Does Long-Term Patient Capital Matter? The Impact of Pension Fund Investments on Firm Productivity *

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May, 2024

Abstract

The digital and green transitions require long-horizon investments on an unprecedented scale. Pension funds, with their long-term liabilities, are natural providers of such investments. In this paper, we construct a comprehensive dataset that integrates firm ownership information with Danish registers, enabling us to empirically document a significant relationship between pension fund investment and firm productivity. Following such an investment, we observe a substantial increase in firm productivity, averaging between 3% and 5%. This finding is robust and persists across various methodological approaches, including accounting for selection issues and a broad array of refinements, such as controlling for the types of co-investors. Our results suggest that public policies aimed at stimulating pension funding and encouraging pension fund equity holdings could enhance the productivity of the economy.

Key words: pension funds, long-termism, firm productivity, equity.
JEL codes: D24, G32, D22.

*We gratefully acknowledge comments from participants at conferences and seminars held at the University of Amsterdam, Bruegel, Copenhagen Business School, ICPM, as well as faculty members at the NBER and the Boston College Center for Retirement Research. In particular, we would like to express our gratitude to Aleksandar Andonov, Roger Bandick, Sebastien Betermier, Victoria Ivashina, Jordi Jaumandreu, Natalia Khorunzhina, Josh Lerner, Alexander Ljungqvist, James Poterba, Joshua Rauh, Mikkel Svenstrup, Stephen Terry, and Frederic Warzynski for their helpful suggestions and discussions. Andreas Ingdal Roenne provided valuable research assistance. David Pinkus acknowledges support from the Pension Scholarship Trust, which partly funded this research. The views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of any entities they represent.

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1 Introduction

The digital and green transitions require long-horizon investments on an unprecedented scale. The ambitious goal of achieving net zero greenhouse emissions alone necessitates substantial annual investments totaling USD 9.5 trillion through 2050.[1] Pension funds, with their long-term liabilities, may be natural providers of such investments. In fact global assets in retirement savings plans amounted to over 60 trillion USD for the first time at the end of 2021 (OECD, 2023). A large part of these savings is accumulated in pension funds, already making them key investors in global financial markets. Given their rising importance, it is not surprising that funded pensions have attracted the attention of policymakers and researchers alike. For example, the G20 has identified pension funds as a key source of long-term capital to finance growth and development (OECD, 2019).[2]

Hence, the question arises: Can pension funds deliver on this promise? The understanding of the economic implications of pension funds is still rather limited. This study aims to reduce this gap by providing empirical evidence on the effects of pension funds' equity investments on firms' productivity with high-quality data, which offers three main advantages. First, the data are based on a large and comprehensive sample of firms drawn from Danish administrative registers. Second, they include detailed information on the complete ownership structure of the firms included involved in the analysis, which allows us to cover both listed and unlisted companies. Third, they carefully identify domestic pension funds' investments in Danish firms. Armed with this dataset, we find that firms experience an average productivity increase in the range of 3% to 5% after receiving a pension fund investment.[3] This result withstands rigorous scrutiny and is robust to various methodological refinements, including controls for the firm's exporter status (which is often correlated with increased productivity) and the presence of potential investors, other than domestic pension funds, within the firm. We also provide suggestive evidence that the effect on productivity tends to be larger, the larger the investment in the firm and the longer its duration. Finally, our findings reveal that unlisted and smaller firms derive greater benefits from pension fund investments compared to their listed and larger counterparts. This differential impact suggests two primary mechanisms through which pension funds contribute to enhancing firm productivity: the supply of financing and their long-term commitment to it. Our baseline results pertain to cases in which pension funds invest directly and indirectly in companies. In a refinement, we focus solely on direct (disintermediated) investments and continue to find positive productivity effects, although slightly smaller and less precisely estimated, likely due to the relative rarity of direct investments in our dataset.

We use the Danish matched employer-employee dataset for the period 2003–2019, combined with our comprehensive dataset on the ownership of listed and unlisted Danish firms. Denmark is a fitting setting for this type of analysis for two main reasons. First, the unique features of the Danish data allow us to link pension funds' investments to both listed and unlisted firms' characteristics. To the best of our knowledge, most previous studies analyzing similar research questions focus mainly on listed firms. Second, Danish pension funds play an important role in the domestic economy. At the end of 2021, assets in retirement savings plans in Denmark were the largest as a share of GDP among the OECD countries, standing at over 230% (OECD, 2023). Furthermore, the Danish pension system is frequently described as one of the best in the world (Mercer, 2023) and serves as an example of a well-functioning system largely reliant on funded pension pillars.

[1] "The net-zero transition: What it would cost, what it could bring", McKinsey Report (2022)

[2] See also, for example, Andonov et al. (2021).

[3] In this paper, "pension fund investment" always refers to equity investment by Danish pension funds, unless explicitly noted otherwise.

Our findings, while rooted in the Danish context, possess broader relevance and implications. Since an increasing number of countries are shifting from pay-as-you-go pension schemes towards funded pension arrangements, they inevitably grapple with complex questions concerning the optimal design, implementation, and oversight of these systems. For example, our results underscore the necessity for regulatory caution in setting investment restrictions for pension funds, as these may inadvertently stifle the financing of growth-enhancing projects.

It is important to note that while our data do not include information on pension fund investments in company debt, focusing on equity investments should not be a major limitation because equity is by and large the most important source of financing for Danish non-financial companies.[4] Whereas previous literature has suggested that both equity and debt financing affect productivity, equity is seen as a more relevant driver of productivity increases, because it is more likely to finance risky projects such as R&D intensive investments that are crucial for productivity growth. Aghion et al. (2004) show that innovative firms are more likely to raise funds by issuing new equity compared to firms that do not report R&D, and that this probability of issuing new equity increases with R&D intensity. [5]

A major challenge in investigating the effect of investors on the firms that they invest in is that investors may carefully select the latter. The issue of selection is relevant in our case if pension funds choose to invest in firms that are already relatively more productive to start with because this selection effect would confound with the observed productivity increases implied by the pension fund investment itself. While controlling for selection is empirically difficult without any exogenous variation, we adopt the following strategies aimed at isolating the causal effect of pension funds' investment net of selection. First, we show with an event study that "treated" (through a pension fund's investment) and "control" firms share almost identical pre-trends in productivity. Furthermore, the same event study provides suggestive evidence of a positive correlation between a pension fund's investment and subsequent firm productivity, commencing from the inception of the investment. We argue that this positive trend is consistent with a whole host of benefits that pension funds bring to the table, such as an increase in the supply of financing and a commitment to long-term investment. The possibility that pension funds select firms with growth potential after the investment does not invalidate the interpretation of our results as causal (Ljungqvist et al., 2020). In fact, our hypothesis is that pension funds do not randomly select firms, but rather that they choose (directly and indirectly) firms for which they expect their investment to facilitate the realization of this growth potential by providing stable and patient capital, which might not occur otherwise.

Second, we estimate the impact of a pension fund investment directly in a structural production function framework that allows us to control for past productivity and therefore selection. Similarly to the event study, in the structural estimations, we find that a pension fund investment positively affects firm productivity.

Furthermore, the concern that the estimated effects are merely driven by selection is mitigated by our refinement analyses. For example, we find suggestive evidence that investments of long duration tend to provide even larger benefits in terms of productivity. These results are consistent with the hypothesis that pension funds offer a stable and long-term financing commitment that allows firms to invest in projects that are less liquid but yield a higher long-term return.[6] The hypothesis that pension funds aim to match

[4] National accounts data show that at the end of 2019 equity and loans were the main liabilities of Danish non-financial companies, with equity accounting for 59.5% of total liabilities and loans for 30.1% (Danmarks Nationalbank, 2022). In one of our refinements, we also estimate the impact of pension fund investments controlling for a proxy of debt financing.

[5] See Heil (2018) for an overview of the literature on finance and productivity.

[6] For example, ATP, Denmark's largest pension fund, writes: "ATP Long Term Danish Equity, which must invest with a long-time horizon in Danish growth companies, has in 2022 made its first two investments in the companies called Veo Technologies and Ferrosan Medical Devices" (ATP, 2022).

their long-term liabilities with long-term assets, is also confirmed in our data showing that pension funds typically have a longer investment horizon compared to other institutional investors. Indeed, other studies have shown that pension funds tend to commit their investments for longer periods than other investors (Artiga González et al., 2020; Cremers & Pareek, 2016). Our findings resonate with previous evidence that investors' time horizon matters for corporate outcomes, such as the quality of corporate governance (Garel, 2017).

The significance of pension fund investment for productivity remains even after accounting for high base-year productivity, indicating that our estimated effect is not solely due to pension funds initially selecting highly productive firms. Interestingly, even firms with higher initial productivity tend to benefit from pension fund investment.

Finally, we observe that the productivity gains from pension fund investments are more substantial for larger equity stakes and for small and non-listed firms than for large and listed firms, respectively. This suggests that the estimated effects are not solely due to long-term investment commitments, but also result from alleviating financial constraints, which are more relevant for the former groups of firms. While we acknowledge the potential influence of other channels, in particular productivity increases resulting from pension fund engagement and the signal they may provide to attract other investors, we do not have the data needed to investigate their role.

This paper contributes to several strands of the literature. First, we contribute to the work done on funded pensions and economic growth by investigating the hypothesis that pension investments promote productivity growth at the firm level. The literature has, to date, focused mostly on the relationship between the amount of pension savings in an economy and its output growth, largely disregarding how these savings are invested. The conclusions have been mixed so far. Bijlsma et al. (2018) find evidence of higher output growth in sectors that strongly rely on external financing in countries with a larger pension asset pool. Altiparmakov and Nedeljkovic (2018) find no significant effect on economic growth of pension reform toward a funded system.[7] Zandberg and Spierdijk (2013) fail to find short-term effects of pension funding on economic growth when controlling for capital market returns and demographic changes, while the evidence for long-term effects is more mixed and tends to confirm only a small positive effect of pension funding.

Second, we contribute to the growing literature on the effects of ownership composition on corporate outcomes by explicitly investigating the role of pension funds. Aghion et al. (2013), for example, study whether institutional investors help firms improve their innovation outcomes. They find that publicly listed U.S. firms with a higher share of institutional ownership tend to apply for more patents. Our study is one of the few that relate ownership to firm productivity (Bircan, 2019; Braguinsky et al., 2015; Chemmanur et al., 2011; Davis et al., 2014; Fons-Rosen et al., 2021). It is the first to focus on pension funds in this regard and to include both listed and non-listed firms.

Third, our new ownership data allow us to include both listed and unlisted firms in the analysis. Most of the literature on ownership and firm outcomes, particularly on ownership by institutional investors, focuses only on listed firms. Several studies have in fact examined the impact of various investor types, such as private equity (PE) and venture capital (VC) funds, and have documented their positive influence on the performance of the (listed) firms they invest in, extending beyond capital infusion (see e.g. Chemmanur et al., 2011; Davis et al., 2014). Our study distinguishes itself as the first to explore the corresponding consequences of pension funds' investments, recognizing key distinctions between pension funds and PE or VC funds. PE and VC funds often engage actively in shaping target firms to enhance their value, whereas

[7]However, they identify a positive relationship between economic growth and pension reform in countries where pension funds invest less than 50% of assets in domestic government bonds. This finding suggests that the asset allocation of pension funds plays a significant role in their macroeconomic impact.

pension funds typically invest with a more extended investment horizon in well-established companies. We also provide a comprehensive set of results by investigating whether the effects of a pension fund investment are heterogeneous across listed and unlisted firms.

Finally, our paper adds to the extensive literature on the determinants of firm productivity. Existing work has singled out, among other factors, the importance of financial frictions (Caggese, 2019; Coricelli et al., 2012; Levine & Warusawitharana, 2021), leverage (Coricelli et al., 2012), firm size, book-to-market ratio and hiring practices (İmrohoroğlu & Tüzel, 2014; Parrotta & Pozzoli, 2012). Other studies have suggested that the threat of foreign competition (Bao & Chen, 2018), export experience (De Loecker, 2013) and workforce composition characteristics (Parrotta et al., 2014) also play an important role. We contribute by highlighting pension funds' investments as a novel and unexplored driver of productivity at the firm level.

The remainder of this paper is structured as follows. Section 2 describes the economic channels through which pension funds can affect firm productivity. The institutional characteristics of the Danish funded pension sector, data and summary statistics are then discussed in Section 3 and followed by the presentation of our empirical strategy in Section 4. We present our empirical results in Section 5, along with a series of robustness checks and heterogeneity analyses. Finally, Section 6 offers concluding remarks.

2 Channels from Pension Investment to Firm Productivity

Accounting for selection, pension fund investments may affect firm-level productivity through different channels.

First, they may increase the supply of financial capital to the firm. This implies a reduction in the required rate of return on the firm's investment in (physical) capital, leading the firm to expand its investment until its demand for financing again equals the supply of financing. The additional investment could be directed towards items that raise productivity, such as advanced equipment or innovation-related items.[8] We refer to this as the "supply-of-financing channel".

Second, there is what we label as the "long-term-commitment channel". It is important to realise that pension funds and other types of investors, such as private equity/venture capital (PE/VC) funds, differ considerably in their business model. Therefore, the channels through which these investors affect firm productivity may differ. Notably, PE/VC funds are more likely to seek direct influence over the operational structure of target firms and to invest in younger firms or start-ups than do pension funds. The potential effects of pension funds' investment in firms may stem instead from the fact that pension funds tend to be long-term investors and, hence, their involvement raises security over the long-term financing of the firm. This may lead firms to invest in projects that favour long-term objectives, such as productivity enhancement, over short-term dividend pay-outs. The long investment horizon of pension funds is also at the centre of policy discussions on their role in terms of economic growth.

We expect the above channels to be more relevant for privately held firms compared to their publicly listed counterparts. Given that unlisted firms have inherently more difficult access to external capital and a smaller investor base than listed firms, it is plausible to anticipate a larger productivity effect of unlisted firms induced by pension funds. By the same token, we also expect these channels to be more relevant for small firms relative to large ones, owing to the presumed easier access to alternative financial resources

[8] In a related study we find that pension fund investments positively affect firm-level innovation outcomes, particularly in the green innovation area (Pinkus et al., 2023).

available to the latter. Our empirical analysis will provide a rigorous test on the presence of these two important channels in the relationship between pension fund investment and firms' productivity.

In addition to the above two channels, other mechanisms may be operational. First, there is scope for the "engagement channel". Pension funds may actively engage with the firms they invest in to improve their productivity. There is evidence to support this channel from other parts of the financial industry.[9] For example, Chemmanur et al. (2011) find that investments by venture capital (VC) funds lead to higher productivity through increased sales and lower production costs of the firms that they take a stake in. Davis et al. (2014) suggest that private equity buyouts affect firm productivity by accelerating the closure of less productive plants and the opening of more productive ones. Second, there may be a "signaling channel", characterized by the ability of pension fund investment in a firm to provide a positive signal about the firm to the market,[10] thereby reducing the cost of capital and stimulating productivity-improving investments. Specifically, the involvement of prominent institutional investors may be interpreted by the market as a signal of a well-functioning corporate governance structure, attracting other investors. Jara et al. (2019), for example, find evidence that Chilean firms that receive pension fund investments are more likely to issue bonds and pay a lower interest rate on these bonds, crowding out bank lending. The authors attribute this effect to better corporate governance and improved information disclosure.

At present, we lack systematic evidence about these last two channels in the context of pension fund investments, and contrary to the first two channels we do not avail of the data needed to formally test the engagement and signaling channels. However, there is at least some anecdotal evidence in support of them. In this regard, it is crucial to acknowledge that multiple channels might be concurrently operational, and these channels could potentially complement each other. A working group of the International Centre for Pension Management[11], composed of senior representatives of the largest pension funds in the world, examines in detail the mechanisms through which some of their own investment projects have led to corporate successes. One example concerns the participation in a wind energy production company. The involved pension fund actively participates in the company's strategy, including through a seat on the board, thereby facilitating direct engagement with its management. The pension fund points out that its long-term financing commitment empowers the board with actionable strategies and that its presence as an investor is a testament to the competence of the firm's management, which in turn strengthens the firm's position in its relevant markets.

3 Danish Pension Funds and Data

3.1 Institutional Characteristics of Danish Pension Funds

Relative to its GDP, accumulated pension assets in Denmark are among the highest in the world, amounting to more than twice GDP. These assets, including those of public sector employees, are managed by private

[9] Alvarez et al. (2018) evaluate a sample of publicly traded firms from several emerging economies. They conclude that the relationship between investment and institutional block holding follows an inverse U-shape. Hence, when institutional block holders own a large share of controlling rights, investment rates decline. The authors interpret this as evidence that large holdings by institutional investors translate into increased monitoring of managers and lead the firm to take a long-term view regarding investment instead of short-term capital spending, reflected in a reduction of over-investment.

[10] It should be noted that this is conditional on the availability of this information to the market, considering that such investments may be confidential information.

[11] https://www.icpmnetwork.com/

pension funds, which are mostly organized by sector. These funds have substantial freedom in deciding how to invest their asset holdings, including the choice of firms they invest in, provided they act in the best interest of their participants and fulfill their regulatory requirements. Since pension funds are private entities, politicians cannot easily compel them to invest in specific firms. Hence, the pension fund investments considered in this paper are the result of the pension funds' own decisions. Pension funds may invest in listed firms through the stock exchange or initial public offerings, and in unlisted firms, often obtained as private equity, for example, directly from the founder or another party. They can be passive investors, as would be the case if they merely invest in a stock market index, or they can be active investors to the extent that they also directly engage with the firm's management and its decisions.

3.2 Ownership Data

We construct information on pension funds' investment in a firm based on shareholder data of all incorporated Danish firms. The original dataset, provided by Experian, includes only information about direct ownership relationships between an owner and an owned firm, but it lacks information about the owners of the owner firm in that pair. To address this limitation, and include also indirect ownership in our sample, we proceed as follows. First, we construct a panel dataset where the unit of observation is a single firm in a given year. Second, we iterate through the ownership levels to identify the ultimate owner of each firm. The following example illustrates the main features and the salience of this procedure. Suppose that firm A owns 100% of firm B and firm B owns 100% of firm C. Here, firm A is the "ultimate owner" of firm C, meaning that firm A is not owned by any other firm. The original dataset shows only the bilateral relationships between firms A and B and firms B and C but not that firm A owns 100% of firm C through firm B. However, the relationship between firms A and C is the one that we are actually interested in for our empirical purposes. This is especially relevant if firm B is merely a legal entity with the aim of owning firm C. Therefore, we iterate through the ownership levels until all firms in the dataset are ultimate owners (i.e., they should not be owned for more than 80%[12] by other firms) or firms that are owned.[13]

The result is a panel dataset where one observation identifies a relationship between two firms in a given year, or equivalently an owner–owned firm–year combination. To determine ownership by pension funds, we manually search the main CVR number (the Danish business registration number) of each domestic pension fund using public sources, notably the Danish Business Register (Virk, 2022). Finally, we consider a firm to have received a pension fund investment if any of these CVR numbers is among the shareholders of the firm.

The Experian ownership data cover all incorporated Danish firms. Therefore, we can identify pension fund investments in both listed and unlisted firms. The majority of the literature on the firm-level effects of pension funds and of institutional investors more generally covers only listed firms (e.g., Aghion et al., 2013; Alvarez et al., 2018; Jara et al., 2019). Hence, we see our inclusion of unlisted firms as a relevant contribution to the literature.

[12]Ownership of 80% or more in a company typically represents a significant level of control. When a company is owned by more than 80%, it usually loses the authority to make crucial decisions, appoint board members, and influence the company's strategic direction. This level of control is often considered a meaningful threshold in corporate governance.

[13]Appendix A provides further details on the algorithm and the decision rules that we apply.

3.3 Danish Registers

Once we have obtained the ownership data we merge its anonymized version to two Danish registers, FIRE and FIRM, which provide detailed information about a firm's balance sheet, its number of employees and the sector it operates in. We now describe how we process the firm accounting data. In the remainder of this section, we define a firm's sector as the NACE Rev.2 1-digit sector based on the Danish Industry Classification (DB07).[14] The sample period covers the years 2003–2019, for which we have matching accounting and pension fund investment data. First, we exclude all firms with imputed values or missing sector information. To estimate firm productivity as described in Subsection 4.2, we exclude all observations with zero or missing values for capital, labor (number of employees), output, value-added or intermediate inputs. We deflate output, value-added, intermediate inputs and capital with sector-specific deflators.[15] To improve balance sheet consistency, we drop observations with negative equity values.

Next, we drop sectors with very few firms receiving pension fund investments and firms that we observe only in a single year. Afterwards, we winsorize capital, labor, intermediate inputs and output at the 1st and 99th percentiles. Finally, Denmark has many small firms, while pension funds invest mostly in large firms. To improve comparability across firms in the treated and control groups, we restrict the sample used in our analysis to firms that have at least 10 employees in all periods.[16]

3.4 Measures of Pension Fund Investment

In our empirical analysis, we use three different measures of pension fund investment in a firm: (i) a dummy for whether the firm received investment from at least one domestic pension fund, (ii) investment intensity, which is equal to the aggregate share of a firm owned by all domestic pension funds together, and (iii) investment length, captured by the number of consecutive years (up to and including the previous year) of pension fund investment in the firm. The statistical significance of the investment dummy aligns with all the channels highlighted in the previous section, through which productivity can be enhanced, while the significance of the investment intensity is consistent with the "supply-of-financing channel". We anticipate that investment length will be pertinent to the "long-term-commitment channel". Productivity-enhancing investments are typically of a long-term nature, often involving new technology, as they require time to be planned, implemented, and to yield results. Therefore, for a firm to be willing to undertake such investments, it must be confident that financing will remain accessible for a sufficiently long period. Given their long-term liabilities, pension funds are well-positioned to serve as long-term financiers. Precisely because the effects of pension fund investment on productivity manifest gradually over time, we expect the duration of the pension fund investment history to be relevant to current productivity.[17]

[14] Table B.2 shows the sectors included in the analysis and the number of firms in each sector in the sample.

[15] Deflators are compiled at the DB07 10-industry grouping level and sourced from Statistics Denmark.

[16] This restriction is common in the literature working with Danish register data (see, e.g., Fan et al., 2022; Parrotta et al., 2014).

[17] One main limitation of our data is that they only cover equity investments and not debt or loans. However, national accounts data (Danmarks Nationalbank, 2022) show that at the end of 2019 domestic pension funds and insurance companies held 254.6 bn DKK in equity and only 38.6bn DKK in debt and loans of Danish non-financial companies. Therefore, they are much more active as equity rather than debt investors. Danish pension funds and insurance companies held 15.7% of the total equity of non-financial companies held by domestic financial corporations and only 2.1% of debt and loans.

3.5 Descriptive Statistics

Our final sample consists of firms for which we can successfully compute productivity as described below.[18] This includes 102,443 firm–year observations, representing 14,968 different firms. Of these, 574 (3.8%) are treated in at least one year.[19] Following our methodology described below in Section 4, we define treatment as a firm receiving a pension fund investment in the previous year. Descriptive statistics and definitions of all variables used in the analysis can be found in Table 1. We show statistics for four different sub-samples: (i) all firm-year observations, (ii) firm-year observations with treatment, equivalent to receiving a pension fund investment in the previous year (year $t-1$), (iii) firm-year observations without treatment, and (iv) firm-year observations without treatment in the matched sample only (the matching procedure is explained in the next section). Focusing on the second sub-sample, we observe that domestic pension funds invest on average for over 4 consecutive years and hold an aggregate stake of approximately 10.4% in a firm, conditional on investing in the firm in period t.

The second panel of Table 1 reports some interesting facts about the firms that pension funds invest in. If we look at two standard measures of labor productivity, output per worker and value-added per worker, firms with a pension fund investment are relatively more productive than untreated firms in the year following treatment. These firms, on average, also produce higher output (value added) with higher consumption of inputs (labor, capital and intermediary inputs). This is in line with the observation highlighted by the previous literature that institutional investors, including pension funds, tend to invest in larger firms (Ferreira & Matos, 2008). Pension funds also tend to invest in older firms: the average age of a firm one year after treatment exceeds that of untreated firms in the sample by more than three years. On average, pension funds start to invest in a firm in its 21st year of existence. The second panel of the table also reports the fractions of exporters in the different sub-samples. We include the exporter status in the refinement analysis to take into account that exporting firms are generally more productive than otherwise comparable firms (Harrigan et al., 2023).

Furthermore, 48% of the firms that receive a pension fund investment do so in 2003, the first year for which we have pension fund data. Therefore, the variable that measures the length of the investment is left-censored by construction, given that we do not observe ownership data before 2003. For 62% of the firms that pension funds invest in, the first investment coincides with the first year that the firm is in the sample. This is again the result of the left-censoring of the investment tenure variable. Furthermore, we record 347 instances of pension funds fully divesting from a firm, meaning that at least one pension fund invests in the firm in some year $t-1$, but none invests in it in year t. Table B.2 in the appendix shows the number of firms in the sample per NACE Rev.2 1-digit sector. Pension fund investment is clearly concentrated within the manufacturing sector, with 49% of all firms receiving a pension fund investment being in this sector.

[18] The descriptive statistics and sample sizes discussed in this section refer to the final sample that we use to estimate equation (10) below and its variations.

[19] While this may appear to be a relatively small number, it is important to recognize that the active selection, monitoring, and engagement with firms constitute a labor-intensive process. This complexity is especially pronounced when dealing with unlisted firms, where detailed information may be challenging to obtain. Consequently, the number of firms in pension fund equity portfolios is necessarily limited.

Table 1: Descriptive Statistics

Variable	Definition	All Mean		Firms with PFI Mean		Firms without PFI Mean		Firms without PFI (matched sample) Mean	
Pension Fund Investment Variables									
$DPFI_{it-1}$	dummy = 1 if a pension fund invested in the firm	0.022	(0.148)	1.000	(0.000)				
$Length_{it-1}$	duration of current episode of pension fund investment (years)	0.093	(0.788)	4.156	(3.294)				
$Intensity_{it-1}$	total ownership by domestic pension funds (%)	0.233	(2.391)	10.393	(12.250)				
Firm Variables									
Output/worker	output per worker per worker (DKK, log)	7.375	(0.717)	7.589	(0.794)	7.370	(0.715)	7.491	(0.752)
VA/worker	value added per worker (DKK, log)	6.306	(0.414)	6.435	(0.486)	6.303	(0.411)	6.360	(0.408)
Value added	(DKK,log)	10.035	(1.141)	11.411	(1.207)	10.003	(1.119)	10.550	(1.050)
Labour	number of full-time employees (log)	3.729	(0.999)	4.976	(1.113)	3.701	(0.978)	4.191	(0.955)
Capital	fixed capital (DKK, log)	8.995	(1.747)	10.697	(1.727)	8.956	(1.728)	9.609	(1.638)
Intermediary inputs	(DKK, log)	10.540	(1.474)	12.043	(1.477)	10.506	(1.456)	11.142	(1.435)
Age	firm age (years)	24.463	(18.888)	28.135	(21.080)	24.377	(18.824)	25.779	(18.591)
Capital Intensity	capital stock per worker (DKK, log)	5.265	(1.310)	5.721	(1.255)	5.255	(1.310)	5.418	(1.249)
Listed	1, if listed firm	0.032	(0.175)	0.451	(0.498)	0.022	(0.147)	0.039	(0.194)
Export	1, if the firm exports	0.546	(0.498)	0.818	(0.386)	0.540	(0.498)	0.605	(0.489)
Observations		102,443		2,292		100,151		46,262	

Notes: All descriptive statistics are calculated as averages over the 2004–2019 period. Variables in DKK are in real Danish kroner (using 2010 as the base year). Since pension fund investment will enter our estimations lagged by one year, we choose to report lagged pension fund investment variables. The table presents means and standard deviations in parentheses for four different subsamples: (i) all firm-year observations, (ii) firm-year observations with treatment, equivalent to receiving a pension fund investment in the previous year (year $t-1$), (iii) firm-year observations without treatment, and (iv) firm-year observations without treatment in the matched sample only. Values for subsample (ii) are reported conditional on the firm receiving a pension fund investment in the previous year $t-1$.

Our hypothesis that pension funds can affect firm productivity through long-term investments is consistent with the assumption that pension funds seek to match their long-term liabilities with long-term assets (Beyer et al., 2014; Della Croce et al., 2011). This way, they reduce the mismatch risk in their balance. 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 confirms this trend. In the appendix, Table B.1 compares the length of the investment period of domestic pension funds with that of other investors in the domestic financial industry. We classify other investors based on their 6-digit industry code (and 3-digit code for insurance companies). Panel A of Table B.1 in Appendix B reports the mean investment horizon of each investor group, conditional on investing in firm i at time $t-1$, as well as the difference from the average investment horizon of pension funds in that firm, and the p-value of a simple difference-in-means t-test. On average, pension funds invest in a firm for 0.89 years longer than banks. While this difference may seem small, it represents more than 20% of the mean investment horizon of pension funds, making it relatively important.[20] Our data show that, among domestic investors, pension funds feature a longer investment horizon than all other sectors except for non-financial holding companies.[21] Moreover, the differences in the length of the investment horizon between pension funds and other investor types are statistically significant for all sectors except investment companies. Panel B of Table B.1 shows that, prior to divestment, pension funds invested in firms for a larger number of consecutive years than any other investor type.[22] These differences are mostly statistically significant at the 1% level and always at least at the 10% level. The observation that pension funds tend to have longer investment duration compared to other investor types is further confirmed in Figure B.1 in Appendix B, where we present the distribution of the duration variable among different investor types. Pension funds stand out with higher (lower) density corresponding to duration lasting for 6 years and above (1 year). To conclude, our data show domestic pension funds to exhibit a longer investment horizon than other domestic investors.

4 Methodology

In this section, we describe the methods used to address selection and the identification of the impact of a pension fund investment on firms' productivity.

4.1 Addressing Selection

Selection may confound the causal impact of a pension fund investment on productivity, as pension funds may actively select firms with certain characteristics that make them more productive to begin with. This is a very pervasive issue in the literature looking at the effects of investors on target firms (see, e.g., Aghion et al., 2013; Fons-Rosen et al., 2021; Garel, 2017; Lerner et al., 2011; Levine & Warusawitharana, 2021). A

[20]Small absolute differences are also consistent with the empirical finance literature on investor horizon (see e.g. Cella et al., 2013).

[21]Non-financial holding companies correspond to DB07 sector 642020. According to Statistics Denmark, this sector includes holding companies whose main activity is to hold controlling stakes in other non-financial companies. Therefore, this sector does not include outside investors in the sense of asset managers, and therefore it is not surprising that they have a long investment horizon.

[22]In Panel B the length variable is the number of consecutive years of investment in firm i by at least one investor of each type in year $t-1$ conditional on no investor of that specific type investing in the firm in period t. This condition addresses the concern that the length variable is right-truncated, as investment by an investor type might continue after 2019 or the firm exits the sample due to our sampling conditions.

common approach is to use the inclusion of a firm in a large index as an exogenous event (Aghion et al., 2013), which exposes the firm to investment by certain institutional investors. For our case, this is not a suitable approach since 1) the indices on Danish listed equity instruments include only a small number of firms and 2) the composition of the indices does not vary much over time, resulting in very low exogenous variation that can be exploited to tease out causality in our analysis. Furthermore, to the best of our knowledge, there are no other events in our sample period, such as a regulatory change, that would clearly affect the propensity of Danish pension funds to invest in domestic equity. We therefore adopt two strategies to account for potential selection effects.

First, we take an event study approach that allows us to check for differential pre-trends, i.e., to assess whether, before the treatment occurs, firms eventually treated with a pension fund investment differ in terms of productivity from their counterparts that do not receive a pension fund investment. A number of recent studies have highlighted concerns with the traditional event study design when units, in our case firms, receive treatment at different points in time (see, e.g., de Chaisemartin & D'Haultfoeuille, 2022; Goodman-Bacon, 2021). This issue is important in our context since pension funds start investing in firms in different years. Therefore, we use the estimator suggested by Sun and Abraham (2021) that is robust to treatment heterogeneity with respect to the timing of the treatment. For this event study, we use two different measures of labor productivity — i) value added per worker and ii) output per worker — and control for year-by-NACE Rev. 2 1-digit sector fixed effects. We also include the following control variables: firm age, firm size (number of employees), a dummy for whether the firm is listed in the base year (the first year that it is in the sample), and capital intensity, defined as the capital-to-labor ratio.

Second, we implement a structural estimation approach developed by Bøler et al. (2015) and Doraszelski and Jaumandreu (2013) that allows us to explicitly attenuate the issue of selection by controlling for past unobserved productivity, as well as other differences, such as the sector and whether the firm is an exporter, and thus firm-level heterogeneity. We also test the robustness of our main results to omitted variable bias using Oster (2019)'s approach. The next subsection describes this procedure in detail.

It is improbable that most pension funds select firms entirely at random. More likely, in many instances, they choose firms based on their potential for productivity growth. For example, a pension fund may possess information about a new product being developed by a firm or a firm's efforts to implement superior production technology. Our hypothesis instead is that pension fund investment aids in realizing this potential, something that would otherwise not occur.

4.2 Structural Productivity Estimation

Firm productivity is often defined as total factor productivity (TFP), the residual from a regression of firm output on input factors, usually formed by capital and labor. The main advantage of TFP over labor productivity measures such as output per employee is that it captures productivity changes after variation in input factors is accounted for (Chemmanur et al., 2011). This is particularly important in our case, since pension fund investments in a company may imply an injection of new capital and thus an increase in one of the inputs of the production function. We are interested in the productivity changes in response to pension fund investments that are not explained by changes in the amounts of inputs used in the production process.

A key concern in estimating TFP relates to potential simultaneity bias: changes in productivity may affect not only output (the dependent variable) but also the input mix that the firm chooses (the explanatory variables). Based on Ackerberg et al. (2015), we illustrate this problem using a Cobb–Douglas production function in logs:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where lower case letters denote logs and y_{it} is the value added of firm i at time t, k_{it} is its capital stock and l_{it} is its labor input.[23] Furthermore, ε_{it} is an i.i.d. unobservable shock to production (or a measurement error), while ω_{it} is a shock to production that cannot be observed by the econometrician but that can be anticipated by the firm and is a source of potential endogeneity.[24] Simultaneity bias can arise because the firm may choose its capital and labor inputs as a function of its prediction of the future productivity shock that is unobservable to the econometrician. Hence, the choice of the inputs (l_{it}, k_{it}) and ω_{it} may be correlated, resulting in biased OLS estimates of the coefficients on the inputs (Ackerberg et al., 2015).

The use of proxy variables has recently become a popular approach to address this endogeneity issue. The approach uses available information to proxy for the unobservable ω_{it}.[25] Popular estimation techniques include Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and Ackerberg et al. (2015) (henceforth OP, LP, Wooldridge and ACF, respectively). OP uses an inverted demand function for investment as a proxy variable, while LP, ACF and Wooldridge use an inverted demand function for intermediate inputs since investment is often zero for a large share of observations. We follow Bøler et al. (2015), Doraszelski and Jaumandreu (2013), Fan et al. (2022), and Maican et al. (2022) and estimate the impact of a pension fund investment by using a control function approach in two steps. This structural estimation attenuates the selection issue discussed above. Furthermore, this approach addresses the concern that a firm receiving a pension fund investment may alter the use of inputs in a way that may bias the estimation of productivity. De Loecker (2013) finds that controlling for endogeneity is important for the correct estimation of firm productivity. While factors impacting productivity can be the result of firm decisions such as export or R&D expenditure choices (Bøler et al., 2015; De Loecker, 2013; Doraszelski & Jaumandreu, 2013; Fan et al., 2022; Maican et al., 2022), changes in the ownership structure have also been found to be important for firm productivity (Bircan, 2019; Braguinsky et al., 2015).

Productivity is obtained from a Cobb–Douglas production function containing value added, labor and capital. Following ACF in a setup described by equation (1), we assume that:

$$E\left(\varepsilon_{it} \mid l_{it}, k_{it}, m_{it}, l_{it-1}, k_{it-1,}, m_{it-1}, ..., l_{i1}, k_{i1}, m_{i1}\right) = 0 \tag{2}$$

where m refers to our proxy variable (materials). Because past values of ε_{it} are not included in the conditioning set, we allow for serial dependence in the pure shock term. However, we need to restrict the dynamics of the productivity process:

$$E\left(\omega_{it} \mid \omega_{it-1}, \omega_{it-2}, ..., \omega_{i1}\right) = E\left(\omega_{it} \mid \omega_{it-1}\right) = g\left(\omega_{it-1}\right) \tag{3}$$

[23]Industry subscripts are omitted for ease of reading. We define capital as the total value of tangible fixed assets (including real estate), calculated with the perpetual inventory method. Labor is the total number of employees, whereas intermediate inputs equal the sum of the following items: raw materials, consumables, goods for resale, finished goods and packaging (excluding purchases of energy), energy purchases, value of subcontracts, rental and leasing costs. All monetary variables are deflated with sector-specific deflators published by Statistics Denmark.

[24]More precisely, the firm does not observe ω_{it} until time t and has information $p(\omega_{it+1}|\omega_{it})$ about the conditional distribution of the future shock.

[25]For an overview and discussion on the identification assumptions, see Ackerberg et al. (2015).

for a given function $g(\cdot)$. As in ACF, for the timing of the choice of the inputs, we assume the following: i) k_t is a function of k_{t-1} and new investment at $t-1$, so it is fully determined by choices made at $t-1$ or earlier; ii) l_t is chosen between $t-1$ and t; and iii) m_t is chosen at time t. As a result, material demand is a function not only of capital and productivity but also of labor:

$$m_{it} = f(k_{it}, l_{it}, \omega_{it}) \tag{4}$$

Moreover, following the standard assumption in the literature that the material demand function is strictly monotonic in the productivity shock ω_{it} , we can invert the function in (4) to obtain ω_{it} as a function of k_{it}, l_{it} and m_{it}:

$$\omega_{it} = \tilde{h}(k_{it}, m_{it}, l_{it}) \tag{5}$$

Plugging $\tilde{h}(.)$ into production function (1), we obtain:

$$y_{it} = h(k_{it}, m_{it}, l_{it}) + \varepsilon_{it} \tag{6}$$

where the linear terms in capital and labor in the production function have been subsumed in the new function $h(.)$. The goal of this (first-stage) equation is solely to predict output net of measurement error or unanticipated shocks, hence to separate ω_{it} from ε_{it}. We operationalize the first stage by approximating $h(.)$ using a second-degree polynomial of capital, labor and intermediate inputs with full interaction terms.[26] We then estimate the following equation via OLS:

$$y_{it} = \kappa_t + h(k_{it}, m_{it}, l_{it}) + \varepsilon_{it} \tag{7}$$

where κ_t capture year fixed effects. In order to allow for heterogeneity in production technology and demand across sectors, we estimate the revenue function separately for each NACE 1 digit sector (sector subscripts are omitted for brevity). We then define $\hat{h}_{it}$ as the predicted output net of year fixed effects. The predicted output from the first stage $\hat{h}_{it}$ is then used to identify the input elasticities in the second stage.

To obtain the second-stage estimation equation, it is important to note that productivity ω_{it} follows a first-order Markov process. In the standard ACF approach, this Markov process is exogenous to the firm, meaning that the firm cannot affect it. Therefore, the firm can only react to changes in productivity but cannot influence how it evolves. Following Bøler et al. (2015), De Loecker (2013), and Doraszelski and Jaumandreu (2013), we relax this exogeneity assumption by augmenting the Markov process with our endogenous variable of interest, pension fund investment at time $t-1$. In other terms, pension fund investment enters as a shifter in the evolution of productivity ω_{it} over time. We prefer this approach to the inclusion of pension fund investment directly as an input in the production function (1) since pension fund investments in a given firm are not only determined by the firm in question, as is the case for capital and labor. They are in fact the outcome of a complex decision-making process that involves both the investor and the firm. Formally, we assume that productivity ω_{it} depends on firm i receiving a pension fund investment

[26] The results are unaffected when we use an alternative specification of the first stage – see the discussion of robustness in Section 6 below.

through the following law of motion:

$$\omega_{it} = \rho\omega_{it-1} + \gamma PFI_{it-1} + \xi_{it} \tag{8}$$

where PFI_{it-1} denotes a pension fund investment in firm i at time $t-1$. Furthermore, ξ_{it} is an idiosyncratic error term uncorrelated with the other right-hand-side variables.[27]

Rewriting productivity in terms of predicted output $\hat{h}_{it}$ from the first stage yields:

$$\hat{\omega}_{it} = \hat{h}_{it} - \beta_k k_{it} - \beta_l l_{it} \tag{9}$$

Integrating the law of motion (8) into (9) yields the estimating equation for the second stage:

$$\hat{h}_{it} = \alpha + \beta_k k_{it} + \beta_l l_{it} + \rho\left(\hat{h}_{it-1} - \beta_k k_{it-1} - \beta_l l_{it-1}\right) + \gamma PFI_{it-1} + \xi_{it} \tag{10}$$

where we have added the constant α, which is allowed to vary across sectors, to arrive at the empirical specification. We estimate (10) by the generalized method of moments (GMM).[28] Following the standard ACF approach, we use k_{it} and l_{it-1} as instruments. Since $\hat{h}_{it-1}$, k_{it-1}, k_{it} and PFI_{it-1} are determined at time $t-1$ or earlier, they are orthogonal to the error term ξ_{it} and can be used to form the necessary moment conditions. Labor l_{it}, however, is chosen after $t-1$, given our timing assumptions, so we instrument it with l_{it-1}. Finally, we allow the constant α to vary by industry by including sector dummies in the estimation, using these dummies as their own instruments. The instrument set thus contains l_{it-1}, $\hat{h}_{it-1}$, k_{it}, PFI_{it-1} and the industry dummies. The error term ξ_{it} is uncorrelated with the instrument set since it is uncorrelated with all the information at time $t-1$ and, hence also, current capital k_{it}.

The coefficient γ in equation (10) captures the effect of a past pension fund investment on firm productivity. We identify this effect in the second stage by exploiting variation in past pension fund investment PFI_{it-1} conditional on lagged productivity ω_{it-1}. The literature on the effect of ownership on productivity (see, e.g., Bircan, 2019; Braguinsky et al., 2015; Fons-Rosen et al., 2021) mostly uses a three-stage approach that consists of first estimating the elasticities of capital and labor in two steps to produce TFP estimates and then regressing the latter on the variables of interest and firm control variables. However, retrieving the effect of interest directly from the law of motion of productivity as we do allows us to control for past productivity and to address more explicitly the issue of selection.

4.3 Matching

To address the fact that the firms in the control group tend to differ on average in terms of observable characteristics (such as size and industry) from treated firms, we construct a matched sample using a propensity score approach. First, we estimate the probability of a firm receiving a pension fund investment with a logit

[27] PFI_{t-1} and earlier pension fund investment therefore indirectly enter the production function (1) through ω_{it}. Relating this to our timing assumptions, input choices at time t can depend on pension fund investment since it is in the information set at time t.

[28] For the identification of the production function elasticities, our approach requires variation in these inputs conditionally on ω_{it}. Put it differently, our approach requires either exogenous input price differences across firms or differences in input dynamics across firms. However, we obtain similar results (available upon request from the authors) when we include average wages at the firm level in the $\tilde{h}(.)$ function and we rule out variation in the price of the quasi-flexible inputs across firms.

regression of the dummy variable $DPFI_{it}$ on valued added, labor, capital and an indicator for whether firm i is listed (all at time $t-1$).[29] We calculate propensity scores using this method by sector-year and then drop firms from the matched control group that have a propensity score below the sector-year-specific 25th percentile in at least one year.[30] We therefore proceed very conservatively and keep only firms in the matched control group that are likely to receive a pension fund investment over the sample period. Furthermore, while the specification for the propensity score is very parsimonious, estimating it separately for each sector–year alleviates concerns over misspecification. We report the descriptive statistics of the matching variables and the sample used to estimate the propensity score in Appendix B.

5 Empirical Analysis

5.1 Event Study

Figure 1 presents the effect of a pension fund investment on two measures of firm productivity, output per worker and value-added per worker, using the methodology described in Subsection 4.1. We show the impact on these two straightforward measures of firm productivity instead of deriving the latter from structural estimation for two reasons: 1) we explore the selection hypothesis by testing for the presence of differential pre-trends, and this can be feasibly done only with standard measures of productivity, and 2) the justification for extrapolating the productivity term outside the production function and using it as a dependent variable in a separate regression is not theoretically obvious (Ackerberg et al., 2015).[31] Figures 1a and 1b suggest that there are no significant pre-existing differences in productivity trends between treated and non-treated firms prior to the first pension fund investment in the firm (which we refer to as the "event" date).[32] However, we do observe a positive effect on productivity that persists for a number of years following the event date, as shown in the two figures. To further explore this effect, we use a structural estimation approach in the next section. We find that our event study results are robust to alternative specifications and sample restrictions. Specifically, we obtain qualitatively similar results in the event study analysis when we: 1) use a matched sample, 2) use an alternative measure of output,[33] 3) include the share of R&D workers among the control variables, or 4) omit all control variables from the event study regressions. Moreover, our findings remain unaltered when we focus on events in which only one pension fund invests in a given firm over the sample period or when we exclude pension fund investments that last for fewer than five consecutive years.[34] Overall, we find compelling evidence that pension fund investments are associated with firms' productivity improvements.

[29] Using base year values instead of one-period lags yields very similar results.

[30] Sectors are here defined as the standard DB07 36-industry grouping. The 25th percentile is calculated only among firms that do not receive a pension fund investment in any year. We keep firms for which a propensity score could be computed in at least one year. Excluding firms with missing propensity scores in any year from the matched control group does not change our results.

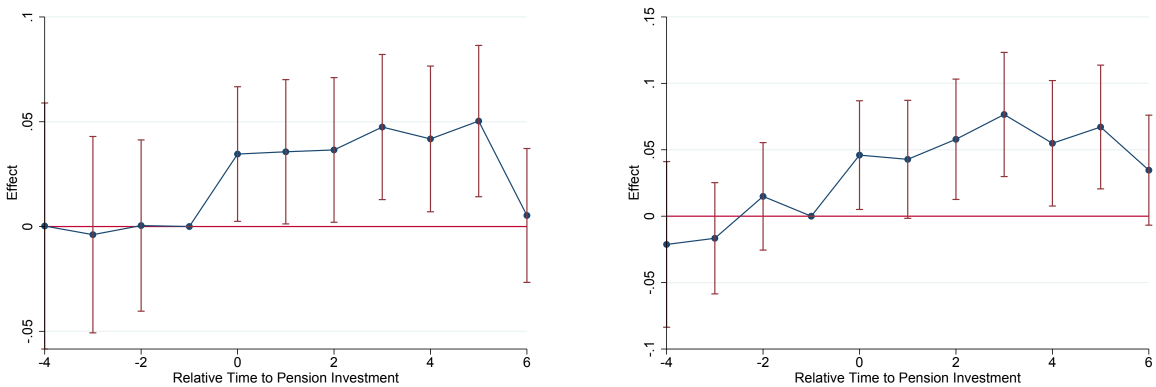
[31] In fact, the possibility of computing the effect of a pension fund investment directly in the productivity estimation is one of the main reasons that we choose this approach rather than the more traditional three-stage analysis used in the literature (e.g., Bircan, 2019; Braguinsky et al., 2015).

[32] We also do not find any evidence of differences in pre-trends using the estimator proposed by de Chaisemartin and D'Haultfoeuille (2022).

[33] Instead of using sales to measure output, the alternative measure is the sum of sales, work carried out at own expense and listed under assets, other operating income, and inventory changes.

[34] These results are reported in Appendix D.

Figure 1: Event Study Results



(a) Output per Worker

(b) Value added per Worker

Notes: The outcome variable is output or value added per worker. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-NACE Rev.2 1-digit sector fixed effects.

5.2 Main Results

All results reported in this section are obtained from the estimation of equation (10) using the log of the firm's value-added as a measure of output y_{it}. We report the results for the baseline sample and the sample resulting from the matching procedure described in Subsection 4.3.[35] For convenience, we report the coefficient estimates of the pension fund investment variable and the related standard errors multiplied by 100.

Table 2 presents the results for the model in which the pension fund investment is included through a dummy variable. Columns 1 and 5 show estimates for the case in which the law of motion of the exogenous productivity process is specified without the pension fund investment variable. Columns 2 and 6 introduce the pension fund dummy in the law of motion. Columns 3 and 7 restrict the pension fund investment dummy to take a value of 1 only if the aggregate holding by all Danish pension funds in firm i is at least 5%. This allows us to abstract from those cases in which investment by pension funds constitutes only a negligible source of capital for the firm, i.e., disregard cases in which pension funds passively invest in a firm as part of a broad portfolio (e.g., one that follows an index) and in which the ”signaling channel“ is the only possible effect present. Previous literature found that export status is important in the estimation of productivity (De Loecker, 2013). Columns 4 and 8 therefore report the results including a dummy in equation (10) taking a value of 1 if firm i is an exporter at $t-1$.

The estimates of the production function elasticities β_l and β_k are in the range of estimates in previous studies, see for example Fox and Smeets, 2011. We observe a positive and significant effect of a pension fund investment in all specifications. Receiving a pension fund investment in the previous year is associated with an increase in productivity ranging from 3.0% to 4.6%, depending on the specification. The effect is stronger, though not statistically significantly so, when we restrict the pension fund investment dummy to take a value of 1 only when aggregate ownership of pension funds in the company is at least 5%. This could

[35] It is important to note that the findings from the event study and the results from the structural estimation cannot be directly compared.

be an indication of the relevance of the "supply-of-financing channel". We also find a stronger effect when we select the matched sample. Interestingly, including the export dummy hardly affects the estimate of the pension investment dummy.

Although we do not control for a large number of firm characteristics, the structural approach that we employ has the advantage of controlling for past productivity. In this way, we control for selection effects driven by heterogeneity, particularly for pension funds selecting firms based on their productivity. Hence, even controlling for such a potential selection effect, we find robust positive and significant effects of a pension fund investment on firm productivity.

Furthermore, to assess the sensitivity of our main results to omitted unobserved variables, we apply Oster (2019)'s approach. This method allows testing for the sensitivity of the estimated effects to omitted variable bias under the assumption that the relationship between the treatment (i.e. pension fund investments) and unobservables can be recovered from the relationship between the treatment and the observables. Specifically, we estimate the degree of selection on unobserved relative to observed variables necessary to obtain a null effect of pension fund investments on productivity if we were to estimate the law of motion (8) with standard OLS and by assuming that the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls (i.e. R_{max} in Oster (2019)'s notation) equals 1. As reported at the bottom of Table 2, we obtain a δ ratio of approximately 30 and 20 in respectively the general and matched samples, which are well above the value of 1 usually seen as an upper bound for selection on unobservables Oster (2019). Overall, these results indicate that under the assumptions implied by Oster (2019)'s approach, omitted variable bias is highly unlikely to change the main conclusions of the analysis.

Another concern with the results presented in Table Table 2 is that the positive effects on productivity may be fully driven by a change in input and output prices. Liu (2022) has shown for example in the context of private equity that institutional investors can lead to changes in output and input prices. If pension fund investments lead, for example, to higher output prices and lower input prices, then we would incorrectly conclude that productivity has increased due to pension fund investments. We therefore test whether pension fund investments indeed affect output and input prices using product-level data collected for a representative sample of manufacturing firms (VARK and VARS). The event study analysis reported in Figures D.7 and D.8 of Appendix D allows us to rule out any significant change in the average and median price of a firm's purchased and sold products following a pension fund investment.

Table 2: Productivity Estimates: Pension Fund Dummy

	Whole sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_l	0.954***	0.953***	0.953***	0.950***	0.912***	0.910***	0.910***	0.908***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.085***	0.084***	0.092***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)
$DPFI_{it-1}$		3.361***	3.460***	2.969***		4.401***	4.638***	3.981***
		(0.992)	(1.129)	(0.989)		(0.975)	(1.067)	(0.979)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	Yes	No	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes	No	No	No	Yes
δ for $PFI_{it-1} = 0$		30.22	34.48	28.95		16.40	19.84	15.58
Obs.	102,443	102,443	102,443	102,443	48,554	48,554	48,554	48,554
Obs. PF	2,292	2,292	1,730	2,292	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	14,968	7,468	7,468	7,468	7,468
# Firms PF	574	574	429	574	574	574	429	574

Notes: This table presents the results from the estimation of equation (10). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in year $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 3 and 8, $DPFI_{it-1}$ equals 1 if the aggregate holding of all pension funds in firm i in year $t-1$ was at least equal to 5%. In columns 4 and 8, we include a dummy equal to 1 if firm i is an exporter in year $t-1$. The coefficient δ for $PFI_{it-1} = 0$ is estimated with the procedure developed in Oster (2019). The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in year $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Next, we investigate whether the size of the pension fund investment matters by defining pension fund investment in equation (10) as the total share of firm i (in percent) held by all domestic pension funds. Table 3 presents the results of this specification. On average, an increase of 1 percentage point in pension fund investment is associated with a TFP increase of approximately 0.2%. The significance of $Intensity_{it-1}$ suggests a potential relevance of the "supply-of-financing channel".[36] Another channel potentially suggested by these results is that a larger equity stake gives more control over the management of the target company, which could lead to higher productivity gains. We rule out a governance mechanism where, for instance, the CEO is fired and replaced by a more skilled CEO, based on the fact that in fewer than 2% of observed cases of pension fund investments in our sample, the stake is above 50%, and that in 90% of observed cases, the total stake held by pension funds in the firm is at most 20%.

[36] Very similar results, which are reported in Appendix D, are obtained by using the inverse hyperbolic sine transformation of the intensity variable to take into account the large number of zeros.

Table 3: Productivity Estimates: Pension Fund Investment Intensity

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.953***	0.953***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$Intensity_{it-1}$	0.220***	0.219***	0.208**	0.243***	0.242***	0.230***
	(0.084)	(0.084)	(0.081)	(0.086)	(0.086)	(0.083)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents results from the estimation of equation (10). $Intensity_{it-1}$ is the aggregate share of firm i (in percent) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. The estimated coefficient of $Intensity_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6, we include a dummy taking value 1 if firm i is an exporter at time $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$ in the sample. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

One of the main differences between pension funds and most other types of investors is their long investment horizon. Therefore, pension funds can provide long-term financing security and stimulate firms to make productivity-enhancing investments (often using new technology). Hence, we now investigate whether the holding period of a pension fund investment makes a difference by capturing the pension fund investment in equation (10) with the variable $Length_{it-1}$, which measures the number of consecutive years that firm i has received pension fund investment up to year $t-1$. Table 4 shows that an additional year of a pension fund investment is associated with a highly significant increase in productivity in the range of 0.4%–0.6%, depending on the specification.[37] Hence, this finding lends support to the hypothesized "long-term-commitment channel“. This is also in line with the event study, which provides suggestive evidence

[37] Very similar results, which are reported in appendix D, are obtained by using the inverse hyperbolic sine transformation of the length variable to take into account the large number of zeros.

for a positive effect on productivity not only in the first year of the investment but also some years after the investment starts. Furthermore, regression results based on equation (10) including $Length_{it-1}$ and its square, which will be discussed in the robustness checks, suggest a concave relationship between productivity and the holding period. While productivity increases with length, the marginal effect of increasing the holding period falls with the length of the holding period. This may not be surprising as we expect productivity-enhancing investments to bear fruit within a reasonable number of years. It is important to note that the length variable may be a downward-biased estimate of the actual length of the investment history in the firm because our sample starts only in 2003. However, because of this truncation at the start of the sample period and the associated measurement error, we are likely to underestimate the effect of investment tenure, and the estimates reported in Table 4 likely represent a lower bound on the true effect of investment tenure.

Table 4: Productivity Estimates: Pension Fund Investment Length

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.953***	0.953***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$Length_{it-1}$	0.469**	0.486**	0.414**	0.589***	0.639***	0.527***
	(0.203)	(0.242)	(0.203)	(0.188)	(0.213)	(0.188)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents the results from the estimation of equation (10). $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ are multiplied by 100. The estimated coefficient of $Length_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Length_{it-1}$ includes only the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6, we include a dummy taking value 1 if firm i is an exporter at time $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$ in the sample. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

We further support the hypothesis on the long-term commitment of pension fund investment by including longer lags of the pension fund dummy in our main specification. Table 5 shows that the coefficients estimated on the second, third, and fourth lags are precisely estimated and fairly similar to the coefficient estimated on the first lag. The combination of these results suggests that the beneficial impact of pension fund investment is not only confined to the short term.

Table 5: Productivity Estimates: Pension Fund Dummy (Longer Lags)

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.949***	0.947***	0.945***	0.909***	0.908***	0.908***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)
β_k	0.090***	0.093***	0.095***	0.098***	0.101***	0.104***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.007)
$DPFI_{it-2}$	2.998***			4.025***		
	(1.029)			(1.023)		
$DPFI_{it-3}$		2.767***			3.719***	
		(1.060)			(1.061)	
$DPFI_{it-4}$			2.674**			3.443***
			(1.143)			(1.090)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	No	No	No	No
Export$_{it-1}$	No	No	No	No	No	No
Obs.	84,164	73,666	64,339	39,861	34,684	30,145
Obs. PF	1,947	1,744	1,580	1,947	1,744	1,580
# Firms	12,329	11,073	9,798	5,955	5,256	4,575
# Firms PF	468	411	361	468	411	361

Notes: This table presents the results from the estimation of equation (10). $DPFI$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i. Coefficient estimates and standard errors for $DPFI$ are multiplied by 100. The estimated coefficient of $DPFI$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in the corresponding year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

5.3 Robustness Analysis

In this subsection, we discuss the robustness of our main results. First, we re-estimate our main models on a matched sample obtained using more stringent criteria for identifying non-treated firms. Specifically, we drop firms from the matched control group that have a propensity score below the sector-year-specific 50th percentile in at least one year. Table 6 shows that our main results on the pension investment variables defined in terms of a dummy, intensity and length continue to hold when we use a different threshold for the matching procedure.

Table 6: Productivity Estimates: Matched Sample Using 50th Percentile Threshold

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_l	0.871***	0.871***	0.870***	0.871***	0.871***	0.870***	0.871***	0.871***	0.870***
	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
β_k	0.102***	0.102***	0.101***	0.102***	0.102***	0.101***	0.102***	0.102***	0.101***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$DPFI_{it-1}$	3.017***	3.489***	2.574**						
	(1.152)	(1.201)	(1.148)						
$Intensity_{it-1}$				0.194**	0.197***	0.180**			
				(0.076)	(0.076)	(0.074)			
$Length_{it-1}$							0.366*	0.476**	0.401*
							(0.218)	(0.237)	(0.217)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes	No	No	Yes
Obs.	27,273	27,273	27,273	27,273	27,273	27,273	27,273	27,273	27,273
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	4,170	4,170	4,170	4,170	4,170	4,170	4,170	4,170	4,170
# Firms PF	574	429	574	574	429	574	574	429	574

Notes: This table presents the results from the estimation of equation (10) using a matched sample obtained with a 50th percentile as a threshold. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In column 2, $DPFI_{it-1}$ equals 1 if the aggregate holding of all pension funds in firm i in year $t-1$ was at least equal to 5%. In column 3, we include a dummy equal to 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in year $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Second, we explore whether our results are sensitive to different levels of sectoral classification. In the baseline analysis, we estimate the first stage of the structural estimation approach separately by NACE 1-digit industry, which is a rather aggregated classification. To check whether this level of aggregation affects our main results, we re-estimate the productivity effect of a pension investment at a more granular level (i.e., at the DB07 36-industry group level instead of the NACE 1-digit level). This classification can be seen as an intermediary level between the NACE 1-digit and 2-digit levels. Our baseline results could be affected by the facts that (i) we estimate the first stage across very broadly defined industries and (ii) we therefore allow the constant term in the second stage to vary across broad industry categories that may mask substantial variation existing across more narrowly defined sectors. The next robustness check addresses data limitations concerning firm ownership. Our baseline estimations use a control group based on all firms in Denmark. However, we have ownership data only for firms that are at least partly owned by one other firm or more. Therefore, the set of firms that receive a pension fund investment is a subset of the latter. To verify that our results are not driven by the inclusion of firms for which ownership data are unavailable, we repeat our baseline exercise excluding these firms.

Table 7 presents the results of both of these checks. The left-hand part of the table includes sector-fixed effects at the DB07 36-industry level, while the right-hand part excludes firms without ownership information from the sample.[38] When we use a more granular sector classification, the magnitudes of the coefficients on all pension fund investment variables slightly decrease, while they slightly increase when we include only firms with ownership data. Notwithstanding these small changes, our baseline results are confirmed for both checks.

[38]The specifications of the models estimated for each variant in Table 7 correspond to those in Column 2 in Table 2 and Column 1 in Tables 3 and 4.

Table 7: Productivity Estimates: Alternate Industry Classification and Sample

	36-industry grouping			Excl. firms without ownership data		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.949***	0.949***	0.949***	0.933***	0.933***	0.933***
	(0.520)	(0.515)	(0.518)	(0.562)	(0.562)	(0.560)
β_k	0.087***	0.087***	0.087***	0.093***	0.093***	0.093***
	(0.350)	(0.350)	(0.350)	(0.395)	(0.396)	(0.396)
$DPFI_{it-1}$	3.289***			4.472***		
	(1.131)			(0.992)		
$Intensity_{it-1}$		0.228***			0.269***	
		(0.081)			(0.079)	
$Length_{it-1}$			0.450**			0.639***
			(0.229)			(0.200)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	No	No	No	No
Export$_{it-1}$	No	No	No	No	No	No
Obs.	102,443	102,443	102,443	73,309	73,309	73,309
Obs. PF	2,292	2,292	2,292	2,236	2,236	2,236
# Firms	14,968	14,968	14,968	10,803	10,803	10,803
# Firms PF	574	574	574	564	564	564

Notes: This table presents the results from the estimation of equation (10). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in period $t-1$. $Intensity_{it-1}$ is the aggregate share of firm i (in percent) held by domestic pension funds in year $t-1$. $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $DPFI_{it-1}$, $Length_{it-1}$ and $Intensity_{it-1}$ are multiplied by 100. The coefficient estimates measure the effect of these variables on productivity. Columns 1–3 include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. Columns 4–6 include industry fixed effects at the NACE Rev. 2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

As a fourth robustness check, Appendix C shows that our results and interpretations are largely robust to the use of a gross output–based instead of a value-added–based production function. Even though the coefficients estimated on our pension fund investment variables are generally not precisely estimated, they remain positive and far from zero.

We proceed in this subsection with several additional checks. First, jointly including the investment intensity and its square yields positive coefficients on the linear term that remain significant for the matched sample, but lose significance for the full sample, although their magnitude is not far from their original magnitude (Table D.2, Appendix D). As mentioned in the previous section, jointly including the holding period and its square yields a highly significant positive coefficient on the former and a (highly) significant negative coefficient on the latter (Table D.3, appendix D), providing an indication of a potential nonlinear relationship between productivity and holding period.

Second, we explore whether including co-investments by other parties from the financial sector in our regressions affects our coefficients of interest. There is in fact the concern that, if pension funds invest in a firm always in conjunction with other investors (such as private equity or insurance companies), then it would be misleading to interpret the estimated positive coefficients reported in the previous tables as the effects on productivity exclusively attributable to the presence of pension fund investments in a firm. We therefore augment our baseline specification from Column 2 of Table 2 by adding a dummy that captures investments by any other financial party, and report the results in Table D.4.[39] These additional results allow us to dismiss the concern that the estimated effects reported in the baseline analysis are confounded by the presence of other investors. Table D.4 shows in fact that no matter how we measure the other investor dummy, our central variable capturing pension fund investments remains positive and significant, with a coefficient estimate ranging from 2.1 to 3.4 percent. Very similar results, reported in Appendix D, are obtained when we include the duration of both pension fund investment and other investments.

[39] We construct this additional variable on the basis of the indicated sub-sector of the domestic financial industry. While foreign subsidiaries are included in our sample, we do not have data on the type of foreign investor. However, less than 1 percent of the firms in our sample are foreign-owned.

Table 8: Productivity Estimates: Including Other Investors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
β_l	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
β_k	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$DPFI_{it-1}$	3.283***	3.277***	3.000***	3.363***	3.272***	3.362***	2.815***	3.252***	3.041***	3.352***	2.079*	3.349***	3.356***
	(0.989)	(0.989)	(1.086)	(0.994)	(1.006)	(0.994)	(1.020)	(1.053)	(0.990)	(1.214)	(1.115)	(1.038)	(0.990)
$Other_{it-1}$	0.176	0.192	1.260	-0.005	0.301	-0.003	1.422**	1.346	1.406**	0.030	2.545***	0.151	0.663
	(0.287)	(0.286)	(1.548)	(0.282)	(0.710)	(0.287)	(0.658)	(1.932)	(0.693)	(1.408)	(0.903)	(1.699)	(1.865)
Obs.	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443
Obs. PF	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292
# Firms	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968
# Firms PF	574	574	574	574	574	574	574	574	574	574	574	574	574
Obs. other	40,994	40,852	959	37,207	3,478	35,156	4,219	290	3,622	919	3,441	229	81
# Firms other	7,384	7,367	315	6,893	973	6,582	1,050	136	909	279	923	88	32
Obs. both	2,020	2,008	664	1,659	738	1,524	990	190	627	706	1,234	180	18
# Firms both	540	539	234	478	258	450	312	100	219	216	358	72	7

Notes: This table presents the results from the estimation of equation (10), the baseline variant in Column 2 of Table 2, adding a dummy for domestic investors that are not pension funds. $DPFI_{it-1}$ is a dummy equal to 1 if at least one domestic pension fund invested in firm i in year $t-1$. $Other_{it-1}$ is a dummy equal to 1 if at least one non-pension fund investor from a specific part (as indicated in the following) of the domestic financial industry, according to the 6 digit DB sector classification, invested in firm i in year $t-1$. This dummy takes value 1 as follows. Column 1: any investor from the domestic financial industry, except for pension funds (the *other* investors in all subsequent columns are subsets of this group). Column 2: banking and financing activities, except insurance and pensions. Column 3: banks, savings banks and cooperative banks. Column 4: holding company. Column 5: financial holding company. Column 6: non-financial holding company. Column 7: investment associations, investment companies etc. Column 8: money market associations. Column 9: investment companies. Column 10: venture companies and capital funds. Column 11: other financial intermediaries except insurance and pension insurance. Column 12: insurance companies. Column 13: asset management. Coefficient estimates and standard errors for $DPFI_{it-1}$ and $Other_{it-1}$ are multiplied by 100. The coefficient estimates of $DPFI_{it-1}$ and $Other_{it-1}$ measure their effects on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. The line Obs. other (# Firms other) gives the number of observations (number of firms) with an investment from the indicated part of the financial sector at time $t-1$. The line Obs. both (# Firms both) gives the number of observations (number of firms) with a simultaneous investment by a pension fund and a firm from the indicated part of the financial sector at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

A further related concern with our main specifications is that we do not control for debt financing at the firm level. To address this issue, we incorporate a dummy equal to 1 if the ratio between long-term debt and total assets as a proxy for debt financing is above the median of the distribution. Table 9 demonstrates that including this additional confounding factor in our regressions does not substantially alter the effects of pension fund investments on firms' productivity. The coefficient on the dummy that identifies firms with high long-term debt ratio is consistently estimated to be negative, i.e. highly indebted firms tend to be less productive. We also find that the interaction between the long-term debt ratio and the pension fund dummy is never statistically significant. Although the positive sign suggests that pension fund investment attenuates the negative effect on productivity for financially constrained firms with high levels of debt, thus providing modest evidence in support of the "supply-of-financing" channel.[40]

[40] Similar results, available upon request, are obtained when we use the continuous version of the long-term debt ratio variable instead of the high debt ratio dummy.

Table 9: Productivity Estimates: Including Long-Term Debt

	Whole sample	Matched sample
	(1)	(2)
β_l	0.944***	0.902***
	(0.005)	(0.008)
β_k	0.091***	0.098***
	(0.003)	(0.006)
PFI_{it}	2.288*	3.383***
	(1.268)	(1.190)
$Debtfin_{it}$	-5.324***	-5.548***
	(0.433)	(0.673)
$PFI_{it} \times Debtfin_{it}$	3.028	2.556
	(1.939)	(1.874)
Industry FE	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No
Export_{it-1}	No	No
Obs.	102,443	48,554
Obs. PF	2,292	2,292
# Firms	14,968	7,468
# Firms PF	574	574

Notes: This table presents the results from the estimation of equation (10), the baseline variant in Column 2 of Table 2, adding the variable $Debtfin_{it}$, which is a dummy equal to 1 if the ratio of total long-term debt to total assets for firm i in year $t-1$ is above the 75th percentile of the distribution, and its interaction with $DPFI_{it-1}$, a dummy equal to 1 if at least one domestic pension fund invested in firm i in year $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ and $Debtfin_{it}$ are multiplied by 100. The coefficient estimates for $DPFI_{it-1}$ and $Debtfin_{it}$ measure their effects on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} \ = p < 0.1$, $^{**} \ = p < 0.05$, and $^{***} \ = p < 0.01$.

We now conclude this section with some final checks. First, limiting the definition of pension fund investment to include only direct pension fund investments in a firm reduces precision because the number of firms with a pension fund investment falls substantially (see Tables D.6 and D.6 of Appendix D).[41] Nevertheless, the coefficients of the pension fund dummy and intensity remain positive. It is noteworthy that the aggregate direct stake that domestic pension funds hold is always at least 5% in our sample.

Second, we exclude firms whose outstanding stocks increased in any sample year. A firm that issues extra shares may do this because it perceives productivity-enhancing opportunities regardless of whether a pension fund invests in it, which would complicate our interpretation of the effect of a pension fund investment. However, excluding these firms confirms our baseline results for the investment dummy and intensity, with

[41] Direct pension fund investments are defined as cases where the direct owner is a pension fund. Hence, relative to the baseline analysis, we now exclude indirect pension fund investments in a firm through another company that owns the firm.

positive and highly significant coefficients in all specifications (Tables D.7 and D.8 of Appendix D). The coefficient on investment length remains also positive (Table D.9 of Appendix D). Third, we replace the pension fund investment dummy with the number of pension funds investing in a firm and obtain a positive and highly significant coefficient (Table D.10). Fourth, our results remain unaffected if we approximate the function $h(.)$ in the first-stage equation (7) by a third-degree polynomial in labour, capital, intermediary inputs, average wage, and investment rate (following Fan et al., 2022) (Tables D.14, D.15 and D.16 of Appendix D). Fifth, our main findings are robust to defining capital as the book value of fixed assets instead of the value obtained via the perpetual inventory method as in our baseline results (Tables D.14, D.15 and D.16 of Appendix D).

5.4 Heterogeneity Analysis

We now explore whether the impact of a pension fund investment is heterogeneous across firms.

5.4.1 Listed and Unlisted Firms

One of the strengths of our dataset is that it includes information on pension fund investments for both listed and unlisted firms. In this subsection, we explore whether the effect of a pension fund investment differs between these two categories of firms. We define a firm as listed if it issued an equity instrument listed on the Copenhagen Stock Exchange over the sample period. Furthermore, we apply a business group mapping to expand the group of listed firms as follows. Using the KONC register published by Statistics Denmark, we map firms that belong to the same business group. If one firm in a business group is listed in a given year, we define all firms in the business group as listed in that year. We apply the same logic to our pension fund investment measures. Therefore, if one company in a business group receives a pension fund investment in a given year, we assume that all companies in the business group receive a pension fund investment in that year.[42] The baseline results are robust to using the mapping, hence defining all firms in the group as treated or non-treated.

This mapping addresses the issue that the actual equity instrument is often issued by a headquarters company, for example, a holding company, that has only administrative tasks in the business group. However, this type of firm is not the ideal object for productivity analysis. The drawback of the approach proposed here would be that any analysis of investment intensity would necessitate the additional stronger assumption that the amount invested in one firm in the business group is equivalent for all firms in the business group. A similar argument holds for the investment length. We refrain from making these assumptions and therefore restrict the analysis in this subsection to the pension fund investment dummy variable.

To estimate the effect of listing versus not listing, we modify equation (10) as follows:

$$\begin{aligned}\widehat{h}_{it} =& \alpha + \beta_k k_{it} + \beta_l l_{it} + \rho\left(\widehat{h}_{it-1} - \beta_k k_{it-1} - \beta_l l_{it-1}\right) + \gamma_1 PFI_{it-1}\\ &+ \gamma_2 List_i + \gamma_3 PFI_{it-1} \times List_i + \xi_{it}\end{aligned} \tag{11}$$

[42] To illustrate the mapping with an example, let firms A and B belong to the same business group. Firm A receives a pension fund investment at time $t-1$, while firm B does not. Furthermore, firm B is publicly listed, while firm A is not. In Table 10, both firms A and B are defined as treated and publicly listed, since they belong to the same business group. In our baseline results, only firm A is defined as treated and firm B is in the non-treated group, because we do not use the business group mapping. The number of non-treated firms in a business group with a treated firm is small relative to the total number of non-treated firms and, hence, the former group hardly influences the key statistics of the non-treated group.

where $List_i$ is a dummy equal to 1 if firm i is part of a business group that includes at least one firm listed on the Copenhagen Stock Exchange in at least one year during 2003–2019. Table 10 reports the results from this specification. The positive and significant estimate of γ_2 indicates that listed firms are on average more productive than unlisted firms. The difference is almost 8%, ceteris paribus. Pension fund investment in unlisted firms raises their productivity by 3 - 4% on average, as indicated by the highly significant estimate of γ_1. However, while listed firms overall seem to be more productive, the estimate of the coefficient on the interaction term γ_3 suggests that the pension fund investment effect is negative for listed firms.[43] Therefore, our estimates indicate that unlisted firms benefit more from pension fund investment than do listed firms. This finding is consistent with the hypothesis that pension fund investment raises productivity through the "supply-of-financing channel“. Listed firms typically have easier access to third-party capital compared to unlisted firms. As a result, an investment from a particular investor, such as a pension fund, may have a greater impact on unlisted firms. However, the finding does not exclude the other channels. For example, unlisted, on average smaller, firms may benefit more from engagement with pension funds or long-term financing commitment.

[43] Adding the estimates of γ_1 and γ_3 suggests that pension fund investment in listed firms lowers their productivity by around 3%.

Table 10: Productivity Estimates: Listed vs. Unlisted Firms

	(1)	(2)
β_l	0.951***	0.947***
	(0.005)	(0.005)
β_k	0.084***	0.083***
	(0.003)	(0.003)
$DPFI_{it-1}$	3.869***	3.474***
	(1.151)	(1.140)
$List_i$	7.921***	7.842***
	(1.761)	(1.741)
$DPFI_{it-1} \times \ List_i$	-6.822***	-6.568***
	(2.224)	(2.214)
Industry FE	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No
Export$_{it-1}$	No	Yes
Obs.	102,443	102,443
Obs. PF	2,753	2,753
# Firms	14,968	14,968
# Firms PF	712	712

Notes: This table presents the results from the estimation of equation (11). $DPFI_{it-1}$ is a dummy equal to 1 if at least one domestic pension fund invested in firm i in year $t-1$. $List_i$ is a dummy equal to 1 if firm i was part of a business group including at least one firm listed on the Copenhagen Stock Exchange in at least one sample year. Coefficient estimates and standard errors for $DPFI_{it-1}$, $List_i$ and their interaction term are multiplied by 100. The coefficient estimates on these regressors measure their effect on productivity. All specifications include industry fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 2, we include a dummy equal to 1 if firm i was an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in year $t-1$. Finally, $^{*} \ = p < 0.1$, $^{**} \ = p < 0.05$, and $^{***} \ = p < 0.01$.

5.4.2 Additional Heterogeneity Analysis

We further explore heterogeneity along the following dimensions: firm size, age, and labor productivity. For each of those variables, we construct a dummy indicator. Specifically, the dummy $small_i$ equals 1 if firm i's employment, defined as the number of employees, in its base year is below the sample median employment.[44]

[44] The base year is defined as the first year in which we observe a firm in our sample.

Furthermore, the dummy $young_i$ is 1 if the number of years since firm i was established is below the sample median. Finally, $hlprod_i$ equals 1 if firm i's base year output per worker is above the sample median.[45] We interact each of these dummies with the pension fund investment dummy analogous to equation (11).

Table 11 presents the results. Whereas the age of the firm does not matter for the effect of a pension fund investment, we find evidence that smaller firms benefit more from a pension fund investment. This larger effect for small firms is again consistent with the "supply-of-financing channel", in line with the notion that pension fund investment is relatively more important as a source of funding for small firms, which are also more likely to be non-listed firms and therefore companies with fewer possibilities of turning to alternative financing sources. However, a role for the other channels cannot be excluded. Finally, base year output per worker does not matter for the effect of a pension fund investment. However, it is noteworthy that the coefficient on the pension fund investment variable is still significant after we control for high base year productivity, supporting the notion that the pension fund investment effect that we estimate is not specifically due to the selection of highly productive firms by pension funds when they start their investment. Interestingly, even firms that are more productive at the start of the investment period, benefit on average from the pension fund getting on board.

[45] When we calculate these dummies on the basis of year-specific medians, we obtain similar results, which are available upon request.

Table 11: Productivity Estimates: Heterogeneity Analysis

	Age			Size			$\frac{output}{worker}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_l	0.953***	0.953***	0.950***	0.950***	0.950***	0.948***	0.950***	0.950***	0.948***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
β_k	0.085***	0.085***	0.084***	0.085***	0.085***	0.084***	0.076***	0.076***	0.075***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$DPFI_{it-1}$	5.238***	4.582***	4.610***	2.083**	2.590**	1.718*	3.145***	3.372***	2.822***
	(1.632)	(1.634)	(1.596)	(0.961)	(1.138)	(0.966)	(0.980)	(1.128)	(0.961)
$young_i$	-0.050	-0.084	-0.425						
	(0.398)	(0.397)	(0.390)						
$DPFI_{it-1} \times young_i$	-2.996	-1.765	-2.622						
	(1.826)	(1.893)	(1.804)						
$small_i$				-0.945	-0.914	-0.637			
				(0.576)	(0.576)	(0.577)			
$DPFI_{it-1} \times small_i$				10.052**	8.681**	9.731**			
				(4.085)	(4.310)	(4.101)			
$hlprod_i$							17.980***	17.980***	17.650***
							(0.665)	(0.664)	(0.657)
$DPFI_{it-1} \times hlprod_i$							-1.886	-2.388	-1.673
							(1.904)	(2.058)	(1.893)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968
# Firms PF	574	429	574	574	429	574	574	429	574

Notes: This table presents the results from estimations of a specification analogous to that in (11) using dummies for young firms ($young_i$=1 if firm age in the base year is below the sample median), small firms ($small_i$=1 if firm size in the base year is below the sample median), and labor productivity ($hlprod_i$=1 if labor productivity in the base year is above the sample median). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in year $t-1$. Coefficient estimates and standard errors for all variables except β_k and β_l are multiplied by 100. The coefficient estimates on the other regressors measure their effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2, 5 and 8, $DPFI_{it-1}$ equals 1 if the aggregate holding of all domestic pension funds in firm i in year $t-1$ was at least equal to 5%. In columns 3, 6, and 9, we include a dummy equal to 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

6 Discussion and Conclusion

Among a multitude of potential initiatives to raise productivity, this paper focuses on the role of investments operating through funded pension schemes. In recent decades, funded pension savings have increased significantly across the globe, and countries with high levels of pension savings relative to GDP typically top the international ranking of pension systems. For example, Mercer (2023) ranks pension systems in terms of adequacy, sustainability, and integrity. The three countries with the best-rated pension systems, Iceland, the Netherlands, and Denmark, also have the highest pension assets to GDP ratios among OECD countries (OECD, 2023). However, while pension funds are potential financiers of firms, it is largely an unresolved question whether and to what extent pension fund investments affect firms' productivity. Given the global trend towards more funded pensions, it is becoming increasingly important to understand the impact of such systems on the wider economy.

This paper highlights several possible channels for a positive effect of a pension fund investment on firms' productivity. For example, by channeling savings toward firms, pension funds can raise the supply of capital, thereby reducing its cost and hence stimulating investment by firms. Additionally, pension funds are long-term investors in the sense that they try to match their long-term liabilities with long-term assets. Investment by a pension fund may thus be taken as a long-term financing commitment. Presumably, such "long-termism" could give firms the assurance they need when undertaking investments that raise productivity in the long run rather than focusing on short-term gains. Furthermore, pension funds could play a role in monitoring firm management, although they tend to be less engaged than some types of activist shareholders, such as private equity firms.

Since which firms receive a pension fund investment may not be a random group, it is important to control for selection when estimating the impact of these investments on productivity. We deal with this issue as follows. First, we conduct an event study that made us sufficiently confident that there were no differential pre-trends. We then proceed by implementing a structural estimation approach in which we explicitly control for selection. An added advantage of structural estimation is that it addresses omitted variable bias issues by fully controlling for firms' heterogeneity in terms of past productivity.

We combine high-quality Danish register data with a detailed database on the domestic shareholders of Danish listed and unlisted firms that we constructed. Including unlisted firms, unlike most studies on institutional investors, required a complex mapping exercise and assumptions that we document in detail.

Our estimates suggest a quantitatively significant positive effect of pension fund investment on firm productivity, with an average increase ranging between 3 and 5%. This outcome, achieved despite the complex ownership structure in our database underscores the validity of our hypothesis that pension fund investments indeed influence firm productivity. As explained in the data section, we can extract the ultimate owners of firms only if we make numerous assumptions while inevitably introducing some unintended "measurement error" in how ownership power is distributed. In our opinion, this complexity further corroborates our main hypothesis. In fact, despite these challenges in accurately determining the ultimate owners of firms, the positive impact on productivity is highly robust to a wide range of refinement analysis. It is still present, for example, when we control for whether a firm exports. We also find suggestive evidence that the productivity effect is stronger the larger the pension funds' stake in a firm and the longer pension funds have been investing in a firm. The former result highlights the significance of the "supply-of-financing channel" while the latter emphasizes the "long-term-commitment channel".

Finally, the effects of pension fund investment are larger for unlisted than for publicly listed firms, in line with the notion that listed firms have more alternative sources of financing. This reaffirms the role of the "supply-of-financing channel". It is important to note, however, that we cannot completely rule out that our results are also driven by other channels, such as the "signaling" and "engagement" channels, that may concur simultaneously and complement the two channels highlighted our analysis. For example, by directly engaging with a firm's management, the commitment to long-term financing may increase the success of an investment project.

Our findings provide leads for policies aimed at increasing firms' productivity. On the one hand, this is important in an era where potential GDP growth has gradually fallen over several decades in the industrialized world. This naturally raises the question of how to reverse this development. On the other hand, many emerging and developing countries are facing the dual challenge of fostering economic development while designing sustainable pension systems for a growing population. The challenge of boosting productivity growth becomes even more important given the prospect of aging populations and other contemporary challenges. At the same time, there is a global trend towards more pension funding, increasing the importance of pension funds for the global economy. Against this backdrop, our results at the micro level have the potential to inform policymakers on the macroeconomic implications of funded pension systems and the potential of pension funds to support the real economy.

Specifically, a positive effect of a pension fund investment on productivity supports the introduction or expansion of funded pension schemes, or even motivates the consideration of mandatory participation in such schemes. To the extent that the productivity effect is driven by pension funds' long-term financing commitment, this is an argument for restricting early withdrawal of accumulated pension savings to avoid a danger of premature liquidation of pension investment in firms.[46] Other policies aimed at increasing pension savings and investment could also support domestic productivity. Such policies could rely on tax incentives by, for example, allowing pension contributions to be deducted from taxable income or increasing the maximum deduction limit. Another measure would make the tax rate on capital gain a declining function of the length of the holding period of equities. Although our paper focuses on the impact of pension fund investments, larger equity holdings by other long-term institutional investors, such as insurance companies, may also have a positive effect on firms' productivity. Investigating the impact of these institutional investors on productivity, and how it varies across different types of investors, would be an interesting area for future research.

Our findings may also have consequences for the supervision of institutional investors, particularly pension funds, as well as other investors with long-term liabilities, such as insurance companies. Typically, supervision focuses on the protection of savings held by individual institutions. However, an "excessive" quest for safety at the level of individual institutions may have adverse macroeconomic implications, as it could undermine the availability of long-term financing for firms and the real economy more broadly. On a related point, our finding that the effect of pension fund investment is more pronounced for unlisted than listed firms could be understood as an argument to support more investment by pension funds into unlisted assets and potentially more broadly alternative asset classes. While we do find a positive effect of pension fund investment on productivity, it is important to stress that regulation needs to weigh this against the benefits and the risks for pension savers. Investigation of this trade-off between the risks at the level of individual pension fund participants through fund ownership of firms and the macroeconomic benefits in terms of higher productivity constitutes interesting opportunities for future research.

[46] See Beetsma et al. (2012) on the sustainability of non-mandatory funded pensions and Brown et al. (2022) on take-up trends of retirement income in the U.S.

References

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, *83*(6), 2411–2451 (Go back).

Aghion, P., Bond, S., Klemm, A., & Marinescu, I. (2004). Technology and Financial Structure: Are Innovative Firms Different? *Journal of the European Economic Association*, *2*(2-3), 277–288 (Go back).

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and Institutional Ownership. *American Economic Review*, *103*(1), 277–304 (Go back).

Altiparmakov, N., & Nedeljkovic, M. (2018). Does pension privatization increase economic growth? Evidence from Latin America and Eastern Europe. *Journal of Pension Economics and Finance*, *17*(1), 46–84 (Go back).

Alvarez, R., Jara, M., & Pombo, C. (2018). Do institutional blockholders influence corporate investment? Evidence from emerging markets. *Journal of Corporate Finance*, *53*(September), 38–64 (Go back).

Andonov, A., Kräussl, R., & Rauh, J. (2021). Institutional Investors and Infrastructure Investing. *The Review of Financial Studies*, *34*(8), 3880–3934 (Go back).

Artiga González, T., van Lelyveld, I., & Lučivjanská, K. (2020). Pension fund equity performance: Patience, activity or both? *Journal of Banking & Finance*, *115*, 105812 (Go back).

ATP. (2022). *The ATP Group Annual Report 2022*, ATP Koncernen. (Go back).

Bao, C. G., & Chen, M. X. (2018). Foreign Rivals Are Coming to Town: Responding to the Threat of Foreign Multinational Entry. *American Economic Journal: Applied Economics*, *10*(4), 120–157 (Go back).

Beetsma, R. M., Romp, W. E., & Vos, S. J. (2012). Voluntary participation and intergenerational risk sharing in a funded pension system. *European Economic Review*, *56*(6), 1310–1324 (Go back).

Beyer, A., Larcker, D. F., & Tayan, B. (2014). *2014 Study on how Investment Horizon and Expectations of Shareholder Base Impact Corporate Decision-Making* (tech. rep.). Rock Center for Corporate Governance at Stanford University. (Go back).

Bijlsma, M., Bonekamp, J., van Ewijk, C., & Haaijen, F. (2018). Funded Pensions and Economic Growth. *De Economist*, *166*(3), 337–362 (Go back).

Bircan, Ç. (2019). Ownership Structure and Productivity of Multinationals. *Journal of International Economics*, *116*, 125–143 (Go back).

Bøler, E. A., Moxnes, A., & Ulltveit-Moe, K. H. (2015). R&D, international sourcing, and the joint impact on firm performance. *American Economic Review*, *105*(12), 3704–3739 (Go back).

Braguinsky, S., Ohyama, A., Okazaki, T., & Syverson, C. (2015). Acquisitions, productivity, and profitability: Evidence from the Japanese cotton spinning industry. *American Economic Review*, *105*(7), 2086–2119 (Go back).

Brown, J., Poterba, J., & Richardson, D. (2022). *Trends in Retirement and Retirement Income Choices by TIAA Participants: 2000–2018*, National Bureau of Economic Research. (Go back).

Caggese, A. (2019). Financing constraints, radical versus incremental innovation, and aggregate productivity. *American Economic Journal: Macroeconomics*, *11*(2), 275–309 (Go back).

Cella, C., Ellul, A., & Giannetti, M. (2013). Investors' Horizons and the Amplification of Market Shocks. *Review of Financial Studies*, *26*(7), 1607–1648 (Go back).

Chemmanur, T. J., Krishnan, K., & Nandy, D. K. (2011). How Does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface. *Review of Financial Studies*, *24*(12), 4037–4090 (Go back).

Coricelli, F., Driffield, N., Pal, S., & Roland, I. (2012). When does leverage hurt productivity growth? A firm-level analysis. *Journal of International Money and Finance*, *31*(6), 1674–1694 (Go back).

Cremers, M., & Pareek, A. (2016). Patient capital outperformance: The investment skill of high active share managers who trade infrequently. *Journal of Financial Economics*, *122*(2), 288–306 (Go back).

Danmarks Nationalbank. (2022). DNNKSFK: National accounts by sector, balance sheets, account entry, financial instrument and counterpart sector. (Go back).

Davis, S. J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J., & Miranda, J. (2014). Private equity, jobs, and productivity. *American Economic Review*, *104*(12), 4184–4204 (Go back).

De Loecker, J. (2013). Detecting Learning by Exporting. *American Economic Journal: Microeconomics*, *5*(3), 1–21 (Go back).

de Chaisemartin, C., & D'Haultfoeuille, X. (2022). *Difference-in-Differences Estimators of Intertemporal Treatment Effects*, National Bureau of Economic Research. (Go back).

Della Croce, R., Stewart, F., & Yermo, J. (2011). Promoting Longer-Term Investment by Institutional Investors. *OECD Journal: Financial Market Trends*, *2011*(1), 145–164 (Go back).

Doraszelski, U., & Jaumandreu, J. (2013). R&D and Productivity: Estimating Endogenous Productivity. *The Review of Economic Studies*, *80*(4), 1338–1383 (Go back).

Döring, S., Drobetz, W., El Ghoul, S., Guedhami, O., & Schröder, H. (2021). Institutional investment horizons and firm valuation around the world. *Journal of International Business Studies*, *52*(2), 212–244 (Go back).

Fan, J., Lee, E., & Smeets, V. (2022). High-Skill Immigration, Offshoring R & D, and Firm Dynamics. *CEPR Press Discussion Paper*, *16870*(January) (Go back).

Ferreira, M. A., & Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of Financial Economics*, *88*(3), 499–533 (Go back).

Fons-Rosen, C., Kalemli-Ozcan, S., Sørensen, B. E., Villegas-Sanchez, C., & Volosovych, V. (2021). Quantifying productivity gains from foreign investment. *Journal of International Economics*, *131*, 103456 (Go back).

Fox, J. T., & Smeets, V. (2011). Does Input Quality Drive Measured Differences In Firm Productivity? *International Economic Review*, *52*(4), 961–989 (Go back).

Gandhi, A., Navarro, S., & Rivers, D. A. (2020). On the Identification of Gross Output Production Functions. *Journal of Political Economy*, *128*(8), 2973–3016 (Go back).

Garel, A. (2017). When ownership structure matters: a review of the effects of investor horizon on corporate policies. *Journal of Economic Surveys*, *31*(4), 1062–1094 (Go back).

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277 (Go back).

Harford, J., Kecskés, A., & Mansi, S. (2018). Do long-term investors improve corporate decision making? *Journal of Corporate Finance*, *50*, 424–452 (Go back).

Harrigan, J., Reshef, A., & Toubal, F. (2023). *Techies and Firm Level Productivity* (CESifo Working Paper Series No. 10468). CESifo. (Go back).

Heil, M. (2018). Finance and Productivity: a Literature Review. *Journal of Economic Surveys*, *32*(5), 1355–1383 (Go back).

İmrohoroğlu, A., & Tüzel, Ş. (2014). Firm-Level Productivity, Risk, and Return. *Management Science*, *60*(8), 2073–2090 (Go back).

Jara, M., López-Iturriaga, F., San Martín, P., Saona, P., & Tenderini, G. (2019). Chilean pension fund managers and corporate governance: The impact on corporate debt. *North American Journal of Economics and Finance*, *48*, 321–337 (Go back).

Lerner, J., Sorensen, M., & Strömberg, P. (2011). Private Equity and Long-Run Investment: The Case of Innovation. *The Journal of Finance*, *66*(2), 445–477 (Go back).

Levine, O., & Warusawitharana, M. (2021). Finance and productivity growth: Firm-level evidence. *Journal of Monetary Economics*, *117*, 91–107 (Go back).

Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, *70*, 317–341 (Go back).

Liu, T. (2022). Bargaining with private equity: Implications for hospital prices and patient welfare [false]. *SSRN* (Go back).

Ljungqvist, A., Bircan, C., & Biesinger, M. (2020). *Value Creation in Private Equity* (CEPR Discussion Papers No. 14676). C.E.P.R. Discussion Papers. (Go back).

Maican, F. G., Orth, M., Roberts, M. J., & Vuong, V. A. (2022). The Dynamic Impact of Exporting on Firm R&D Investment. *Journal of the European Economic Association*, *21*(4), 1318–1362 (Go back).

Mercer. (2023). *Mercer CFA Institute Global Pension Index 2023* (tech. rep.). (Go back).

OECD. (2019). *Annual Survey of Large Pension Funds and Public Pension Reserve Funds: Report on pension funds' long-term investments* (tech. rep.). (Go back).

OECD. (2023). *Pension Markets In Focus 2022* (tech. rep.). (Go back).

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, *64*(6), 1263–1297 (Go back).

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187–204 (Go back).

Parrotta, P., & Pozzoli, D. (2012). The effect of learning by hiring on productivity. *The RAND Journal of Economics*, *43*(1), 167–185 (Go back).

Parrotta, P., Pozzoli, D., & Pytlikova, M. (2014). Labor diversity and firm productivity. *European Economic Review*, *66*, 144–179 (Go back).

Pinkus, D., Pozzoli, D., & Schneider, C. (2023). *Pension Fund Investment and Firm Innovation*, Copenhagen Business School. (Go back).

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199 (Go back).

Virk. (2022). CVR - Det Centrale Virksomhedsregister. (Go back).

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, *104*(3), 112–114 (Go back).

Zandberg, E., & Spierdijk, L. (2013). Funding of pensions and economic growth: are they really related? *Journal of Pension Economics and Finance*, *12*(2), 151–167 (Go back).

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^{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^{th}, we

record the relationship as having concluded in the preceding calendar year. The selection of November 15^{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.[47] This methodology is exemplified by Firm A in Table A1, 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.

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

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

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 before 2015 report only Firm B as an 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 on 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 retained if no earlier data deliveries included details on the owners of the specific owned firm (firm A in the example of Table A.1). 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.

A.2.1 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.[48]

[48] 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.

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

A.2.2 Intermediate Owners

When iterating through the various levels of ownership, it is crucial to consider the role of intermediary firms. As illustrated in Table A3, 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 A3, 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 A3 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 A3, 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 $0.2 \times (1 - 0.3) = 0.14$. This can be conceptualized as the portion of Company A that Company G effectively "controls." Absent this modification, the final data would inaccurately depict Firm G as owning 20% of Firm A, while Firm H would be shown as owning an additional 0.06% of Firm A, thereby erroneously double counting the stake held by Firm H. This stake adjustment is performed after all layers of ownership have been fully iterated.

Table A3: 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

A.2.3 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 A4 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 A4: 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

A.2.4 Duplicates

In the example presented in Table A5, 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 is 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 A5: Duplicate Owners Example

First round of iteration:					Second round of iteration:				
Owner	Owned	Year	Stake	Level	Owner	Owned	Year	Stake	Level
B	A	2010	33	1	B	E	2010	33	2
C	A	2010	33	1	C	E	2010	33	2
D	A	2010	33	1	D	E	2010	33	2
E	A	2010	100	1					

Final Data:

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

A.3 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 Statistics

Table B.1: Investment Length: Pension Funds and Other Investors

Investor sector	N	Mean $Length_{it-1}$	Difference	Difference p-value
Panel A				
Pension funds	2,292	4.16	.	.
Banks, savings banks and cooperative banks	959	3.26	0.89	0.00
Financial holding companies	3,478	3.53	0.63	0.00
Non-financial holding companies	35,156	4.82	-0.67	0.00
Investment associations	290	1.91	2.25	0.00
Investment companies	3,622	4.10	0.05	0.54
Venture companies and capital funds	919	3.27	0.88	0.00
Other financial intermediation except insurance and pension insurance	3,441	3.73	0.43	0.00
Asset management	81	3.22	0.93	0.01
Insurance companies	229	2.76	1.39	0.00
Panel B				
Pension funds	347	4.41	.	.
Banks, savings banks and cooperative banks	219	3.36	1.06	0.00
Financial holding companies	527	2.94	1.47	0.00
Non-financial holding companies	2,098	3.99	0.42	0.03
Investment associations	103	2.26	2.15	0.00
Investment companies	521	3.54	0.87	0.00
Venture companies and capital funds	164	3.85	0.56	0.06
Other financial intermediation except insurance and pension insurance	529	3.32	1.09	0.00
Asset management	13	1.92	2.49	0.01
Insurance companies	79	2.32	2.10	0.00

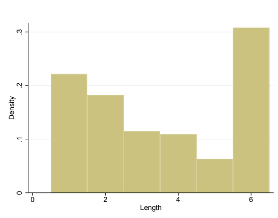
Notes: This table shows the average value of our treatment variable measuring investment length, $Length_{it-1}$, for the six-digit investor sectors included in Table D.4 and insurance companies (three-digit sector), as well as pension funds. The table also includes the difference in means of the length variable between pension funds and each investor sector as well as the p-value of the t-test for the difference. All results are conditional on at least one investor of the sector investing in firm i at time $t-1$. In panel A, all such observations are considered. In panel B, we additionally condition on observing active divestment of the sector, so on at least one investor of the sector investing in firm i at time $t-1$ and no investment by the investor sector in company i in period t.

Table B.2: Number of Firms per NACE Rev.2 1-Digit Sector

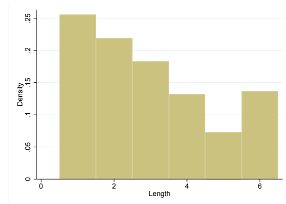
Sector	**Firms with PFI**	**Firms without PFI**
Manufacturing	283	3,391
Construction	37	2,383
Wholesale and retail trade; repair of motor vehicles and motorcycles	87	4,374
Transportation and storage	28	1,154
Information and communication	73	707
Real estate activities	12	219
Professional, scientific and technical activities	34	1,345
Administrative and support service activities	20	821
Total	**574**	**14,394**

Notes: This table illustrates the sector distribution among firms in the sample. Since a firm is treated if it received a pension fund investment in the previous year, this table splits the sample into firms that are treated at least once over the sample period (left column) and firms that are never treated (right column). PFI denotes pension fund investment.

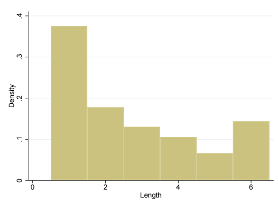
Figure B.1: Distribution of the Investment Length



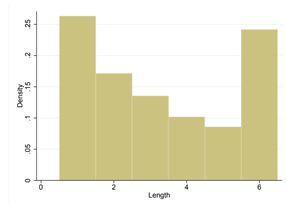
(a) Pension Funds



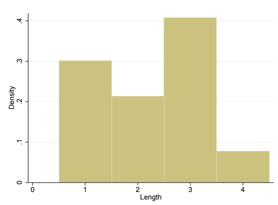
(b) Banks, savings banks and cooperative banks



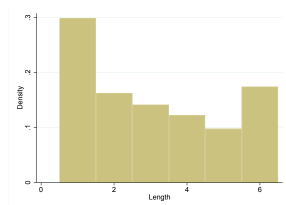
(c) Financial holding companies



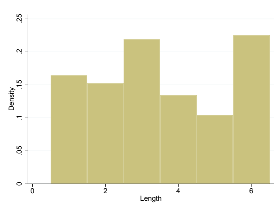
(d) Non-financial holding companies



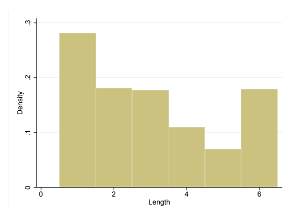
(e) Investment associations



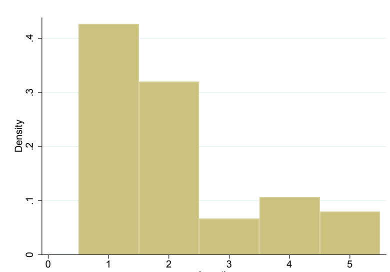
(f) Investment companies



(g) Venture companies and capital funds



(h) Other financial intermediation except insurance and pension insurance



(i) Insurance companies

Note: The figure shows the distribution of the length variable for different types of investor. The length variable is calculated as the number of continuous years of investment by a given investor type up until the year in which we observe the divestment (see restrictions set in panel B of Table B.1. Note that all lengths longer than 6 are collapsed into the category 6 and that the number of data points for each bin is set to be larger than 5 to comply with the data security rules set by Statistics Denmark. Lastly, the asset management sector is excluded from this figure (contrary to Table B.1) due to a very low number of observations.

Table B.3: Descriptive Statistics Matching Variables

		Firms with PFI	Firms without PFI	Firms without PFI (matched sample)
Value added	(DKK,log)	11.178	9.941	10.487
		(1.262)	(1.085)	(1.006)
Capital	fixed assets (DKK, log)	10.402	8.817	9.459
		(1.899)	(1.725)	(1.626)
Labour	number of full-time employees (log)	4.720	3.651	4.142
		(1.166)	(0.952)	(0.926)
Listed	1, if listed firm	0.326	0.012	0.019
		(0.469)	(0.110)	(0.135)
Observations		7,099	116,117	51,366

Notes: This table reports the main descriptive statistics of the variables included in the specification of the propensity score. Note that the sample used in the matching procedure coincides with the sample used in the first stage of the structural estimation approach described in 4.2.

Appendix C Gross Output Production Function

In our main specifications, we use a value-added production function. An alternative approach is to model the production function with a gross output production function. The main difference is that in a gross output production function, intermediate inputs enter the right-hand side of the production function. Formally, the production function in logs is:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{C.1}$$

and the second-stage equation, analogous to equation (10), is:

$$\begin{aligned} \widehat{h}_{it} =& \alpha + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} \\ &+ \rho \left(\widehat{h}_{it-1} - \beta_k k_{it-1} - \beta_l l_{it-1} - \beta_m m_{it-1} \right) + \gamma PFI_{it-1} + \xi_{it} \end{aligned} \tag{C.2}$$

where all variables are defined as in the main text. Ackerberg et al. (2015) conclude that the lagged value of intermediate inputs m_{it-1} is not a suitable instrument for the input m_{it} in the context of gross output production functions; therefore, the parameter β_m cannot be estimated as in our main approach. To address this, we exploit the firms' first-order condition for intermediate inputs following (Gandhi et al., 2020) and Fan et al. (2022). In particular, Fan et al. (2022) show that the following condition holds:

$$\frac{P_{mt} \times \exp(m_{it})}{\exp(y_{it})} \times \exp(\tilde{\varepsilon}_{it}) = \widehat{\beta}_m \tag{C.3}$$

where P_{mt} is the price of material inputs and $\tilde{\varepsilon}_{it}$ is the estimated residual from the first stage of the estimation procedure. The first term on the left-hand side of equation (C.3) is the share of intermediate inputs in revenue (output) of the firm. With that share readable from the data and $\tilde{\varepsilon}_{it}$ in hand from the first-stage estimation, we follow Fan et al. (2022) and estimate the $\widehat{\beta_m}$ equation (C.3) by the method of moments, assuming that

$\exp(\tilde{\varepsilon}_{it})$ has a mean of 1. We then plug $\widehat{\beta_m}$ into equation (C.2) and estimate all other parameters via GMM as in our baseline approach. Tables C.1–4 are the counterparts to Tables 2–4, which display the main results using a gross output production function. This alternative specification confirms our results regarding the dummy and the investment length. However, contrary to our baseline results, the coefficient of the investment intensity variable is no longer statistically significant. Therefore, using a gross output production function, the amount that pension funds invest does not seem to have a significant impact on firm productivity. The amount invested, however, is a noisy measure, and we are able to confirm our baseline results for two out of the three dimensions of pension fund investment that we investigate.

Table C.1: Productivity Estimates: Pension Fund Dummy, Gross Output Production Function

	Whole sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_l	0.414***	0.414***	0.413***	0.413***	0.400***	0.399***	0.399***	0.399***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
β_k	0.030***	0.030***	0.030***	0.030***	0.033***	0.032***	0.032***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
β_m	0.605***	0.605***	0.605***	0.605***	0.618***	0.618***	0.618***	0.618***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$DPFI_{it-1}$		2.111*	3.490**	1.990		2.054	3.493**	1.966
		(1.226)	(1.493)	(1.225)		(1.307)	(1.622)	(1.305)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	Yes	No	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes	No	No	No	Yes
Obs.	102,443	102,443	102,443	102,443	48,554	48,554	48,554	48,554
Obs. PF	2,203	2,292	1,730	2,292	2,203	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	14,968	7,468	7,468	7,468	7,468
# Firms PF	570	574	429	574	570	574	429	574

Notes: This table presents the results from the estimation of equation (C.2). $DPFI_{it-1}$ is a dummy equal to 1 if at least one domestic pension fund invested in firm i in year $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 3 and 7, $DPFI_{it-1}$ equals 1 if the aggregate holding of all domestic pension funds in firm i in year $t-1$ was at least equal to 5%. In columns 4 and 8, we include a dummy equal to 1 if firm i is exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.2: Productivity Estimates: Pension Fund Investment Intensity, Gross Output Production Function

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.414***	0.414***	0.413***	0.400***	0.400***	0.399***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.030***	0.030***	0.030***	0.033***	0.033***	0.032***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
β_m	0.605***	0.605***	0.605***	0.618***	0.618***	0.618***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Intensity_{it-1}$	0.061	0.064	0.057	0.052	0.056	0.049
	(0.084)	(0.084)	(0.082)	(0.099)	(0.099)	(0.098)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents the results from the estimation of equation (C.2). $Intensity_{it-1}$ is the aggregate share of firm i (in percent) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. The estimated coefficient of $Intensity_{it-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Intensity_{it-1}$ equals 0 if the aggregate holding of all domestic pension funds in firm i in year $t-1$ is less than 5%. In columns 3 and 6, we include a dummy equal to 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

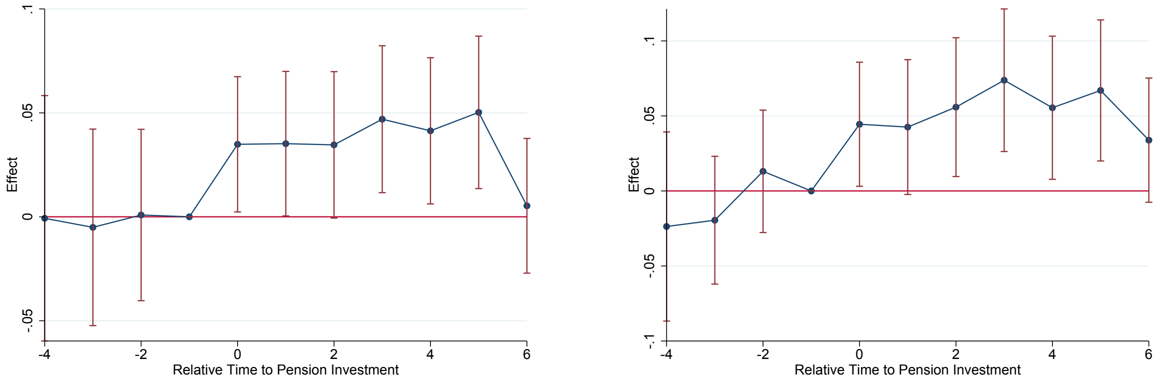
Table C.3: Productivity Estimates: Pension Fund Investment Length, Gross Output Production Function

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.414***	0.414***	0.413***	0.400***	0.399***	0.399***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.030***	0.030***	0.030***	0.032***	0.032***	0.032***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
β_m	0.605***	0.605***	0.605***	0.618***	0.618***	0.618***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Length_{it-1}$	0.326	0.522*	0.309	0.264	0.467	0.250
	(0.248)	(0.305)	(0.248)	(0.252)	(0.335)	(0.252)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents results from the estimation of equation (C.2). $Length_{it-1}$ is the number of consecutive years that firm i received an investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ are multiplied by 100. The estimated coefficient of $Length_{it-1}$ measures its effect on productivity. All specifications include industry fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Length_{it-1}$ includes only the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6, we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Appendix D Additional Results

Figure D.1: Event Study Results, Matched Sample

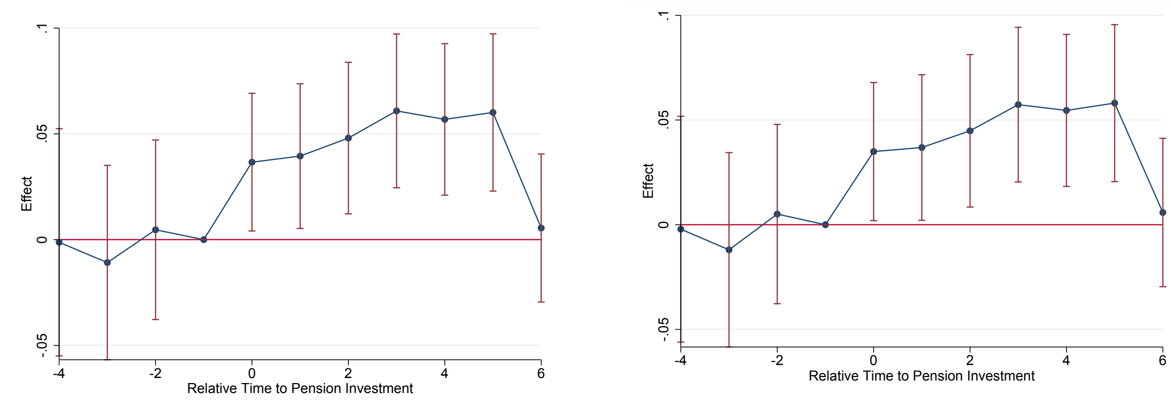


(a) Output per Worker

(b) Value added per Worker

Notes: Results obtained with the matched sample. The outcome variable is output or value-added per worker. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.2: Event Study Results, Alternative Measure of Output

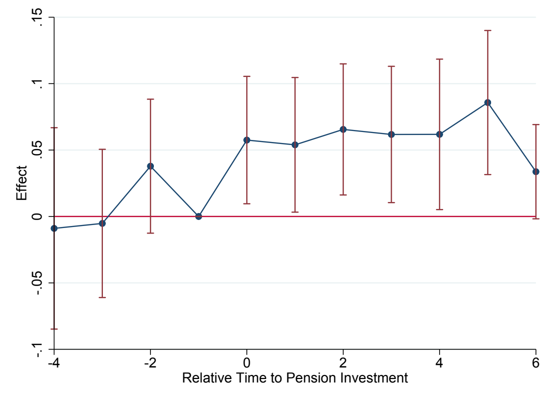


(a) Output per Worker (alt. def.)

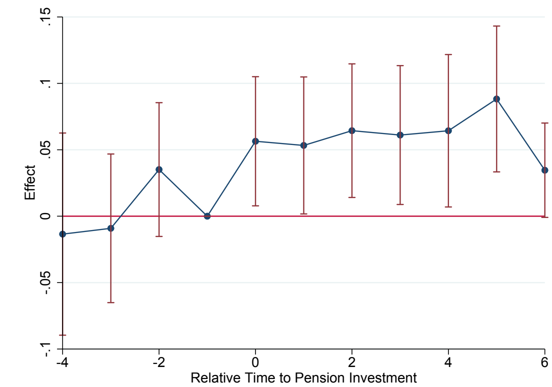
(b) Output per Worker (alt. def.) and Matched Sample

Notes: The outcome variable is output per worker where output is defined as the sum of sales, work carried out at own expense and listed under assets, other operating income, and inventory changes. Results in the second panel obtained with the matched sample. The sample considers 594 distinct events of treatment. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.3: Event Study Results, Specification without Control Variables



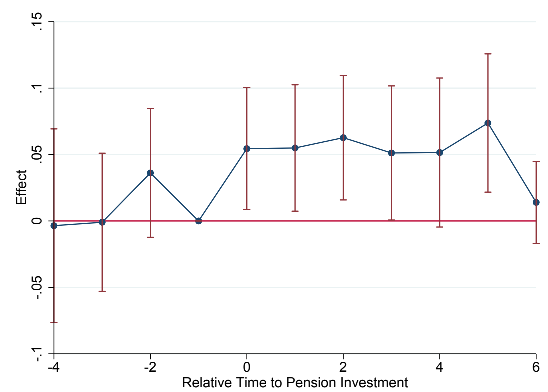
(a) Value-added per Worker



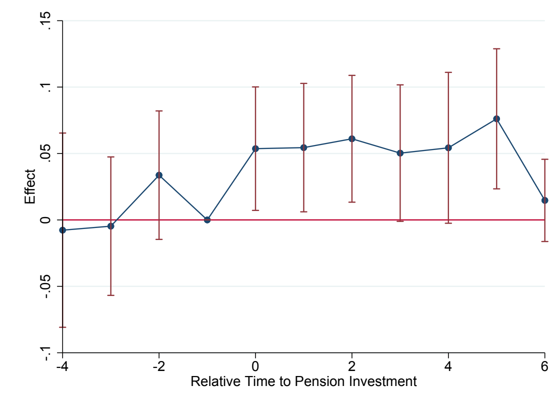
(b) Value-added per Worker and Matched Sample

Notes: The outcome variable is value-added per worker. Results in the second panel obtained with the matched sample. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. We only include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.4: Event Study Results, Controlling for the Share of R&D Workers



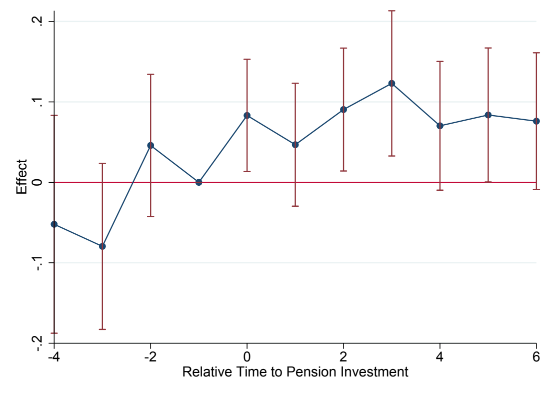
(a) Value-added per Worker



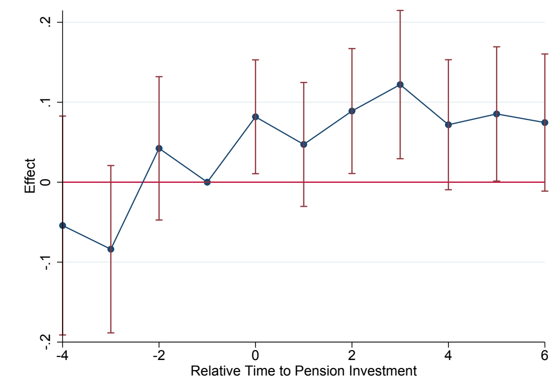
(b) Value-added per Worker and Matched Sample

Notes: The outcome variable is value-added per worker. Results in the second panel obtained with the matched sample. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. We add to the control variables the share of R&D workers. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.5: Event Study Results, Excl. Multiple Investments



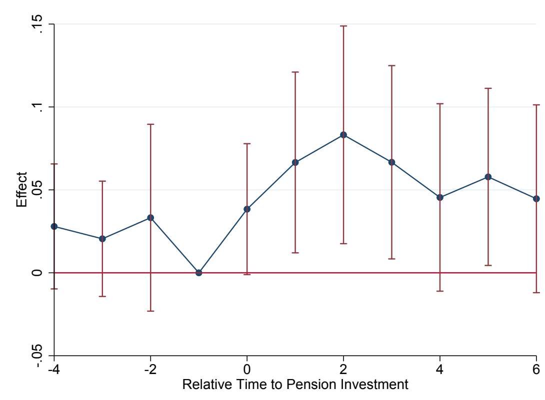
(a) Value added per Worker



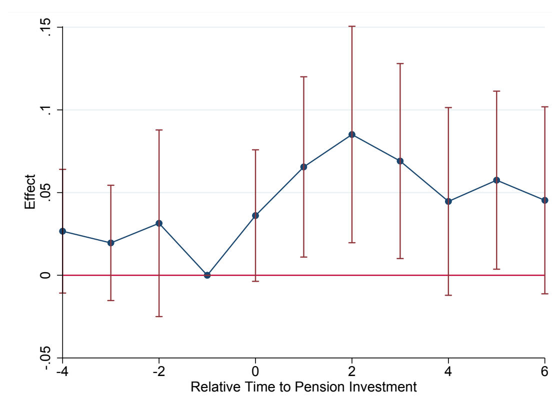
(b) Value added per Worker and Matched Sample

Notes: The outcome variable is value-added per worker. Results in the second panel obtained with the matched sample. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). We focus on events in which only one pension fund invests in a given firm over the sample period. The sample considers 407 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.6: Event Study Results, Excl. Short Investments



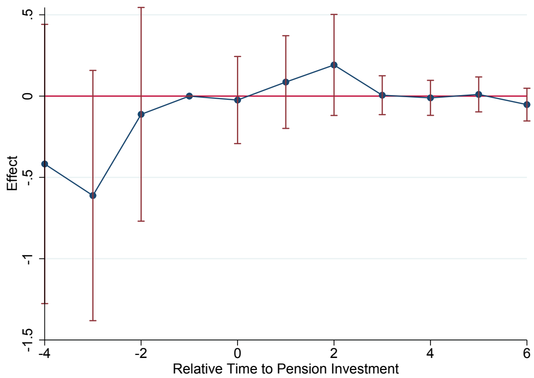
(a) Value added per Worker



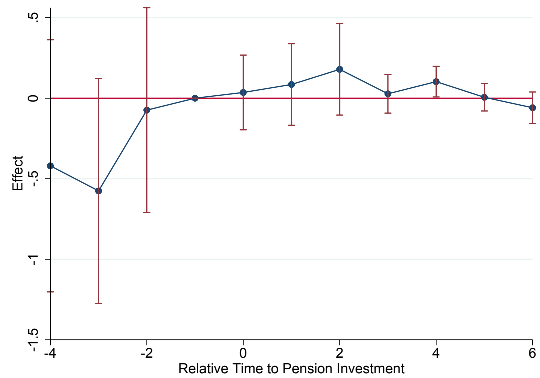
(b) Value-added per Worker and Matched Sample

Notes: The outcome variable is value-added per worker. Results in the second panel obtained with the matched sample. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). We exclude pension fund investments that last for fewer than 5 consecutive years. The sample considers 424 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.7: Event Study Results, Output Price



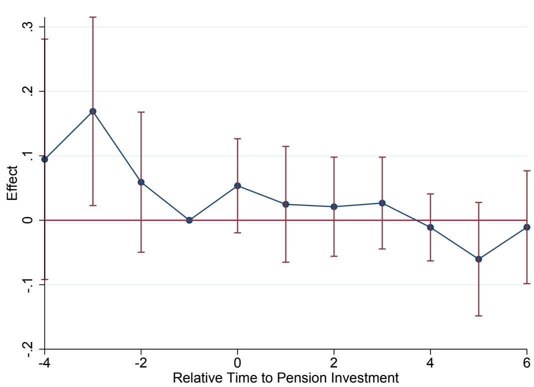
(a) Av. Output Price



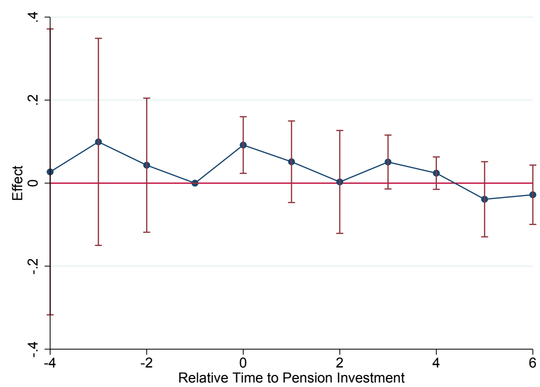
(b) Median Output Price

Notes: In the first panel, the outcome variable is the log of the average price of a firm's product(s) in a given year. In the second panel, the outcome variable is the log of the median price of a firm's product(s) in a given year. Output product prices at the firm-level are collected for a representative sample of manufacturing firms from VARS. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Figure D.8: Event Study Results, Input values



(a) Av. Input values



(b) Median Input values

Notes: In the first panel, the outcome variable is the log of the average value of a firm's purchased product(s) in a given year. In the second panel, the outcome variable is the log of the median value of a firm's product(s) in a given year. Input product prices at the firm-level are collected for a representative sample of manufacturing firms from VARK. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). The sample considers 594 distinct events of treatment. The following controls enter the specification: firm age, a dummy for the firm being listed in the base year, firm size (number of employees), and capital intensity. We also include year-by-industry (NACE Rev.2 1-digit) fixed effects.

Table D.1: Productivity Estimates: Pension Fund Investment Intensity and Length (IHS transformation)

	(1)	(2)
β_l	0.953***	0.953***
	(0.005)	(0.005)
β_k	0.085***	0.085***
	(0.003)	(0.003)
$Length_{it-1}$	1.521***	
	(0.535)	
$Intensity_{it-1}$		1.150***
		(0.363)
Industry FE	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No
Export$_{it-1}$	No	No
Obs.	102,443	102,443
Obs. PF	2,292	2,292
# Firms	14,968	14,968
# Firms PF	574	574

Notes: This table presents results from the estimation of equation (10). $Intensity_{it-1}$ is the inverse hyperbolic sine function of the aggregate share of firm i (in percent) held by domestic pension funds in year $t-1$. $Length_{it-1}$ is the inverse hyperbolic sine function of the duration of the pension investment for firm i in year $t-1$. Coefficient estimates and standard errors are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table D.2: Including Investment Intensity and Intensity Squared

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.953***	0.953***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$Intensity_{it-1}$	0.190	0.188	0.144	0.278**	0.276**	0.231*
	(0.143)	(0.144)	(0.142)	(0.131)	(0.131)	(0.130)
$Intensity^2_{it-1}$	0.001	0.001	0.001	-0.001	-0.001	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents results from the estimation of equation (10) including $Intensity_{it-1}$ and $Intensity^2_{it-1}$. $Intensity_{it-1}$ is the aggregate share of firm i (in percentage points) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ and $Intensity^2_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter at time $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table D.3: Including Investment Length and Length Squared

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.953***	0.953***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$Length_{it-1}$	1.197***	1.199***	1.018**	1.583***	1.666***	1.398***
	(0.399)	(0.452)	(0.396)	(0.396)	(0.426)	(0.398)
$Length^2_{it-1}$	-0.081**	-0.079*	-0.067*	-0.109***	-0.114***	-0.096***
	(0.035)	(0.041)	(0.035)	(0.036)	(0.039)	(0.036)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	2,292	1,730	2,292	2,292	1,730	2,292
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	574	429	574	574	429	574

Notes: This table presents results from the estimation of equation (10) including $Length_{it-1}$ and $Length^2_{it-1}$. $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ and $Length^2_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In columns 2 and 5, $Length_{it-1}$ only includes the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter at time $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table D.4: Productivity Estimates: Including Other Investors (Length)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
β_l	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***	0.953***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
β_k	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***	0.085***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$Length_{it-1}$	0.467**	0.466**	0.397*	0.476**	0.461**	0.476**	0.397*	0.456**	0.431**	0.426*	0.341	0.473**	0.469**
	(0.203)	(0.203)	(0.205)	(0.203)	(0.204)	(0.203)	(0.211)	(0.206)	(0.206)	(0.235)	(0.209)	(0.209)	(0.203)
$Length_{Oit-1}$	0.003	0.006	0.416	-0.022	0.064	-0.026	0.230*	0.963	0.217	0.229	0.469**	-0.111	0.043
	(0.041)	(0.041)	(0.333)	(0.043)	(0.162)	(0.044)	(0.125)	(0.755)	(0.136)	(0.334)	(0.194)	(0.453)	(0.462)
Obs.	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443	102,443
Obs. PF	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292	2,292
# Firms	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968	14,968
# Firms PF	574	574	574	574	574	574	574	574	574	574	574	574	574
Obs. other	40,994	40,852	959	37,207	3,478	35,156	4,219	290	3,622	919	3,441	229	81
# Firms other	7,384	7,367	315	6,893	973	6,582	1,050	136	909	279	923	88	32
Obs. both	2,020	2,008	664	1,659	738	1,524	990	190	627	706	1,234	180	18
# Firms both	540	539	234	478	258	450	312	100	219	216	358	72	-

Notes: This table presents the results from the estimation of equation (10), the baseline variant in Column 2 of Table 4, adding the length of investment for domestic investors that are not pension funds. $Length_{Oit-1}$ is the number of consecutive years that firm i received investment from other investors up to year $t-1$ included. Other investors are classified as follows. Column 1: any investor from the domestic financial industry, except for pension funds (the *other* investors in all subsequent columns are subsets of this group). Column 2: banking and financing activities, except insurance and pensions. Column 3: banks, savings banks and cooperative banks. Column 4: holding company. Column 5: financial holding company. Column 6: non-financial holding company. Column 7: investment associations, investment companies etc. Column 8: money market associations. Column 9: investment companies. Column 10: venture companies and capital funds. Column 11: other financial intermediaries except insurance and pension insurance. Column 12: insurance companies. Column 13: asset management. Coefficient estimates and standard errors for $Length_{it-1}$ and $Length_{Oit-1}$ are multiplied by 100. The coefficient estimate of $Length_{it-1}$ and $Length_{Oit-1}$ measures its effect on productivity. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table D.5: Pension Fund Dummy Results, Direct Investments Only

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.954***	0.954***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$DPFI_{it-1}$	1.565	1.565	1.411	3.356	3.356	3.080
	(2.785)	(2.785)	(2.823)	(2.438)	(2.438)	(2.481)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	311	311	311	311	311	311
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	52	52	52	52	52	52

Notes: This table presents results from the estimation of equation (10). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund directly invested, meaning not through other firms or subsidiaries, in firm i at time $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5 $DPFI_{it-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ was at least equal to 5%. In columns 3 and 6, we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.6: Pension Fund Investment Intensity Results, Direct Investments Only

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.954***	0.954***	0.950***	0.911***	0.911***	0.909***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.085***	0.085***	0.084***	0.092***	0.092***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
$Intensity_{it-1}$	0.148	0.148	0.156	0.157	0.157	0.162
	(0.163)	(0.163)	(0.160)	(0.185)	(0.185)	(0.179)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export_{it-1}	No	No	Yes	No	No	Yes
Obs.	102,443	102,443	102,443	48,554	48,554	48,554
Obs. PF	311	311	311	311	311	311
# Firms	14,968	14,968	14,968	7,468	7,468	7,468
# Firms PF	52	52	52	52	52	52

Notes: This table presents results from the estimation of equation (10). $Intensity_{it-1}$ is the aggregate share of firm i (in percentage points) held directly, meaning not through other firms or subsidiaries, by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. All specifications include industry fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.7: Pension Fund Dummy Results, Excluding Firms with Capital Increases

	Whole sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_l	0.966***	0.965***	0.965***	0.962***	0.907***	0.906***	0.906***	0.904***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)	(0.010)
β_k	0.081***	0.081***	0.081***	0.080***	0.095***	0.095***	0.095***	0.093***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
$DPFI_{it-1}$		4.157***	3.834***	3.855***		4.775***	4.602***	4.478***
		(1.434)	(1.472)	(1.423)		(1.426)	(1.466)	(1.414)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	Yes	No	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes	No	No	No	Yes
Obs.	73,375	73,375	73,375	73,375	32,495	32,495	32,495	32,495
Obs. PF	1,185	1,185	903	1,185	1,185	1,185	903	1,185
# Firms	11,752	11,752	11,752	11,752	5,662	5,662	5,662	5,662
# Firms PF	336	336	250	336	336	336	250	336

Notes: This table presents results from the estimation of equation (10). We exclude firms that increase their number of stocks (Selbskabskapital) in any year over the sample period. $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i at time $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 3 and 7, $DPFI_{it-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ was at least equal to 5%. In columns 4 and 8 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8: Pension Fund Investment Intensity Results, Excluding Firms with Capital Increases

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.965***	0.965***	0.962***	0.906***	0.906***	0.904***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
β_k	0.081***	0.081***	0.080***	0.095***	0.095***	0.093***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
$Intensity_{it-1}$	0.296**	0.295**	0.294**	0.303**	0.301**	0.301**
	(0.127)	(0.127)	(0.121)	(0.141)	(0.140)	(0.134)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	73,375	73,375	73,375	32,495	32,495	32,495
Obs. PF	1,185	903	1,185	1,185	903	1,185
# Firms	11,752	11,752	11,752	5,662	5,662	5,662
# Firms PF	336	250	336	336	250	336

Notes: This table presents results from the estimation of equation (10). We exclude firms that increase their number of stocks (Selbskabskapital) in any year over the sample period. $Intensity_{it-1}$ is the aggregate share of firm i (in percentage points) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5 $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.9: Pension Fund Investment Length Results, Excluding Firms with Capital Increases

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.966***	0.966***	0.962***	0.907***	0.907***	0.904***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
β_k	0.081***	0.081***	0.080***	0.095***	0.095***	0.093***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
$Length_{it-1}$	0.385	0.285	0.347	0.421	0.355	0.382
	(0.291)	(0.302)	(0.288)	(0.300)	(0.317)	(0.301)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	73,375	73,375	73,375	32,495	32,495	32,495
Obs. PF	1,185	903	1,185	1,185	903	1,185
# Firms	11,752	11,752	11,752	5,662	5,662	5,662
# Firms PF	336	250	336	336	250	336

Notes: This table presents results from the estimation of equation (10). We exclude firms that increase their number of stocks (Selbskabskapital) in any year over the sample period. $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Length_{it-1}$ only includes the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.10: Number of Pension Funds

	Whole sample		Matched sample	
	(1)	(2)	(3)	(4)
β_l	0.953***	0.950***	0.911***	0.909***
	(0.005)	(0.005)	(0.008)	(0.008)
β_k	0.085***	0.084***	0.092***	0.091***
	(0.003)	(0.003)	(0.005)	(0.005)
NPF_{it-1}	1.505***	1.307***	1.712***	1.511***
	(0.443)	(0.440)	(0.409)	(0.409)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	No	No
Export$_{it-1}$	No	Yes	No	Yes
Obs.	102,443	102,443	48,554	48,554
Obs. PF	2,292	2,292	2,292	2,292
# Firms	14,968	14,968	7,468	7,468
# Firms PF	574	574	574	574

Notes: This table presents results from the estimation of equation (10). NPF_{it-1} is the number of domestic pension funds that invested in firm i at time $t-1$. Coefficient estimates and standard errors for NPF_{it-1} are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 4 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.11: Pension Fund Dummy Results, Alternative First-Stage Polynomial

	Whole sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_l	0.957***	0.955***	0.955***	0.949***	0.920***	0.918***	0.918***	0.914***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
β_k	0.088***	0.088***	0.088***	0.085***	0.093***	0.093***	0.093***	0.091***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
$DPFI_{it-1}$		6.082***	6.761***	5.231***		7.627***	8.508***	6.759***
		(1.532)	(1.764)	(1.536)		(1.412)	(1.691)	(1.419)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	Yes	No	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes	No	No	No	Yes
Obs.	101,034	101,034	101,034	101,034	48,090	48,090	48,090	48,090
Obs. PF	2,278	2,278	1,720	2,278	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	14,833	7,404	7,404	7,404	7,404
# Firms PF	568	568	427	568	568	568	427	568

Notes: This table presents results from the estimation of equation (10) after approximating the function $h(.)$ in the first stage equation (7) by a third-degree polynomial in labour, capital, intermediary inputs, average wage and the investment rate (following Fan et al. (2022)). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i at time $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 3-4 and 7-8 $DPFI_{it-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ was at least equal to 5%. In columns 4 and 8 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.12: Pension Fund Investment Intensity Results, Alternative First Stage Polynomial

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.955***	0.955***	0.949***	0.918***	0.918***	0.914***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.088***	0.088***	0.086***	0.093***	0.093***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
$Intensity_{it-1}$	0.504***	0.501***	0.478***	0.540***	0.537***	0.513***
	(0.097)	(0.098)	(0.103)	(0.099)	(0.099)	(0.103)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export_{it-1}	No	No	Yes	No	No	Yes
Obs.	101,034	101,034	101,034	48,090	48,090	48,090
Obs. PF	2,278	1,720	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	7,404	7,404	7,404
# Firms PF	568	427	568	568	427	568

Notes: This table presents results from the estimation of equation (10) after approximating the function $h(.)$ in the first stage equation (7) by a third-degree polynomial in labour, capital, intermediary inputs, average wage and the investment rate (following Fan et al. (2022)). $Intensity_{it-1}$ is the aggregate share of firm i (in percentage points) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.13: Pension Fund Investment Length Results, Alternative First Stage Polynomial

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.955***	0.955***	0.949***	0.918***	0.918***	0.914***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
β_k	0.088***	0.088***	0.085***	0.093***	0.093***	0.091***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
$Length_{it-1}$	1.273***	1.412***	1.155***	1.515***	1.703***	1.389***
	(0.319)	(0.389)	(0.320)	(0.315)	(0.388)	(0.315)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export_{it-1}	No	No	Yes	No	No	Yes
Obs.	101,034	101,034	101,034	48,090	48,090	48,090
Obs. PF	2,278	1,720	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	7,404	7,404	7,404
# Firms PF	568	427	568	568	427	568

Notes: This table presents results from the estimation of equation (10) after approximating the function $h(.)$ in the first stage equation (7) by a third-degree polynomial in labour, capital, intermediary inputs, average wage and the investment rate (following Fan et al. (2022)). $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Length_{it-1}$ only includes the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.14: Pension Fund Dummy Results, Alternative Definition of Capital

	Whole sample				Matched sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_l	0.990***	0.989***	0.989***	0.985***	0.952***	0.951***	0.951***	0.948***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
β_k	0.053***	0.053***	0.053***	0.053***	0.054***	0.054***	0.054***	0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$DPFI_{it-1}$		3.749***	3.999***	3.327***		5.065***	5.488***	4.564***
		(0.988)	(1.144)	(0.990)		(1.117)	(1.255)	(1.112)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	No	Yes	No	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes	No	No	No	Yes
Obs.	101,034	101,034	101,034	101,034	48,090	48,090	48,090	48,090
Obs. PF	2,278	2,278	1,720	2,278	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	14,833	7,404	7,404	7,404	7,404
# Firms PF	568	568	427	568	568	568	427	568

Notes: This table presents results from the estimation of equation (10) with k_{it} defined as the log book value of fixed assets (instead of calculated through the perpetual inventory method as in the main results). $DPFI_{it-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i at time $t-1$. Coefficient estimates and standard errors for $DPFI_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 3 and 7 $DPFI_{it-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ was at least equal to 5%. In columns 4 and 8 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.15: Pension Fund Investment Intensity Results, Alternative Definition of Capital

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.989***	0.990***	0.985***	0.951***	0.951***	0.948***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
β_k	0.053***	0.053***	0.053***	0.054***	0.054***	0.054***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
$Intensity_{it-1}$	0.232***	0.232***	0.220***	0.260***	0.259***	0.244***
	(0.085)	(0.085)	(0.081)	(0.097)	(0.098)	(0.092)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	101,034	101,034	101,034	48,090	48,090	48,090
Obs. PF	2,278	1,720	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	7,404	7,404	7,404
# Firms PF	568	427	568	568	427	568

Notes: This table presents results from the estimation of equation (10) with k_{it} defined as the log book value of fixed assets (instead of calculated through the perpetual inventory method as in the main results). $Intensity_{it-1}$ is the aggregate share of firm i (in percentage points) held by domestic pension funds in year $t-1$. Coefficient estimates and standard errors for $Intensity_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Intensity_{it-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i at time $t-1$ is less than 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.16: Pension Fund Investment Length Results, Alternative Definition of Capital

	Whole sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
β_l	0.989***	0.989***	0.985***	0.951***	0.951***	0.948***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
β_k	0.053***	0.053***	0.053***	0.054***	0.054***	0.054***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
$Length_{it-1}$	0.573***	0.614**	0.511***	0.755***	0.832***	0.679***
	(0.196)	(0.239)	(0.196)	(0.220)	(0.258)	(0.219)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{it-1} \geq 5\%$	No	Yes	No	No	Yes	No
Export$_{it-1}$	No	No	Yes	No	No	Yes
Obs.	101,034	101,034	101,034	48,090	48,090	48,090
Obs. PF	2,278	1,720	2,278	2,278	1,720	2,278
# Firms	14,833	14,833	14,833	7,404	7,404	7,404
# Firms PF	568	427	568	568	427	568

Notes: This table presents results from the estimation of equation (10) with k_{it} defined as the log book value of fixed assets (instead of calculated through the perpetual inventory method as in the main results). $Length_{it-1}$ is the number of consecutive years that firm i received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{it-1}$ are multiplied by 100. All specifications include industry-fixed effects at the NACE Rev.2 1-digit level. Bootstrapped standard errors, clustered by firm, with 200 repetitions in parentheses. In columns 2 and 5, $Length_{it-1}$ only includes the years when aggregate investment by domestic pension funds in the firm is at least 5%. In columns 3 and 6 we include a dummy taking value 1 if firm i is an exporter in year $t-1$. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment at time $t-1$. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.