energy consumption by its revenue.[19] Second, we identify the minimum energy per gross output ratio within each industry. Third, we divide the industry minimum by each firm's energy efficiency ratio to obtain a relative measure of energy efficiency. This ratio goes from 0 to 1 and the closer is this ratio to 1, the more energy efficient the firm is relative to its peers within the same industry (Telle, 2006). We then use this ratio as an outcome variable in an event study regression, as we have done for the innovation outcomes in the previous section. The first panel of Figure 2 in the Appendix provides evidence to suggest that the event of a pension fund investment is associated with an improvement in the relative measure of energy efficiency at least in the first four years since the event of a pension fund investment. For example, in the year after the investment the firm's energy efficiency improves by 0.006, which represents a 60 percent improvement relatively to the sample average (0.01). The coefficient estimated from the static two-way fixed effects model delivers a coefficient of 0.004 (s.e. 0.002), which suggests that a pension fund investment is associated with an average improvement in the firm's energy efficiency of 40 percent over the long run. The second panel confirms these findings by using the most refined classification of industries to identify the minimum energy per gross output ratio within each industry. Overall, these results corroborate the hypothesis

[19] We use the variable "KENE" from the FIRE register to measure firm-level energy purchases in 1000 DKK. This variable includes expenses for electricity, oil, gas, and district heating, but excludes fuel expenses for registered motor vehicles used for external transport and deductible energy taxes. See https://www.dst.dk/extranet/staticsites/TIMES3/html/ca145bb4-4483-4607-9e60-57af2fb4c8b2.htm for a more detailed description. An important limitation of this variable is that it does not distinguish between green and brown energy. However, according to the official statistics provided by Statistics Denmark, the fraction of clean energy in the economy does never exceed 13 percent over the sample period, as reported in www.statbank.dk/ENE2HO. Note that also this variable is only available up until 2016, and it is provided in a version of the firms' accounting register (FIRE) that is more detailed than FIRM.

that pension fund investments may help companies in the green transition by stimulating the development of new green technologies.

[Figure 2 HERE]

6.2 The role of other investors and debt financing

We now explore the impact of other investors from the financial sector and examine how they affect the coefficient estimated on our pension fund investment variable. Given that pension funds may invest in a company alongside or independently but concurrently with other investors, such as private equity or insurance companies, it is possible that the positive coefficients observed in our main findings are not solely driven by pension fund investments. To address this issue, we re-estimate our baseline models from Table 2 using three alternative specifications.

In the first alternative specification, we extend our baseline specifications by adding a dummy variable that captures investments by any other domestic financial sector entity.[20] Results reported in Table 9 show that even when including the dummy variable for other investors, our key variable of interest capturing pension fund investments remains positive and statistically significant, with similar magnitudes to those reported in the baseline analysis.

[TABLES 9 HERE]

In the second specification, we expand the main regressions by including a full set of dummy variables that capture the presence of other investors in the firm. Specifically, we include a binary variable equal to one if any of the following investor types are shareholders of firm i in period t: (1) banking and financing activities, except insurance and pensions; (2) holding company; (3) financial holding company; (4) non-financial holding company; (5) venture companies and capital funds; (6) investment companies; (7) money market associations; (8) investment associations and investment companies; (9) banks, savings banks and cooperative banks; (10) other financial intermediaries except insurance and pension insurance; (11) insurance companies; (12) asset management; (13) foreign investor. The results obtained from this detailed specification are presented in Table 10, and they indicate that only the dummy variable associated with pension fund investments consistently exhibits a positive and precisely estimated coefficient across all regression models. Conversely, none of the other investor types appear to consistently impact firm-level innovation. In the third and final specification, we adopt a parsimonious approach to address the presence of other

[20] We identify financial sector firms based on their 2-digit industry code.

investor types. We include the 13 dummies described above individually, along with our pension fund investment variable, to investigate whether the lack of significance in the second specification is due to multicollinearity. The results in Table 11 consistently demonstrate that our pension fund variable remains unaffected by the different control measures for other investors. In most cases, these control measures do not positively influence firms' innovation, as indicated by the panel Poisson model.[21]

[TABLES 10 and 11 HERE]

A further concern with our main specifications is that we don't control for debt financing at the firm level. To address this issue, we incorporate the ratio between long-term debt and total assets as a proxy for debt financing. Long-term debt is available only for a subsample of firms in the accounting registers (FIRE). Table 12 demonstrates that including this additional confounding factor in our regressions, conducted on a smaller sample of firms, does not substantially alter the effects of pension fund investments on firms' innovation. The coefficient on the long term debt ratio is consistently imprecisely estimated.[22]

[TABLE 12 HERE]

6.3 Robustness checks

In this section we briefly summarize a number of robustness checks on our main results that reported in Appendix. We begin by excluding publicly listed companies from our analysis to test if the relationship between pension funds and innovation is driven by listed firms, as they may possess established management structures and practices that facilitate the involvement of pension funds in their governance and innovation. Publicly listed companies often belong to large business groups, but only one of the firms in these groups is publicly listed. To take into account this issue, we define a firm as publicly listed if it belongs to a business group that includes at least a firm listed on the Nasdaq Copenhagen Stock Exchange during any year of the sample period.[23] Appendix Table C.4 demonstrates that the positive association

[21]Similar results are obtained by using the other models for extensive and intensive margins of innovation. We have also estimated a specification in which we interact our pension fund investment variable with the other investor dummies only for investor types in which we observe a large enough number of co-investments in our sample, i.e. cases of co-investments involving at least 300 observations. The investor types included in this interaction specification are the following ones: banking and financing activities, except insurance and pensions; holding company; non-financial holding company. The interaction coefficients are not statistically significant.

[22]Additional results available on request from the authors also show that the interaction between long term debt ratio and the pension fund dummy is never statistically significant. This is also the case when we estimate a specification in which we include a dummy equal to 1 if the firm's long term debt ratio is above the 75th percentile of the distribution and its interaction with the pension fund dummy.

[23]Information on business group composition is sourced from Statistic Denmark, while data on listing status is obtained from Refinitiv Eikon.

between pension funds and firms' innovation persists even when we exclude listed companies, thereby dismissing the hypothesis that the beneficial effects of pension fund investment are predominantly attributable to listed firms.

Next, we check whether our main results are affected when excluding firms with imputed accounting data.[24] The results, presented in Appendix Table C.5, confirm the robustness of our main findings. Even after excluding the firms with imputed values, we find that the coefficients remain positive and precisely estimated, indicating that our results are not contingent upon the presence of imputed data.

To further validate our findings, we perform additional analyses on two distinct samples. First, we exclude firms with fewer than 10 employees from the sample used in the main analysis. Second, we expand our analysis to include all industries, beyond the manufacturing sector. The results, presented in Appendix Tables C.6 and C.7, show that the main coefficients of interest remain positive and significant. The magnitudes of the coefficients are similar to the ones discussed in the baseline analysis. Specifically, the presence of pension funds' investments at time t is associated with a 5.7 and 5.9 percentage point increase in the firm's extensive margin of innovation, respectively, in the samples that exclude firms with fewer than 10 employees (Appendix Table C.6) and include all industries (Appendix Table C.7). Furthermore, a pension fund investment is on average associated with an increase in the number of citation-weighted patent applications by a factor of 2. We also find that firms that receive investments from pension funds are more likely to file a green patent by approximately 1 percentage point and that they increase their share of R&D workers by 4-4.5 percentage points. The evidence reported in Appendix Tables C.6 and C.7 suggests that our findings are robust and not driven by the selection of the main sample.

We conclude this section of robustness checks as follows. First, we redefine the extensive margin of patenting as a dummy variable equal to one if the firm received at least one patent citation in year t, thus accounting for the quality of patents. Column 1 of Appendix Table C.8 shows that the coefficient estimated on our pension investment variable remains positive and significant when we use this alternative measure of the extensive margin of patenting. Second, we re-run all of our main regressions with a pension fund investment dummy variable lagged by one period. Columns 2-8 of Appendix Table C.8 confirm the baseline analysis by revealing a positive association between pension funds investments in year $t-1$ and innovation outcomes in year t. Third, our main results hold when we use different thresholds for the matching procedure used to construct the matched sample of control firms (see Appendix Tables C.10 for the results obtained with a 50th percentile as a threshold and C.11 for those obtained with a 75th percentile). Finally, we re-estimate our

[24] Denmark Statistics employs imputation techniques for missing accounting values. The reliability of such imputed information could potentially influence our results.

main regressions by focusing only on cases of direct investments. Appendix Table C.9 shows that the estimated impact on the pension fund dummy narrowly defined to include only direct investments tends to be larger in magnitude than our baseline coefficients but less precisely estimated for two of the definitions of innovation due to a decrease in the number of treated observations.[25]

7 Conclusion

Innovation is widely acknowledged as a key driver of economic growth, generating substantial interest in research, policy, and industry regarding the promotion and financing of innovation. Previous studies have examined the role of institutional investors in financing innovation, yielding mixed conclusions (Aghion et al., 2013; Samila et al., 2021; Schain & Stiebale, 2021).

This study specifically investigates the connection between corporate innovation in Denmark and domestic pension funds as institutional investors. Pension funds are well-suited for innovation financing due to their significant assets under management and long investment horizon.

Using a unique panel dataset on ownership of all Danish limited liability companies, this study differs from previous research in two crucial aspects. First, it focuses solely on pension funds instead of a more extensive institutional investor category. Secondly, it examines both public and private manufacturing firms, rather than solely publicly listed firms. The analysis addresses the potential selection of pension fund investment by assessing innovation disparities between firms that receive pension fund investment and those that do not prior to the investment. The findings indicate no evidence that pension funds select firms based on prior patenting activity.

The paper establishes a positive and statistically significant relationship between pension fund investment and innovation, as measured by citation-weighted total patents and climate related patents. Additional robustness checks corroborate the main findings and allow us to dismiss the hypothesis that the effect of pension fund investment is due to the presence of other investors, such a private equity. Furthermore, our analysis suggests that competition weakens the relationship between innovation and pension fund investment, which can be explained by the "lazy manager" hypothesis (Aghion et al., 2013). Institutional investors can stimulate corporate innovation by motivating managers to engage in innovative endeavors, yet this effect is weaker in highly competitive sectors. In such sectors, managers must be more proactive even in the absence of pension fund investments. Consequently, the results support a weaker relationship between pension fund investments and corporate innovation in

[25] Similar results are obtained by excluding from the sample cases of indirect investments performed by pension funds instead of considering them as part of non treated sample.

industries with heightened competition, thus suggesting the validity of the “lazy manager” hypothesis. Additionally, the study uncovers a positive correlation between the duration of pension fund investment and innovation, indicating that pension funds offer the capital necessary for investing in risky, long-term projects.

The relationship that we find also extends to green innovation, with pension fund investment being associated with an increased green patenting activity. Pension funds employ different strategies to account for ESG factors, with active ownership, exclusionary screening and divestment the most commonly employed tools (OECD, 2021). While the question of the effectiveness of these different strategies lies outside the scope of this paper, our results indicate that pension funds can play a role in fostering green innovation in the economy.

This study highlights the potential contribution of pension funds to economic growth through their longer investment horizon and patient capital. As funded pension systems become more prominent, understanding how pension funds can contribute to economic growth is becoming increasingly important. Future research could therefore further investigate the channels from pension fund investment to corporate innovation.

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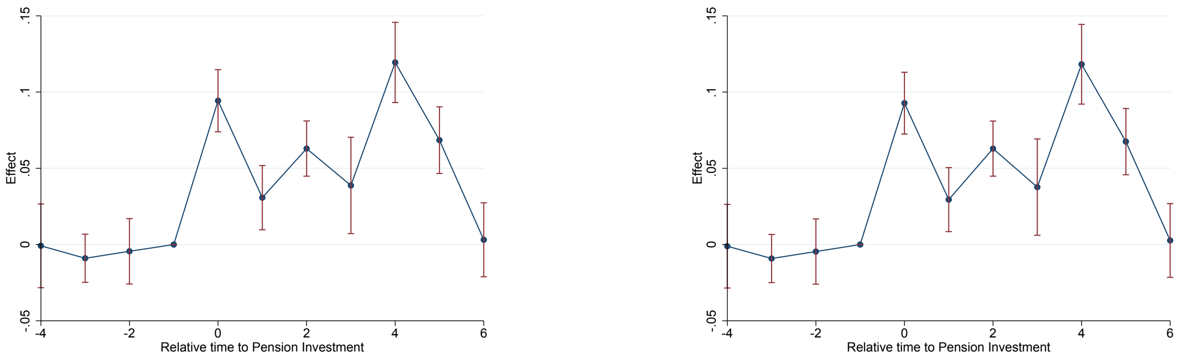
Figure 1: Pension Fund Investments and Innovation Outcomes, Dynamic Specification

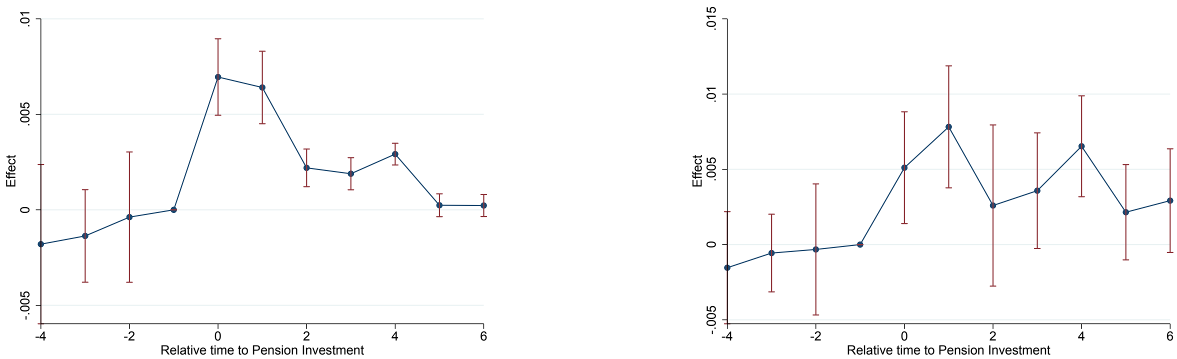


(a) Intensive Margin of Innovation (Whole Sample)

(b) Intensive Margin of Innovation (Matched Sample)

Note: This figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). The dependent variable is the IHS transformation of the number of patent applications weighted by citations (intensive margin) in year t. The sample considers 476 distinct events of treatment. Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Figure 2: Pension Fund Investments and Relative Energy Efficiency, Dynamic Specification



(a) Relative Energy Efficiency (NACE 2)

(b) Relative Energy Efficiency (DB07)

Note: This figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). The dependent variable is the energy efficiency ratio in year t. The sample considers 419 distinct events of treatment. Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Table 1: Descriptive Statistics

Variables	Definition	Whole Sample		At least one Patent	
Outcome variables		Mean	SD	Mean	SD
Patent(0/1)	1, if the firm applies for a patent	0.013	0.113	0.235	0.424
#patents	number of firms' patent citations	0.084	3.040	1.520	12.864
Green Patent(0/1)	1, if the firm applies for a green patent	0.002	0.045	0.037	0.189
# green patents	number of firms' green patent citations	0.013	0.922	0.239	3.922
Share of R&D Workers	Share of R&D workers in total employment	0.011	0.064	0.160	0.178
Pension investment variables					
PFI_{it}	1, if a pension fund invests in firm i at time t	0.011	0.104	0.076	0.266
$Intensity_{it}^{a}$	percentage of shares outstanding held by pension funds in firm i at time t	4.345	8.019	10.069	9.684
$Duration_{it}^{a}$	duration of the pension fund investment in firm i at time t	3.737	3.004	4.094	3.190
Firm variables					
Productivity	log of sales per employee	13.682	0.809	14.193	0.699
Capital Intensity	log of capital stock per employee	12.079	1.372	12.761	1.339
Female	share of female workers	0.258	0.288	0.262	0.171
Tertiary	share of workers with tertiary education	0.033	0.103	0.044	0.068
N		179,301		9,867	
Number of firms		30,802		849	

Notes: All descriptive statistics are calculated as averages over the 2003-2019 period. Firm variables are in real Danish Kroner (using 2010 as the base year). ^{a}: the descriptive statistics for this variable are calculated only conditional on receiving any pension fund investment.

Table 2: Pension Fund Investments and Innovation: Main results

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.068***	1.041*	0.098***	0.908**	0.803**	0.012**	0.051***
	(0.013)	(0.589)	(0.035)	(0.370)	(0.350)	(0.005)	(0.008)
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF Investment	509	509	509	91	509	509	509
Adj. R^2	0.130	0.107	0.128			0.013	0.152
χ^2				283.7	5,627.9		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 3: Pension Fund Investments and Innovation: Main results (Matched Sample)

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.065***	1.017*	0.095***	0.892**	0.780**	0.011**	0.050***
	(0.013)	(0.590)	(0.034)	(0.354)	(0.367)	(0.005)	(0.008)
Mean of the dependent variable	0.016	0.116	0.017	3.032	0.116	0.003	0.014
# observations	117,209	117,209	117,209	4,451	117,209	117,209	117,209
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	24,718	24,718	24,718	346	24,718	24,718	24,718
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.144	0.112	0.136			0.015	0.165
χ^2				420.4	4,872.3		

Notes: The sample only includes "matched" firms in the control group, as described in section 3.3. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 4: Pension Fund Investments and Innovation: Competition Results (Herfindahl Index)

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.092***	1.550*	0.140***	0.974***	0.898***	0.014**	0.072***
	(0.017)	(0.824)	(0.049)	(0.370)	(0.345)	(0.006)	(0.010)
$PFI_{it} \times High\ Competition$	-0.083***	-1.759**	-0.147***	-1.665***	-2.470***	-0.008	-0.074***
	(0.020)	(0.827)	(0.052)	(0.621)	(0.505)	(0.008)	(0.012)
P-value, $H_0 : PFI_{it} + PFI_{it} \times High\ Competition = 0$	0.193	0.149	0.765	0.865	0.115	0.262	0.816
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.131	0.108	0.129			0.013	0.155
χ^2				293.5	5,714.9		

Notes: The variable $High\ Competition$ is a dummy variable equal to 1, if the firm operates in a sector in which the inverse of the Herfindahl index is above the 75th percentile of the sector distribution. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 5: Pension Fund Investments and Innovation: Competition Results (Lerner Index)

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.081***	1.714	0.136**	1.368***	0.951***	0.016**	0.044***
	(0.023)	(1.151)	(0.061)	(0.367)	(0.362)	(0.008)	(0.011)
$PFI_{it} \times High\ Competition$	-0.018	-0.978	-0.056	-1.173***	-0.245	-0.006	-0.011
	(0.029)	(1.342)	(0.079)	(0.362)	(0.555)	(0.010)	(0.015)
P-value, $H_0 : PFI_{it} + PFI_{it} \times High\ Competition = 0$	0.080	0.743	0.342	0.000	0.633	0.181	0.134
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.130	0.107	0.128			0.013	0.152
χ^2				349.5	6,129.7		

Notes: The variable $High\ Competition$ is a dummy variable equal to 1, if the firm operates in a sector in which the inverse of the Lerner index based on gross margins is above the 75th percentile of the sector distribution. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy variable for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 6: Pension Fund Investments and Innovation: Duration Results

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
$Duration_{it}$	0.028***	0.277*	0.040***	0.114	0.197**	0.005**	0.019***
	(0.006)	(0.151)	(0.013)	(0.129)	(0.096)	(0.002)	(0.004)
$Duration^2_{it}$	-0.002***	-0.009	-0.002*	-0.002	-0.009	-0.000*	-0.001***
	(0.001)	(0.022)	(0.001)	(0.011)	(0.010)	(0.000)	(0.000)
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.130	0.107	0.128			0.013	0.151
χ^2				335.4	5,845.6		

Notes: The variable $Duration_{it}$ is the number of years of consecutive investment by at least one domestic pension fund in firm i. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 7: Pension Fund Investments and Innovation: Intensity Results

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
$Intensity_{it}$	0.020***	0.284*	0.028***	0.162**	0.290**	0.003	0.014***
	(0.004)	(0.157)	(0.010)	(0.076)	(0.148)	(0.002)	(0.002)
$Intensity_{it}^2$	-0.000***	-0.007*	-0.001***	-0.005	-0.019	-0.000	-0.000***
	(0.000)	(0.004)	(0.000)	(0.004)	(0.013)	(0.000)	(0.000)
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.133	0.108	0.130			0.014	0.156
χ^2				326.3	6,613.0		

Notes: The variable $Intensity_{it}$ is the aggregate share of firm i held by domestic pension funds at time t. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 8: Pension Fund Investments and Innovation: Alternate Definition of Investment Dummy Results

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.067***	1.516*	0.124**	0.873**	-	0.012**	0.042***
	(0.017)	(0.841)	(0.050)	(0.388)	-	(0.006)	(0.009)
Mean of the dependent variable	0.013	0.084	0.013	2.670	-	0.002	0.011
# observations	179,301	179,301	179,301	5,601	-	179,301	179,301
# observations with PF investment	1,371	1,371	1,371	358	-	1,371	1,371
# Firms	30,802	30,802	30,802	425	-	30,802	30,802
# Firms with PF investment	354	354	354	75	-	354	354
Adj. R^2	0.129	0.107	0.128			0.013	0.149
χ^2				264.9	-		

Notes: PFI_{it} equals 1 if the aggregate holding of all pension funds in firm i in year t was at least equal to 5%. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In Column 5 the maximum likelihood estimation does not converge. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 9: Pension Fund Investments and Innovation: Adding Other Investor (First Specification)

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.067***	1.046*	0.097***	0.909**	0.785**	0.012**	0.050***
	(0.013)	(0.595)	(0.035)	(0.369)	(0.326)	(0.005)	(0.008)
$Other\_Investor_{it}$	0.005***	-0.031	0.003	0.003	-0.125	0.001	0.004***
	(0.001)	(0.043)	(0.003)	(0.164)	(0.302)	(0.000)	(0.001)
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.131	0.107	0.128			0.013	0.153
χ^2				283.8	5,696.3		

Notes: $Other\_Investor_{it}$ takes the value 1 if at least one firm from the domestic financial sector which is not a pension fund is among the shareholders of firm i in period t, and zero otherwise. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 10: Pension Fund Investments and Innovation: Adding Other Investor (Second Specification)

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.069***	1.172*	0.107***	1.112***	1.114***	0.011**	0.045***
	(0.014)	(0.640)	(0.038)	(0.397)	(0.414)	(0.005)	(0.008)
$Other\_Investor_{it}(1)$	0.005	-0.269*	-0.014	-0.707	-1.453**	-0.005**	0.000
	(0.011)	(0.163)	(0.015)	(0.634)	(0.594)	(0.002)	(0.008)
$Other\_Investor_{it}(2)$	-0.024	0.123	0.047	2.832**	0.977	-0.002	-0.017
	(0.020)	(0.223)	(0.061)	(1.280)	(0.733)	(0.005)	(0.011)
$Other\_Investor_{it}(3)$	0.020	0.080	-0.028	-2.282*	-0.550	0.007	0.020**
	(0.017)	(0.208)	(0.060)	(1.240)	(0.627)	(0.004)	(0.008)
$Other\_Investor_{it}(4)$	0.024	0.137	-0.027	-1.928*	0.334	0.007	0.020**
	(0.017)	(0.214)	(0.060)	(1.127)	(0.596)	(0.004)	(0.008)
$Other\_Investor_{it}(5)$	0.023	-0.377	-0.025	-0.245	0.033	-0.004	0.132***
	(0.030)	(0.291)	(0.030)	(0.900)	(0.783)	(0.003)	(0.030)
$Other\_Investor_{it}(6)$	0.001	0.159	0.009	0.311	0.744	0.005*	0.010
	(0.013)	(0.150)	(0.018)	(0.797)	(0.804)	(0.003)	(0.008)
$Other\_Investor_{it}(7)$	(.)	(.)	(.)	(.)	(.)	(.)	(.)
	(.)	(.)	(.)		(.)	(.)	(.)
$Other\_Investor_{it}(8)$	-0.033	-0.627**	-0.089***	-4.727***	-4.717***	0.010	0.031
	(0.027)	(0.314)	(0.032)	(1.091)	(0.717)	(0.016)	(0.025)
$Other\_Investor_{it}(9)$	-0.038	-0.837**	-0.071*	-0.250	-1.408*	-0.002	0.004
	(0.024)	(0.415)	(0.036)	(1.058)	(0.830)	(0.008)	(0.012)
$Other\_Investor_{it}(10)$	0.015	-0.092	0.001	0.794	1.206*	0.013***	0.018*
	(0.015)	(0.367)	(0.021)	(0.681)	(0.655)	(0.005)	(0.010)
$Other\_Investor_{it}(11)$	0.064*	0.122	0.089	0.602	0.575	0.050*	0.056***
	(0.037)	(0.661)	(0.074)	(0.406)	(0.684)	(0.029)	(0.020)
$Other\_Investor_{it}(12)$	0.003	-0.016	-0.002	-4.272***	-3.587***	-0.002***	0.001
	(0.011)	(0.028)	(0.003)	(0.829)	(0.308)	(0.000)	(0.006)
$Other\_Investor_{it}(13)$	0.045	-0.113	-0.027	-4.069***	-4.304***	0.015	0.003
	(0.050)	(0.162)	(0.019)	(1.025)	(1.030)	(0.024)	(0.022)
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.128	0.107	0.127			0.014	0.153
χ^2				1,197.0	16,891.8		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). The variables $Other\_Investor_{it}()$ take the value 1 if one of the following investors is among the shareholders of firm i in period t: (1) banking and financing activities, except insurance and pensions; (2) holding company; (3) financial holding company; (4) non-financial holding company; (5) venture companies and capital funds; (6) investment companies; (7) money market associations; (8) investment associations and investment companies; (9) banks, savings banks and cooperative banks; (10) other financial intermediaries except insurance and pension insurance; (11) insurance companies; (12) asset management; (13) foreign investor. Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 11: Pension Fund Investments and Innovation: Adding Other Investor (Third Specification)

Dep. var:	E[#patents] (1)	E[#patents] (2)	E[#patents] (3)	E[#patents] (4)	E[#patents] (5)	E[#patents] (6)	E[#patents] (7)	E[#patents] (8)	E[#patents] (9)	E[#patents] (10)	E[#patents] (11)	E[#patents] (12)	E[#patents] (13)
							fixed-effect Poisson QML						
PFI_{it}	0.845***	0.851**	0.913**	0.856**	0.909**	0.910**	0.908**	0.914**	0.919**	0.915**	0.915**	0.908**	0.909**
	(0.319)	(0.335)	(0.371)	(0.337)	(0.369)	(0.370)	(0.370)	(0.368)	(0.367)	(0.363)	(0.368)	(0.370)	(0.369)
$Other\_Investor_{it}(1)$	-0.122												
	(0.137)												
$Other\_Investor_{it}(2)$		-0.117											
		(0.118)											
$Other\_Investor_{it}(3)$			-0.346										
			(0.467)										
$Other\_Investor_{it}(4)$				-0.104									
				(0.123)									
$Other\_Investor_{it}(5)$					-1.140**								
					(0.502)								
$Other\_Investor_{it}(6)$						-0.164							
						(0.339)							
$Other\_Investor_{it}(7)$							(.)						
							(.)						
$Other\_Investor_{it}(8)$								-1.501*					
								(0.860)					
$Other\_Investor_{it}(9)$									-1.326**				
									(0.640)				
$Other\_Investor_{it}(10)$										0.110			
										(0.314)			
$Other\_Investor_{it}(11)$											0.733		
											(0.498)		
$Other\_Investor_{it}(12)$												4.821***	
												(1.028)	
$Other\_Investor_{it}(13)$													-3.724***
													(1.041)
Mean of the dependent variable	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670	2.670
# observations	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601	5,601
# observations with PF investment	496	496	496	496	496	496	496	496	496	496	496	496	496
# Firms	425	425	425	425	425	425	425	425	425	425	425	425	425
# Firms with PF investment	91	91	91	91	91	91	91	91	91	91	91	91	91
χ^2	293.7	300.0	292.2	305.6	291.5	286.7	283.7	291.2	288.5	293.5	286.5	496.8	440.6

Notes: In all columns the dependent variable is the number of patent applications (weighted by citations) in year t. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. The variables $Other\_Investor_{it}()$ take the value 1 if one of the following investors is among the shareholders of firm i in period t: (1) banking and financing activities, except insurance and pensions; (2) holding company; (3) financial holding company; (4) non-financial holding company; (5) venture companies and capital funds; (6) investment companies; (7) money market associations; (8) investment associations and investment companies; (9) banks, savings banks and cooperative banks; (10) other financial intermediaries except insurance and pension insurance; (11) insurance companies; (12) asset management; (13) foreign investor. Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 12: Pension Fund Investments and Innovation: Adding Long Term Debts

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.071***	1.450*	0.135***	0.873***	0.798**	0.013**	0.043***
	(0.016)	(0.820)	(0.049)	(0.327)	(0.338)	(0.006)	(0.008)
$Debtfin_{it}$	-0.003	-0.213	-0.008	-0.353	-1.299	-0.003*	-0.009***
	(0.004)	(0.177)	(0.009)	(0.989)	(1.258)	(0.002)	(0.002)
Mean of the dependent variable	0.014	0.116	0.015	3.854	0.116	0.002	0.010
# observations	102,405	102,405	102,405	3,076	102,405	102,405	102,405
# observations with PF investment	1,265	1,265	1,265	339	1,265	1,265	1,265
# Firms	18,085	18,085	18,085	273	18,085	18,085	18,085
# Firms with PF investment	369	369	369	64	369	369	369
Adj. R^2	0.176	0.168	0.166			0.017	0.223
χ^2				1,671.9	5,402.5		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. The variable $Debtfin_{it}$ is calculated as the ratio of total long term debt to total assets. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Appendices: Not For Publication

Appendix A Danish Pension Funds: A Dataset on Domestic Firm Investments

This section outlines the methodology employed to construct a specialized dataset capturing the investments of Danish pension funds in both publicly traded and privately held Danish firms. The dataset is based on business relationship data sourced from Experian.

Experian's data covers all limited liability companies registered in Denmark and contains two distinct modules concerning ownership. The first module provides data on individual ownership stakes in Danish firms, while the second focuses on corporate ownership stakes in other Danish enterprises. For the purposes of this study, only the latter module is utilized to isolate pension fund investments in domestic firms. Consequently, individual ownership stakes in these corporations are excluded from the final dataset.

A.1 The Construction of the Ownership Panel Dataset

The raw ownership data is annually delivered from Experian, encompassing information for the most recent fiscal year as well as data from prior years that have been previously delivered. This redundancy in the dataset leads to duplicate observations, an issue that is subsequently addressed. Firms within the dataset are uniquely identified using Experian's proprietary identification numbers. The first step of our methodology involves constructing a panel dataset. Each entry in this panel represents a single year of an active ownership relationship and includes four key variables: the owning entity, the owned entity, the fiscal year, and the proportion of equity held by the owning entity in the owned firm. It is crucial to clarify that the dataset exclusively captures equity stakes and omits details on the allocation of voting rights. In the absence of such information, we assume that the equity stake is a proxy for the corresponding share of voting rights held by the owner.

A single 'OWNER-OWNED' observation in the raw dataset signifies a relationship between two distinct entities: an 'owning' firm and an 'owned' firm. The 'stake' variable quantifies the percentage of equity held by the owning firm, which can either be an integer or a specified range (bracket). In instances where a bracket is provided, the lower bound is generally selected, with two exceptions. For the bracket (0%, 5%], the stake is replaced with 2.5%. Similarly, for the bracket (50%, 67%], the stake is adjusted to 51%. Each observation additionally includes both a start and an end date for the ownership relationship. We undertake the following procedures to assign a year to each observation, thereby facilitating the construction of a panel dataset:

1. Drop observations lacking any of the following variables: ID of the owning firm, ID of the owned firm, stake.

2. Exclude observations with missing start or end dates if another observation is identical in all variables but the missing date.

3. In the absence of a start date, the relationship is assumed to have existed from 2003 until the reported end date. If an end date is not provided, the relationship is assumed to be ongoing.

4. If the reported end date is later than November 15$^{\text{th}}$ of the given calendar year, we record the relationship as existing for that calendar year. If the reported end date is before November 15$^{\text{th}}$, we record the relationship as having concluded in the preceding calendar year. The selection of November 15$^{\text{th}}$ as the cut-off date aligns with the methodology employed by Statistics Denmark.

5. A year is assigned to each observation based on the reported start and end dates of the ownership relationship. To mitigate the risk of introducing survival bias into the dataset, only information from the first delivery containing that specific year is utilized. Given that the data is delivered annually but includes information for all preceding years, multiple deliveries often contain overlapping data. Subsequent deliveries may include revised information for earlier periods; however, such modifications are exclusively made for firms that remain active. Since the inclusion of this modified information is contingent upon the firm's continued existence, it could introduce survival bias into the sample. To address this concern, data from the earliest delivery containing a specific 'OWNER-OWNED-YEAR' combination is exclusively used.[26] This methodology is exemplified by Firm A in Table A.1, with further elaboration provided in the accompanying text below.

6. At this stage, a small number of OWNER-OWNED-YEAR duplicates remain. We proceed as follows to eliminate instruments:

   (a) Retain the observation with the larger equity stake.

   (b) In cases where a pair of duplicates includes one exact stake and one stake represented by a bracket, the observation with the exact stake is preserved.

7. Upon completing the aforementioned data processing steps, Experian identifiers are employed to map each owning and owned firm in the dataset to its corresponding CVR number.

[26] Although this approach results in the exclusion of potentially valuable information, it leads to the removal of only approximately 3% of observations.

The outcome of this procedure is a dataset where each observation uniquely corresponds to an 'OWNER-OWNED-YEAR' combination. Each such observation delineates the relationship between two firms for a specific year.

Timing example

Table A.1: Timing Example

Original Data:

Owner	Owned	Year	Delivery	Stake
B	A	2010	2011	0.5
B	A	2011	2012	0.5
B	A	2012	2013	0.5
B	A	2013	2014	0.5
B	A	2014	2015	0.5
C	A	2012	2015	0.5
C	A	2013	2015	0.5
C	A	2014	2015	0.5
C	A	2015	2016	0.5
C	A	2016	2017	0.5

Final Panel Data:

B	A	2010	2011	0.5
B	A	2011	2012	0.5
B	A	2012	2013	0.5
B	A	2013	2014	0.5
B	A	2014	2015	0.5
C	A	2014	2015	0.5
C	A	2015	2016	0.5
C	A	2016	2017	0.5

Table A.1 serves as an illustrative example to clarify the issue discussed in Step 5. In the data delivery from 2015, Firm C is retroactively identified as an owner of Firm A, with ownership dating back to 2012. However, data deliveries prior to 2015 indicate that Firm B was the sole owner of Firm A up until 2014. The 2015 delivery, therefore, contains retroactive updates to the ownership structure of Firm A. Incorporating this updated information would introduce survival bias, as such updates are only made for firms that remain active. Specifically, the information that Firm C owned Firm A in 2012 and 2013 is available solely because Firm A was still operational at the time of the 2015 data delivery. Had Firm A been inactive in 2015, this updated information would not have been included. To mitigate the risk of introducing survival bias, we rely solely on the 2013 data delivery for information pertaining to the year 2012 and the 2014 delivery for the year 2013. The 2015 data delivery is utilized exclusively for information related to the year 2014, as evidenced in the lower panel of Table A.1.

Finally, information for years preceding the immediate delivery year is inserted if no earlier data deliveries included details on the owned firm. For instance, if the 2015 data delivery were the inaugural source to provide information on the ownership of Firm A, then data from this 2015 delivery would be utilized for the year 2014 and all preceding years.

A.2 The Identification of Ultimate Owners

The panel dataset constructed using the procedure described in the previous section exclusively captures direct ownership relationships. As illustrated in Table A.1, Firms B and C are direct owners of Firm A; however, it remains unspecified whether additional entities hold stakes in Firm A *via* ownership of Firms B and C. Given that it is commonplace for an 'owning' firm to itself be partially owned by another entity, the focus of the analyses reported in this study is on identifying the *ultimate owner*—that is, the entity at the endpoint of the ownership chain. Consequently, it becomes necessary to iterate through multiple layers of ownership for each firm until all ultimate owners are identified.

To illustrate the complexity of this issue: assume Pension Fund A fully owns its subsidiary B (100%), and in turn, B owns Firm C entirely (100%). To accurately identify that Firm C is a recipient of pension fund investment, it is essential to establish a direct link between Pension Fund A (the entity at the 'top' of the ownership chain) and Firm C (the entity at the 'bottom' of the ownership chain). Given the extensive size of the dataset, iterating through every layer of ownership across all firms constitutes a complex task. To facilitate this process, a set of rules for iteration must be established, which are delineated below.

Majority Ownership

The first issue to tackle is the accurate quantification of the ultimate owner's stake when multiple layers of ownership are involved. Table A.2 elucidates this complexity and demonstrates how it is resolved in our dataset. A naive approach of simply multiplying the ownership stakes—for example, $0.7 \times 0.7 = 49\%$- would suggest that Firm E in Table A.2 owns 49% of Firm A. However, this fails to capture the nuance that Firm E is the controlling shareholder of Firm C, which in turn holds a controlling stake in Firm A. To rectify this, we adopt a rule where any ownership stake exceeding 50% (not pertaining to the end of ownership chain) is set to 1 in subsequent calculations. This methodology is illustrated in

Table A.2. Consequently, in the final dataset, Firm E is shown to own 70% of Firm A, as it holds a majority stake in Firm C, which itself owns 70% of Firm A.

A clear limitation of this stake manipulation approach is the potential for total ownership in a firm to exceed 100%. To mitigate this issue, we retain the ownership stake that is closest to the bottom of the ownership chain, provided that majority ownership is maintained throughout the chain.[27]

Table A.2: Majority Ownership Example

Original Data:

Owner	Owned	Year	Stake
C	A	2010	0.7
E	C	2010	0.7
F	C	2010	0.3

Final Data:

Owner	Owned	Year	Stake	Chain
E	A	2010	0.7	C
F	A	2010	0.3	C

Intermediate Owners

When iterating through the various levels of ownership, it is crucial to consider the role of intermediary firms. As illustrated in Table A.3, Firms B and C are predominantly owned by other entities, suggesting that they function merely as intermediaries. Consequently, the true entities warranting analysis are their owners—Firms D, E, and A. To formalize this, we establish a threshold for the total equity share of a firm that is owned by other firms within the dataset. If ownership of a firm exceeds this threshold, then this firm is not identified as an owner in the dataset. We set this threshold at 80%. In the case presented in Table A.3, both Firms B and C are owned beyond this 80% threshold by other entities, and thus are not considered as ultimate owners of Firm A in the final dataset.

Table A.3 introduces an additional rule for calculating ownership stakes. Specifically, we adjust the stake that Owner X has in another firm to account for the proportion of Owner X's equity held by other entities. To illustrate using Table A.3, the stake that Company G holds in Company A is adjusted downward by the share of Company G's equity owned by Firm H. Consequently, the effective stake of Company G in Company A becomes

[27] It's worth noting that this issue has limited impact on the dataset. Total ownership exceeding 100% occurs in only 3.09% of observations in the final dataset. Nonetheless, this decision rule represents a trade-off between data accuracy and the ability to consistently track majority ownership stakes.

$0.2 \times (1 - 0.3) = 0.14$. This can be conceptualized as the portion of Company A that Company G effectively "controls." This stake adjustment is performed after all layers of ownership have been fully iterated.

Table A.3: Intermediate Owners Example

Original Data:

Owner	Owned	Year	Stake
B	A	2010	0.1
C	A	2010	0.7
G	A	2010	0.2
D	B	2010	0.9
E	C	2010	0.7
F	C	2010	0.3
H	G	2010	0.3

Final Data:

Owner	Owned	Year	Stake	Chain
D	A	2010	0.1	B
E	A	2010	0.7	C
F	A	2010	0.3	C
G	A	2010	0.14	
H	A	2010	0.06	G

Circular Ownership

Another challenge arises when reciprocal ownership exists, as in cases where Firm A owns a stake in Firm B, and Firm B reciprocally owns a stake in Firm A. Without intervention, this would create a circular loop during the iteration process. To circumvent this issue, we exclude an ownership relationship if its inverse is observed at a lower hierarchical level. In this context, a level of 1 signifies that the owner holds a direct stake in the target firm. A level of 2 indicates that the owner possesses equity in the target firm through investment in an intermediary entity, and so on.

Table A.4 below provides an illustrative example of the issue at hand, focusing on identifying the ultimate owners of Firm A. In this scenario, Firm B holds a 100% stake in Firm A. Company D owns Firm B through an intermediary, Firm C; however, Firm B also owns Company D. To resolve this, we terminate the iteration for that particular branch at Company D. This means that any owners of Company D, via Firm B, will not be included as owners of Firm A in the final dataset. Nevertheless, the iteration continues along the branch extending from Company D to Company E, as no circular ownership issue exists with Company E. Ultimately, the final dataset includes only the stake that Company F holds in Firm A. Company D is excluded from the final dataset as an owner, as it is owned by more than 80% by other firms in the dataset, thereby falling under the exclusion criteria established by the previous rule.

Table A.4: Circularity Example

Original Data:

Owner	Owned	Year	Stake
B	A	2010	1
C	B	2010	1
D	C	2010	1
E	D	2010	0.5
B	D	2010	0.5
F	E	2010	1

Final Data:

Owner	Owned	Year	Stake	Chain
F	A	2010	0.5	E; D; C; B

Duplicates

In the example presented in Table A.5, the focus is on identifying the owners of Firm A. Companies B, C, and D each hold a 33% stake in Firm A, while Company E directly owns 100% of Firm A. This discrepancy is likely attributable to inconsistencies in the raw data originating from different reporting years.

To manage such scenarios, we implement a rule: when the algorithm produces multiple OWNER-OWNED-YEAR-STAKE combinations, we retain the observation with the fewest intermediary owners—in essence, the "more direct" ownership relationship or those at a lower hierarchical level. It's crucial to emphasize that this rule only comes into play if the exact same ownership stake is observed for two different entities following the iteration process. Finally, we eliminate an owner if all its ownership stakes are duplicates originating from a "shorter" ownership chain. In the given example, since Company E is solely owned by Companies B, C, and D, and their stakes in Firm A are identical, we exclude Company E as an owner in the final dataset.

Table A.5: Duplicate Owners Example

First round of iteration:

Owner	Owned	Year	Stake	Level
B	A	2010	33	1
C	A	2010	33	1
D	A	2010	33	1
E	A	2010	100	1

Second round of iteration:

Owner	Owned	Year	Stake	Level
B	E	2010	33	2
C	E	2010	33	2
D	E	2010	33	2

Final Data:

Owner	Owned	Year	Stake	Level	Chain
B	A	2010	33	1	
C	A	2010	33	1	
D	A	2010	33	1	

Pseudo-Algorithm

We now provide a concise outline of the algorithm employed to navigate through the various levels of ownership. Let $i \in I$ be the universe of firms in the dataset. Let $J \subset I$ be the set of firms that are owned by at least one other firm and simultaneously own at least one other firm. Let $K \subset I$ be the set of firms that are owned by at least one other firm, but do not hold stakes in any other firms.

1. Drop observations with missing stakes, missing firm identifier or foreign owners.

2. Drop observations where the owner or owned firm is not headquartered in Denmark

3. For each remaining firm $i \in J$:

   3.1 Start with firm i as the owned firm.

   3.2 Look for the owners of firm i (first ownership layer). Let this set be called Z_1.

   3.3 Look for the owners of each firm $i \in Z_1$ (second ownership layer). Let this set be called Z_2.

   3.4 Stop the iteration on a branch if circularity arises.

3.5 Multiply the stakes according to the established rules. Record the distance between firm i and the owner. Direct owners of firm i have distance 1.

3.6 Repeat steps 3.1 - 3.5 until $Z_2 = \emptyset$.

At this stage the ownership structure of all firms $i \in J$ is complete.

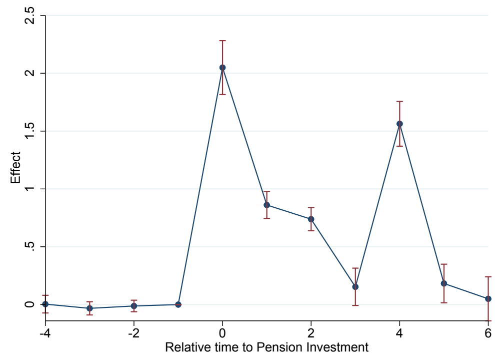
4. Merge the ownership structure of each firm $i \in J$ onto the set of firms $k \in K$ that it owns so that the elements retained in J together make up the ownership of all elements of K (all firms that own no stake in another firm).

5. Apply the established calculation rules.

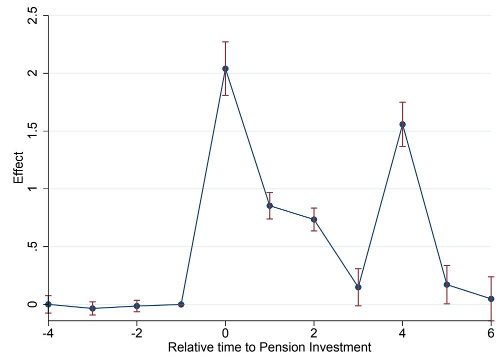
6. Adjust the stakes for the percentage of the owner firm held by other firms.

Appendix B Additional Figures

Figure B.1: Pension Fund Investments and Innovation Outcomes, Alternative Intensive Margin



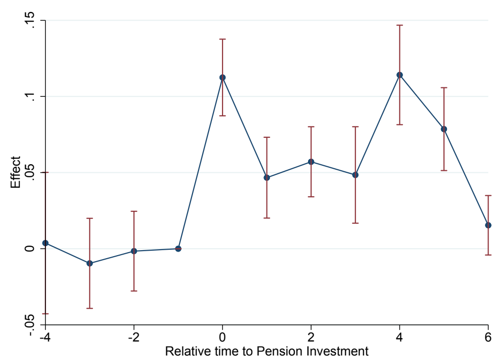
(a) Intensive Margin of Innovation (Whole Sample)



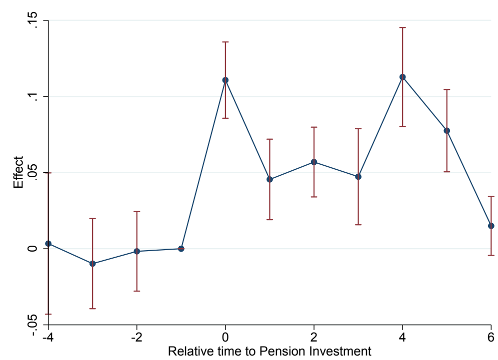
(b) Intensive Margin of Innovation (Matched Sample)

Note: The figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). The dependent variable is the number of patent applications weighted by citations (intensive margin) in year t. The sample considers 476 distinct events of treatment. Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Figure B.2: Pension Fund Investments and Innovation Outcomes, Excl. Short-Term Investments



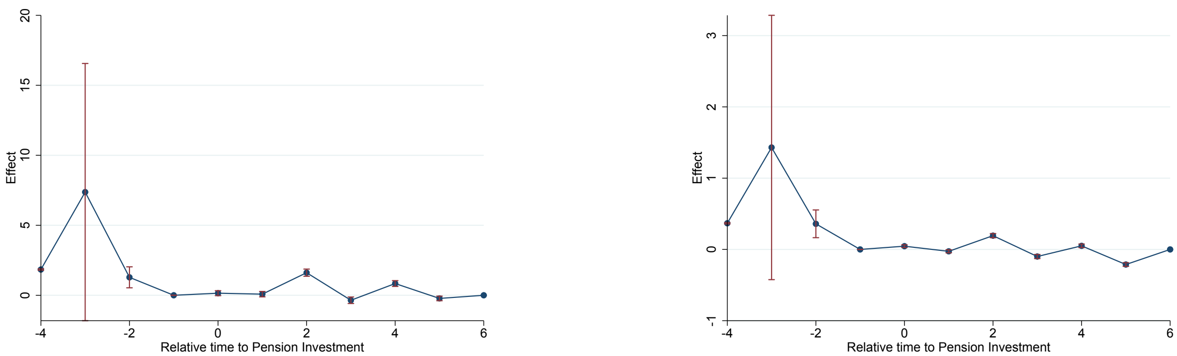
(a) Intensive Margin of Innovation (Whole Sample)



(b) Intensive Margin of Innovation (Matched Sample)

Note: The figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). The dependent variable is the IHS transformation of the number of patent applications weighted by citations (intensive margin) in year t. The sample excludes cases of pension funds investing in a firm only for one year and considers 375 distinct events of treatment. Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Figure B.3: Pension Fund Investments and Innovation Outcomes, Simulated "Fake" Event

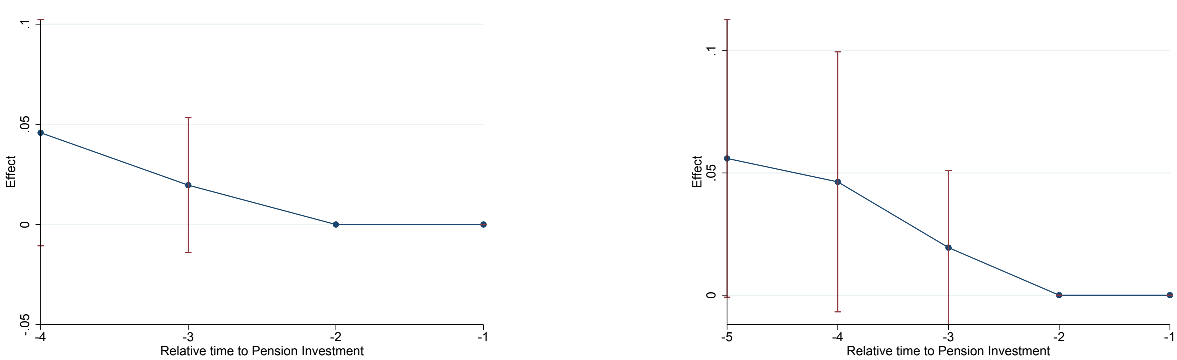


(a) Intensive Margin of Innovation (IHS)

(b) Intensive Margin of Innovation (Level)

Note: The figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). In the first panel, the dependent variable is the IHS transformation of number of patent applications weighted by citations (intensive margin) in year t. In the second panel, the dependent variable is the IHS transformation of number of patent applications weighted by citations (intensive margin) in year t. The sample considers 17,472 distinct "fake" events of treatment. Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Figure B.4: Pension Fund Investments and Innovation Outcomes, Additional Placebo Tests



(a) Intensive Margin of Innovation (IHS)

(b) Intensive Margin of Innovation (IHS)

Note: The figure shows event time coefficients and 95% confidence intervals estimated using the algorithm developed in Sun and Abraham (2021). In both panels, the dependent variable is the IHS transformation of number of patent applications weighted by citations (intensive margin) in year t. The sample considers 476 distinct events of treatment and excludes from the estimations the period following the event (including the event year). Control variables include the firms' productivity, capital intensity, share of female workers and share of tertiary educated workers.

Appendix C Additional Tables

Table C.1: List of Occupations – (Bernard et al., 2017)

DISCO Codes	Description in Danish	Description in English
2000	Arbejde, der forudsætter færdigheder på højeste niveau inden for pågældende område	Jobs that require skills at the highest level in that area
2100	Forskning og/eller anvendelse af færdigheder inden for de ikke- biologiske grene af naturvidenskab samt datalogi, statistik,	Research and / or use of skills within the non-biological branches of science and computer science, statistics,
2110	Arbejde med emner inden for fysik, kemi, astronomi, meteorologi, geologi og geofysik	Working with topics in physics, chemistry, astronomy, meteorology, geology and geophysics
2111	Arbejde med emner inden for fysik og astronomi	Working with topics in physics and astronomy
2112	Arbejde med emner inden for meteorologi	Working with topics in meteorology
2113	Arbejde med emner inden for kemi	Working with themes in chemistry
2114	Arbejde med emner inden for geologi og geofysik	Working with topics in geology and geophysics
2120	Arbejde med matematiske og statistiske begreber, teorier og metoder	Working with mathematical and statistical concepts, theories and methods
2121	Arbejde med matematiske begreber, teorier og metoder	Work with mathematical concepts, theories and methods
2122	Arbejde med statistiske begreber, teorier og metoder	Working with statistical concepts, theories and methods
2130	Edb-planlægning og systemudvikling	Computer programming and systems development
2131	Design, analyse og overordnet planlægning af edb-systemer	Design, analysis and overall planning of computer systems
2132	Systemudvikling samt konstruktion/programmering af edb- systemer	System Development and construction / programming computer systems
2139	Andet edb-arbejde på højeste faglige niveau	Other computer work at the highest professional level
2140	Arkitekt- og ingeniørarbejde med videre	Architectural and engineering work on further
2141	Arkitektarbejde og planlægning af anlægsarbejder	Architectural work and planning of construction works
2142	Ingeniørarbejde vedrørende bygninger og anlæg	Engineering for buildings and facilities
2143	Ingeniørarbejde vedrørende stærkstrøm	Engineering regarding electrical power
2144	Ingeniørarbejde vedrørende svagstrøm	Engineering for low power
2145	Ingeniørarbejde vedrørende ikke-elektriske motorer og maskinanlæg	Engineering for non-electric engines and engine installations
2146	Ingeniørarbejde vedrørende kemiske processer ved industriel produktion	Engineering for chemical processes in industrial production
2147	Mineingeniørarbejde	Mine Engineering
2148	Landinspektørarbejde	Surveyor Jobs
2149	Andet arkitekt- og ingeniørarbejde med videre	Other architectural and engineering work on further
2200	Forskning og/eller anvendelse af færdigheder inden for medicin, farmaci og de biologiske grene af naturvidenskab samt	Research and / or use of skills in medicine, pharmacy and the biological activities of science and midwifery
2210	Arbejde med emner inden for de biologiske grene af naturvidenskab	Working with topics in the biological activities of science
2211	Arbejde med emner inden for biologi, genetik, zoologi, botanik og økologi samt levnedsmiddelområdet	Working with topics in biology, genetics, zoology, botany and ecology and food sector
2212	Arbejde med emner inden for anatomi, biokemi, fysiologi, patologi og farmakologi	Working with topics in anatomy, biochemistry, physiology, pathology and pharmacology
2213	Arbejde med emner inden for agronomi vedrørende plante- og husdyravl	Working with themes in agronomy for plant and animal production
2220	Arbejde med emner inden for medicin, odontologi, veterinærvidenskab og farmaci	Working with issues in medicine, dentistry, veterinary science and pharmacy
2221	Lægearbejde	Medical Work
2222	Tandlægearbejde	Dental Work
2223	Veterinærarbejde	Veterinary Work

Continued on next page

Table C.1 – continued from previous page

DISCO Codes	Description in Danish	Description in English
2224	Farmaceutarbejde	Pharmaceutical Jobs
2229	Arbejde med emner inden for medicin, odontologi, veterinærvidenskab og farmaci i øvrigt	Working with topics in medicine, dentistry, veterinary medicine and pharmacy in addition
3100	Teknikerarbejde inden for ikke-biologiske emner	Technician Working in non-biological issues
3110	Teknikerarbejde inden for fysik, kemi, mekanik med videre	Technicians work in physics, chemistry, mechanics and so on
3111	Teknikerarbejde inden for fysik, kemi, astronomi, meteorologi, geologi med videre	Technicians work in physics, chemistry, astronomy, meteorology, geology and so on
3112	Teknikerarbejde vedrørende bygninger og anlæg	Technician Work on buildings and installations
3113	Teknikerarbejde vedrørende elektriske anlæg med videre	Technician Work on electrical installations with further
3114	Teknikerarbejde vedrørende elektroniske anlæg med videre	Technicians work on electronic systems with more
3115	Teknikerarbejde vedrørende maskiner og røranlæg, eksklusive vedligeholdelse af maskiner om bord på skibe	Technician Working on machinery and pipe, excluding maintenance of machinery on board ships
3116	Teknikerarbejde vedrørende kemiske processer ved industriel produktion	Technicians work on chemical processes in industrial production
3117	Teknikerarbejde vedrørende industrielle udvindingsanlæg	Technician Working on industrial extraction plant
3118	Teknisk tegnearbejde	Technical signs work
3119	Teknikerarbejde i øvrigt inden for fysik, kemi, mekanik med videre	Technician Working in the area of the physics, chemistry, mechanics and so on
3120	Edb-teknisk arbejde	Computer technical work
3121	Programmørarbejde	Programmer Jobs
3122	Edb-operatørarbejde samt planlægning af edb-drift	Computer Operator work and planning of computer operation
3123	Arbejde med industrielle robotprogrammer	Working with industrial robot applications
3130	Arbejde med lyd, lys og billeder ved film- og teaterforestillinger med videre samt betjening af medicinsk udstyr	Working with sound, light and images through film and theater, with more and operation of medical
3131	Arbejde med lyd, lys og billeder ved fotografering, optagelse, film- og teaterforestillinger med videre	Working with sound, light and images through photography, recording, film and theater, with further
3132	Betjening af maskiner ved udsendelse af radio- og fjernsynsudsendelser samt ekspedition af samtaler ved anvendelse	Operating the machines for broadcasting radio and television broadcasts as well as dispatching calls using
3133	Betjening af medicinsk udstyr såsom scannings- og narkoseapparatur samt maskiner til optagelse af røntgenbilleder og	Control of medical devices such as scanning and anesthesia equipment and machines for recording of X-
3139	Arbejde med lyd, lys og billeder i øvrigt	Working with sound, light and images in addition
3200	Teknikerarbejde inden for biologiske emner	Technician Working in biological subjects
3210	Teknikerarbejde inden for biologi, medicin, landbrug med videre	Technician Working in biology, medicine, agriculture etc.
3211	Teknikerarbejde inden for biologi, medicin med videre	Technician Working in biology, medicine and so on
3212	Teknikerarbejde inden for landbrug og skovbrug	Technician Working in agriculture and forestry
3213	Rådgivningsarbejde inden for landbrug og skovbrug	Consultancy work in agriculture and forestry

Table C.2: Additional Descriptive Statistics

Nace Rev.2 sector	N	#Firms	#Firms with PFI	#Firms with at least one patent	#Firms with patent and PFI	#Patent App.	#Green Patents App.	High Competition
Manufacture of basic metals	1,968	347	-	-	-	159	103	no
Manufacture of basic pharmaceutical products and pharmaceutical preparations	976	196	14	30	-	1,713	16	no
Manufacture of beverages	1,216	246	-	-	-	-	-	no
Manufacture of chemicals and chemical products	3,011	433	19	25	-	1,026	115	no
Manufacture of coke and refined petroleum products	62	11	57	119	-	-	-	no
Manufacture of computer, electronic and optical products	6,640	1,081	25	52	-	5,111	38	no
Manufacture of electrical equipment	5,224	785	53	76	-	433	110	no
Manufacture of fabricated metal products, except machinery and equipment	36,167	5,426	30	24	-	108	27	yes
Manufacture of food products	16,243	3,356	26	13	-	164	-	no
Manufacture of furniture	5,602	999	-	254	-	26	-	no
Manufacture of leather and related products	672	156	113	18	-	-	-	no
Manufacture of machinery and equipment n.e.c.	20,885	2,978	-	21	-	4,129	1,813	no
Manufacture of motor vehicles, trailers and semi-trailers	1,967	276	23	14	-	32	-	no
Manufacture of other non-metallic mineral products	6,465	1,022	-	13	-	150	63	no
Manufacture of other transport equipment	1,398	264	13	52	-	75	-	no
Manufacture of paper and paper products	1,936	289	33	18	-	155	-	no
Manufacture of rubber and plastic products	7,400	943	14	-	-	893	55	no
Manufacture of textiles	4,097	684	-	-	-	123	-	no
Manufacture of tobacco products	98	12	20	-	-	32	-	no
Manufacture of wearing apparel	3,695	916	14	68	-	-	-	no
Manufacture of wood and of products of wood and cork, except furniture; manufacture	6,672	1,153	12	-	-	20	-	no
Other manufacturing	12,193	2,328	15	23	-	594	-	no
Printing and reproduction of recorded media	10,285	1,890	-	-	-	-	-	yes
Repair and installation of machinery and equipment	24,429	5,011	-	-	-	54	-	yes
Total	179,301	30,802	509	849	105	15,002	2,361	44,332

Notes: All descriptive statistics are calculated over the 2003-2019 period. Cells with fewer than 10 observations are omitted to comply with DST data disclosure policy.

Table C.3: Descriptive Statistics Matching Variables

		Firms with PFI	Firms without PFI	Firms without PFI (matched sample)
Value added	(DKK,log)	18.441	15.662	15.908
		(1.660)	(1.808)	(1.929)
Capital	fixed assets (DKK, log)	17.092	14.053	14.333
		(2.167)	(2.092)	(2.197)
Labour	number of full-time employees (log)	4.164	1.937	2.167
		(1.447)	(1.471)	(1.545)
Listed	1, if listed firm	0.171	0.003	0.025
		(0.376)	(0.054)	(0.068)
Assets	total assets (DKK, log)	18.186	15.266	15.489
		(1.825)	(1.839)	(1.979)
Liabilities	total liabilities (DKK, log)	17.621	14.646	14.951
		(1.815)	(1.949)	(2.041)
Net income	net income (DKK, log)	15.403	12.884	12.979
		(2.094)	(1.758)	(1.891)
Sales growth	annual sales growth	0.036	0.038	0.047
		(0.369)	(0.447)	(0.464)
Assets ratio	ratio of fixed to total assets	0.403	0.396	0.395
		(0.204)	(0.233)	(0.211)
Age	firm age (years)	25.086	17.182	16.478
		(19.107)	(13.361)	(13.453)
Tertiary	share of workers with tertiary education	0.042	0.031	0.033
		(0.052)	(0.095)	(0.095)
Observations		4,838	134,108	80,391

Notes: This table reports the main descriptive statistics for the lag of the variables included in the specification of the propensity score.

Table C.4: Pension Fund Investments and Innovation: Excluding Listed Firms

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.076***	0.426**	0.052***	0.505	1.042***	0.013**	0.067***
	(0.012)	(0.190)	(0.014)	(0.329)	(0.365)	(0.005)	(0.010)
Mean of the dependent variable	0.011	0.041	0.009	1.440	0.041	0.002	0.010
# observations	177,231	177,231	177,231	4,957	177,231	177,231	177,231
# observations with PF investment	1,392	1,392	1,392	281	1,392	1,392	1,392
# Firms	30,595	30,595	30,595	380	30,595	30,595	30,595
# Firms PF	401	401	401	59	401	401	401
Adj. R^2	0.011	0.001	0.004			0.002	0.020
χ^2				345.2	2,093.8		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.5: Pension Fund Investments and Innovation: Excluding Imputed Values

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.069***	1.251*	0.117***	0.936**	0.757**	0.013**	0.045***
	(0.015)	(0.703)	(0.041)	(0.372)	(0.338)	(0.006)	(0.008)
Mean of the dependent variable	0.016	0.121	0.018	3.047	0.121	0.003	0.012
# observations	118,688	118,688	118,688	4,699	118,688	118,688	118,688
# observations with PF investment	1,592	1,592	1,592	462	1,592	1,592	1,592
# Firms	19,289	19,289	19,289	357	19,289	19,289	19,289
# Firms with PF investment	422	422	422	85	422	422	422
Adj. R^2	0.162	0.109	0.141			0.017	0.234
χ^2				303.3	4,403.6		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.6: Pension Fund Investments and Innovation: Excluding Small Firms

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.057***	1.088*	0.096**	0.913**	0.778**	0.010**	0.040***
	(0.014)	(0.649)	(0.038)	(0.371)	(0.340)	(0.005)	(0.008)
Mean of the dependent variable	0.029	0.219	0.032	2.997	0.219	0.005	0.023
# observations	66,888	66,888	66,888	4,884	66,888	66,888	66,888
# observations with PF investment	1,782	1,782	1,782	475	1,782	1,782	1,782
# Firms	9,509	9,509	9,509	362	9,509	9,509	9,509
# Firms with PF investment	443	443	443	88	443	443	443
Adj. R^2	0.152	0.108	0.136			0.016	0.238
χ^2				305.0	3,702.3		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.7: Pension Fund Investments and Innovation: Including All Industries

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.059***	0.546**	0.072***	0.316	0.750**	0.011***	0.053***
	(0.007)	(0.243)	(0.016)	(0.463)	(0.311)	(0.003)	(0.005)
Mean of the dependent variable	0.003	0.018	0.003	2.786	0.018	0.000	0.003
# observations	1,512,767	1,512,767	1,512,767	9,544	1,512,767	1,512,767	1,512,767
# observations with PF investment	5,533	5,533	5,533	935	5,533	5,533	5,533
# Firms	302,261	302,261	302,261	747	302,261	302,261	302,261
# Firms with PF investment	1,489	1,489	1,489	172	1,489	1,489	1,489
Adj. R^2	0.107	0.071	0.105			0.013	0.131
χ^2				324.4	7,302.1		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.8: Pension Fund Investments and Innovation: Alternate Definition of Extensive Margin and Lagged Specification

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.035***							
	(0.010)							
PFI_{it-1}		0.066***	0.805*	0.106***	0.588**	0.629**	0.012**	0.050***
		(0.014)	(0.431)	(0.039)	(0.235)	(0.307)	(0.005)	(0.008)
Mean of the dependent variable	0.006	0.014	0.088	0.014	2.739	0.088	0.002	0.012
# observations	179,301	148,499	148,499	148,499	4,742	148,499	148,499	148,499
# observations with PF investment	1,967	1,713	1,713	1,713	418	1,713	1,713	1,713
# Firms	30,802	23,863	23,863	23,863	366	23,863	23,863	23,863
# Firms with PF investment	509	445	445	445	77	445	445	445
Adj. R^2	0.101	0.135	0.071	0.126			0.014	0.169
χ^2					331.7	4,831.0		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t that receives at least one forward citation. In column 2, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 3, 5 and 6 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 4 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 7, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 8, the dependent variable is the share of R&D workers. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,4,6, 7 and 8, we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.9: Pension Fund Investments and Innovation: Direct Investments

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.147*	9.326	0.524*	1.415***	1.263***	0.047	0.053
	(0.081)	(5.819)	(0.282)	(0.463)	(0.363)	(0.030)	(0.036)
Mean of the dependent variable	0.046	0.416	0.057	3.585	0.416	0.007	0.031
# observations	33,825	33,825	33,825	3,923	33,825	33,825	33,825
# observations with PF investment	131	131	131	96	131	131	131
# Firms	3,804	3,804	3,804	295	3,804	3,804	3,804
# Firms with PF Investment	25	25	25	16	25	25	25
Adj. R^2	0.168	0.114	0.148			0.019	0.281
χ^2				277.8	3,805.0		

Notes: In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t (only direct investments considered). In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.10: Pension Fund Investments and Innovation: Main results (Matched Sample with 50th Percentile as Threshold)

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.062***	0.897	0.082**	0.998***	0.700*	0.011**	0.049***
	(0.013)	(0.598)	(0.034)	(0.350)	(0.390)	(0.005)	(0.008)
Mean of the dependent variable	0.019	0.153	0.021	3.720	0.153	0.003	0.015
# observations	80,893	80,893	80,893	3,323	80,893	80,893	80,893
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	21,028	21,028	21,028	267	21,028	21,028	21,028
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.162	0.117	0.154			0.018	0.191
χ^2				700.6	3,714.3		

Notes: The sample only includes "matched" firms in the control group. Any firm with a propensity score below the 50th percentile of its respective sector-year is dropped. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.11: Pension Fund Investments and Innovation: Main results (Matched Sample with 75th Percentile as Threshold)

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.059***	0.900	0.082**	0.886***	0.880*	0.012***	0.045***
	(0.012)	(0.617)	(0.032)	(0.329)	(0.491)	(0.005)	(0.008)
Mean of the dependent variable	0.020	0.168	0.023	4.077	0.168	0.003	0.016
# observations	57,402	57,402	57,402	2,352	57,402	57,402	57,402
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	18,521	18,521	18,521	202	18,521	18,521	18,521
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.175	0.124	0.167			0.016	0.199
χ^2				2,464.5	3,908.1		

Notes: The sample only includes “matched” firms in the control group. any firm with a propensity score below the 75th percentile of its respective sector-year is dropped. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.12: Pension Fund Investments and Innovation: Competition Results (Def.1), 50th percentile threshold

Dep. var:	Patent(0/1)	#patents	IHS(#patents)	E[#patents]	E[#patents]	Green Patent(0/1)	Share of R&D Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	fixed-effect Poisson QML	Poisson QML	OLS	OLS
PFI_{it}	0.092***	1.550*	0.140***	0.974***	0.898***	0.014**	0.072***
	(0.017)	(0.824)	(0.049)	(0.370)	(0.345)	(0.006)	(0.010)
$PFI_{it} \times High\ Competition$	-0.083***	-1.759**	-0.147***	-1.665***	-2.470***	-0.008	-0.074***
	(0.020)	(0.827)	(0.052)	(0.621)	(0.505)	(0.008)	(0.012)
P-value, $H_0 : PFI_{it} + PFI_{it} \times High\ Competition = 0$	0.401	0.047	0.619	0.192	0.001	0.211	0.793
Mean of the dependent variable	0.013	0.084	0.013	2.670	0.084	0.002	0.011
# observations	179,301	179,301	179,301	5,601	179,301	179,301	179,301
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	30,802	30,802	30,802	425	30,802	30,802	30,802
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.131	0.108	0.129			0.013	0.155
χ^2				293.5	5,714.9		

Notes: The variable *High Competition* is a dummy variable equal to 1, if the firm operates in a sector in which the inverse of the Herfindal index based on firms' sales is above the 50th percentile of the sector distribution. In column 1, the dependent variable is a dummy variable equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table C.13: Pension Fund Investments and Innovation: Competition Results (Def.1), Matched Sample

Dep. var:	Patent(0/1) (1) OLS	#patents (2) OLS	IHS(#patents) (3) OLS	E[#patents] (4) fixed-effect Poisson QML	E[#patents] (5) Poisson QML	Green Patent(0/1) (6) OLS	Share of R&D Workers (7) OLS
PFI_{it}	0.084***	1.423*	0.128***	0.968***	0.854**	0.012**	0.066***
	(0.016)	(0.781)	(0.046)	(0.351)	(0.364)	(0.006)	(0.010)
$PFI_{it} \times High\ Competition$	-0.076***	-1.630**	-0.135***	-1.879***	-2.409***	-0.005	-0.066***
	(0.020)	(0.783)	(0.049)	(0.584)	(0.561)	(0.008)	(0.012)
P-value, $H_0 : PFI_{it} + PFI_{it} \times High\ Competition = 0$	0.272	0.091	0.976	0.833	0.085	0.286	0.461
Mean of the dependent variable	0.016	0.116	0.017	3.032	0.116	0.003	0.014
# observations	117,209	117,209	117,209	4,451	117,209	117,209	117,209
# observations with PF investment	1,967	1,967	1,967	496	1,967	1,967	1,967
# Firms	24,718	24,718	24,718	346	24,718	24,718	24,718
# Firms with PF investment	509	509	509	91	509	509	509
Adj. R^2	0.144	0.112	0.136			0.015	0.166
χ^2				420.8	4,915.4		

Notes: The variable $High\ Competition$ is a dummy variable equal to 1, if the firm operates in a sector in which the inverse of the Lerner index based on gross margins is above the 75th percentile of the sector distribution. In column 1, the dependent variable is a dummy equal to 1, if the firm has at least one patent application in year t. In columns 2, 4 and 5 the dependent variable is the number of patent applications (weighted by citations) in year t. In column 3 the dependent variable is the inverse hyperbolic sine (IHS) function of the number of patent applications (weighted by citations) in year t. In column 6, the dependent variable is a dummy variable equal to 1, if the firm has at least one green patent application in year t. In column 7, the dependent variable is the share of R&D workers. The dummy variable PFI_{it} takes the value one if at least one domestic pension fund is among the shareholders of firm i in period t. In all columns, we include the following control variables: firms' productivity, capital intensity, share of female workers and share of tertiary educated workers, as well as year fixed effects. In addition, in columns 1,2,3,5,6 and 7 we also include the firms' number of patent applications (weighted by citations) in the pre-sample period (1978-2002) normalized by the total number of patent applications (weighted by citations) in the pre-sample period and a dummy variable for firms that do not have a patent application (weighted by citations) in the pre-sample period, following the approach developed by Blundell et al. (1999). Standard errors clustered at the firm level are in parentheses. Significance levels: ***1%, **5%, *10%.