Pension Fund Equity Investment and Firm Productivity[1]

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Abstract

This paper examines how domestic pension fund equity investment relates to productivity in unlisted firms, using detailed ownership data linked to Danish administrative registers. Pension fund entry is associated with a 3–5% higher level of productivity in the years following entry. The association is stronger when pension funds hold larger stakes, invest for longer, and are closer in the ownership chain. Pension fund entry is also associated with a subsequent increase in the number of a firm's additional investors. We find no investment productivity association for listed firms.

Key words: pension funds, equity financing, firm productivity, unlisted firms.

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1 Introduction

Recent policy debates in Europe highlight the need for a better understanding of the broader economic effects of pension fund activities. The European Commission has emphasized the critical role of expanding the occupational pensions sector within the European Union, aiming to boost investment, deepen capital markets, and promote firm growth across the region (European Commission, 2025). Similarly, the UK government is pursuing major reforms of the domestic pension sector with the goal of increasing the flow of pension fund investment into the real economy (HM Treasury, 2025). Pension funds are widely recognized as key providers of long-term capital, supporting economic growth and development by financing substantial, long-horizon projects (OECD, 2019; Andonov et al., 2021).

Despite their increasing prominence, the overall economic impact of pension funds remains insufficiently understood, primarily due to the dual nature of their effects on the firms in which they invest. On the one hand, pension funds could improve firm productivity in several ways. The provision of long-term capital by pension funds aligns with the long-term investments required for substantial projects, particularly in scenarios where traditional sources of capital are scarce. By providing stable and patient capital, pension funds enable firms to undertake risky but potentially highly rewarding projects that might otherwise go unfunded (Cremers and Pareek, 2016; Artiga González et al., 2020). Moreover, pension funds may participate in governance and strategic decisions, further improving the productivity of firms through active engagement. On the other hand, research, particularly from earlier studies based on listed firms in the US, has cast doubt on the effectiveness of pension fund involvement, especially when it takes the form of shareholder activism. For example, Wahal (1996) finds little evidence that such activism by public pension funds leads to long-term improvements in firm performance. Related research has also indicated that pension funds' investment decisions can be pressured into strategies that do not align with maximizing shareholder value. Such influence, which we expect to be particularly relevant for listed firms as they are visible and large contributors to the economy, can result in governance issues, thereby adversely impacting firm performance (Jiao and Ye, 2013; Andonov et al., 2018).

This study takes a first step toward addressing this ambiguity by documenting empirical patterns in the relationship between pension funds' equity investments and firms' productivity using high-quality data. A central contribution of this study lies in the unique data it employs. Drawing on detailed Danish administrative registers, we use the matched employer–employee dataset for the 2003–2019 period combined with a comprehensive dataset on the ownership of Danish firms to construct a rich firm-level panel that allows us to link pension fund ownership to both unlisted and listed firms, measure productivity, and trace corporate ownership structures with a high degree of accuracy. Denmark is a particularly fitting setting for this analysis. The institutional setup and data infrastructure enable us to identify pension fund equity stakes, including indirect holdings through intermediaries, and to match them to firms' characteristics over time, making it possible to study how firms' productivity relates to pension fund investments beyond the publicly-listed sector that dominates the existing literature. Unlike previous studies such as Aghion et al. (2013), which focus exclusively on listed firms, our analysis incorporates the universe of Danish unlisted (and listed) firms and their ultimate owners. Because unlisted firms constitute the vast majority of firms and account for a substantial share of employment and value added, this provides a more representative picture of the Danish economy and the potential role of pension funds as investors in Denmark. Indeed, 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). Moreover, the Danish pension system is frequently described as one of the best in the world (Mercer, 2023). The granularity of our data permits a clear distinction between investor types, facilitating direct comparisons of pension funds with other institutional investors. In the bulk of our empirical analysis, we focus on the sample of unlisted firms, while, for comparison, we conduct a separate refined analysis limited to listed firms.

Armed with this dataset, we find that pension fund investment in unlisted firms is associated with productivity differences of approximately 3–5% in periods following the investment.[1] A major challenge in interpreting this association is that pension funds may selectively invest in firms that are already more productive. Although fully addressing selection is difficult without exogenous variation, we adopt several strategies to mitigate these concerns. We conduct our analysis on a matched sample to reduce selection on observables. We show in an event-study framework that treated and control firms feature nearly identical pre-trends in productivity. We estimate the relationship between pension fund investment and firms' productivity directly in a structural production function framework that allows us to control for past productivity and partially attenuate selection driven by firm heterogeneity, particularly the possibility that pension funds select firms based on their productivity. Beyond documenting this positive association, our analysis provides suggestive evidence on the economic mechanisms at play. First, the association is stronger for firms that receive

[1] In this paper, the term "pension fund investment" always refers to equity investment by Danish pension funds in Danish firms, unless explicitly noted otherwise.

larger equity stakes, which is consistent with a supply-of-financing channel. Second, the association grows with the length of the investment, indicating the relevance of a long-term-commitment channel. Third, by distinguishing between direct and indirect equity positions, we provide tentative evidence for a governance or engagement channel. Productivity gains are concentrated in firms where pension funds are closer in the ownership chain, that is, direct owners or indirect owners with few intermediary layers, consistent with the view that proximity facilitates oversight and board influence. We also document that pension fund entry is followed by an increase in the number of a firm's additional investors, providing suggestive support for a signalling channel. Taken together, these patterns indicate that pension funds appear to be most strongly associated with higher firm-level productivity when they provide substantial, stable, and long-term capital, and when their ownership position allows for meaningful engagement with the firm. These mechanisms are most likely to matter among unlisted firms, where financing constraints are more binding and governance structures more responsive to large, long-term shareholders. In fact, we find no significant association between pension fund investment and productivity among listed firms, where alternative financing sources are more accessible.

Our findings, while rooted in the Danish context, have broader relevance but there are also clear and important limits to their external validity. Denmark's uniquely mature and well-regulated pension system may strengthen the mechanisms we identify, such as the supply-of-financing and long-term commitment. As a result, the magnitudes we document may not generalize beyond countries with similar institutional frameworks. Nonetheless, the core logic that patient institutional capital can promote firm productivity could plausibly extend to economies with comparable governance structures and expanding funded pension sectors.

This paper contributes to several strands of the literature. First, we add to research on funded pensions and economic growth by examining whether pension investments promote productivity at the firm level, a dimension largely overlooked in prior work that focuses on aggregate pension savings and output growth. Evidence in this macro literature is mixed: Bijlsma et al. (2018) show that countries with larger pension asset pools experience higher output growth in externally-financed sectors; Altiparmakov and Nedeljkovic (2018) find no overall effect of shifts toward funded pensions,[2] and Zandberg and Spierdijk (2013) report no short-term growth effects and only modest long-run impacts.

Second, we contribute to the literature on ownership composition and corporate outcomes by focusing specifically on pension funds and by extending the analysis beyond listed firms. Prior work links institutional ownership to innovation (Aghion et al., 2013) and to productivity-related outcomes (Braguinsky et al., 2015; Bircan, 2019; Fons-Rosen et al., 2021), but largely concentrates on publicly traded firms.

Existing research also documents positive effects of investor types such as private equity and venture capital (PE/VC) on firm performance (e.g. Chemmanur et al., 2011; Davis et al., 2014; Bernstein et al., 2017). We extend this line by examining pension funds, investors that differ from PE and VC in important ways. Unlike PE and VC funds, which actively shape younger firms to raise their value, pension funds typically invest in more mature companies and operate with a longer investment horizon. This long-term approach may enable firms to invest in projects that improve productivity. Our study is the first to isolate the relationship between pension fund ownership and firm productivity for unlisted firms.

Finally, we contribute to the literature on the determinants of firm productivity. Prior

[2] They do, however, document a positive effect in countries where pension funds allocate less than 50% of assets to domestic government bonds, suggesting the importance of asset allocation.

studies emphasize financial frictions (Levine and Warusawitharana, 2021; Coricelli et al., 2012; Caggese, 2019), leverage (Coricelli et al., 2012), firm characteristics and hiring practices (İmrohoroğlu and Tüzel, 2014; Parrotta and Pozzoli, 2012), as well as competition, exporting, and workforce composition (Bao and Chen, 2018; De Loecker, 2013; Parrotta et al., 2014). We introduce pension fund investment as a previously unexplored factor influencing productivity at the firm level.

The remainder of this paper is structured as follows. In Section 2, we describe potential economic channels through which pension funds can affect firm productivity. The data and summary statistics are then discussed in Section 3, followed by the presentation of our empirical strategy in Section 4. We present our empirical results in Section 5. Section 6 contains a series of robustness checks, as well as some heterogeneity analysis. Finally, in Section 7, we offer concluding remarks.

2 Investment-Productivity Channels

Pension fund investments may affect firm-level productivity both positively and negatively.

On the one hand, pension funds can positively influence firm productivity through several channels. First, they may increase the supply of financial capital available to the firm. This reduces 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 toward activities that enhance productivity, such as acquiring advanced equipment or undertaking innovation-related projects

(Aghion and Howitt, 1998).[3] We refer to this as the "supply-of-financing channel".

Second, pension fund investment could boost firm productivity through what we label the "long-term-commitment channel". Pension funds and other types of investors, such as PE/VC funds, differ considerably in their business models. Consequently, the channels through which these investors affect firm productivity may also 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 pension funds do. The potential effects of pension fund investment may instead stem from the fact that, because of their long-term liabilities, these investors tend to be long-term holders of capital and, hence, their involvement enhances the security of long-term financing for firms. This may lead firms to pursue projects that favor long-term objectives, such as productivity enhancement, over short-term dividend pay-outs. The long investment horizon of pension funds is also central to ongoing policy discussions regarding their role in fostering economic growth.

We expect the two channels described above to be more relevant for unlisted than for listed firms. Given that unlisted firms generally face greater difficulty accessing external capital and have a smaller investor base, it is plausible to anticipate a larger productivity effect of pension fund investment among unlisted firms.

In addition to the two channels discussed above, there are two further plausible channels through which pension fund investment could boost productivity. One is the "engagement channel", whereby pension funds actively engage with the firms they invest in to enhance productivity. Evidence supporting this mechanism has been documented in other parts of the

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

financial sector.[4] For example, 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. Another potential mechanism is the "signalling channel", whereby pension fund investment serves as a positive signal to the market about the firm's quality,[5] thereby lowering the cost of capital and stimulating productivity-enhancing investment. Specifically, the involvement of prominent institutional investors may be interpreted by the market as a sign of sound corporate governance, attracting additional investors. Jara et al. (2019), for instance, find that Chilean firms receiving pension fund investment are more likely to issue bonds and pay lower interest rates, crowding out bank lending. The authors attribute this effect to improved governance and better information disclosure.

On the other hand, pension fund investment may also negatively affect firms when their ownership leads to weaker performance due to external pressures or visibility concerns. In such cases, investment strategies may not be fully aligned with maximizing shareholder value, which can create governance challenges and misaligned incentives (Jiao and Ye, 2013; Andonov et al., 2018). We expect these effects to be more likely for listed firms, whose public profile and economic significance expose them to greater scrutiny and external (public and political) pressure.

While the above discussion outlines several plausible channels, our data impose certain limitations. We do not observe firm-level information on the types of projects undertaken or their riskiness, nor do we have measures of firms' access to government resources (e.g.,

[4] 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 with block size. The authors interpret this as evidence that large holdings by institutional investors increase managerial monitoring and lead firms to adopt a longer-term investment perspective, thereby reducing over-investment.

[5] This is conditional on the availability of such information to the market, given that investments in unlisted firms may be confidential.

subsidies). As a result, we cannot directly test these specific mechanisms. Instead, we triangulate using information on investment intensity, proxies for financial constraints, and the unlisted–listed divide (for the supply-of-financing channel); investment length (for the long-term-commitment channel); ownership proximity (for the engagement channel); and the number of additional investors (as a signalling channel). It is, in addition, possible that several channels are simultaneously active and jointly affect the relationship between pension fund investment and productivity.

3 Data

Before merging with the Danish registers, we construct a detailed ownership dataset that identifies whether a firm has received an equity investment from a domestic pension fund. Using shareholder records from Experian, which contain only direct ownership links, we reconstruct ultimate ownership by iterating through ownership layers until we identify the final controlling owner of each firm, using the algorithm described in online Appendix A.3. This allows us to capture both direct and indirect ownership through domestic subsidiaries. Because the underlying administrative registers contain only domestic ownership information, we observe only domestic ultimate owners, including domestic pension funds. Pension fund investors are identified by matching the CVR (identification) numbers of all Danish pension funds to the reconstructed ownership records. A firm is considered to have received a pension fund investment if any pension fund appears among its ultimate domestic owners. It is important to clarify that pension funds can invest in firms either directly or through owned subsidiaries, or via structures such as Limited Partnerships (LP) with private equity vehicles. Due to data limitations inherent in administrative ownership registers, investments made through LP–PE structures are not visible to us as ultimate ownership stakes in the underlying portfolio firms. Our empirical analysis therefore pertains to the first conduit, ownership links for which domestic pension funds can be identified as ultimate equity owners. Recall that our analysis focuses on unlisted firms, while a refinement analysis is conducted separately for listed firms.

Once we have obtained the ownership data we merge its anonymized version with two Danish registers, namely FIRE and FIRM, which provide detailed information about a firm's balance sheet, its number of employees and the industry it operates in. We now describe how we process the firm accounting data. In the remainder of this section, we define a firm's industry as the NACE Rev.2 1-digit industry based on the Danish Industry Classification (DB07).[6] 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 industry information. To estimate firm productivity as described in Section 4 below, 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 industry-specific deflators.[7] To improve balance sheet consistency, we drop observations with negative equity values. Next, we exclude industries with no firms receiving pension fund investments and firms that are observed only in a single year. Afterwards, we winsorize capital, labor, intermediate inputs and output at the 1st and 99th percentiles. Finally, because Denmark has many small firms while pension funds

[6] Table B.1 shows the industries included in the analysis and the number of firms in each industry in the sample.
[7] Deflators are compiled at the DB07 10-industry grouping level and sourced from Statistics Denmark.

invest mostly in larger firms, we restrict the analysis sample to unlisted firms with at least 10 employees in every year of the sample period during which they are active. Note that this is standard practice in the literature working with Danish register data (see, e.g., Fan et al., 2022; Parrotta et al., 2014).

3.1 Descriptive Statistics

Our final sample for the main analysis consists of unlisted firms for which we can successfully compute productivity and that fall within the common support of the propensity score distributions for treated and non-treated observations with respect to pension fund investments, as described in Section A.2 of the online Appendix A.[8] This includes around 58,000 firm-year observations, representing approximately 10,000 different firms. Of these, 272 firms (corresponding to 1.5% of the sample observations) are treated in at least one year.[9] Our central variable of interest is a dummy for whether the firm received investment from at least one domestic pension fund.[10] Throughout the sample period, the number of pension funds investing in the firms in our sample ranges from 8 to 12. These funds have been in existence for at least 30 years and collectively manage assets well in excess of DKK 50 billion as of 2019, suggesting that the funds in our sample are large and sophisticated institutional investors.[11] Descriptive statistics and definitions of all variables used in the analysis can be

[8]The descriptive statistics and sample sizes discussed in this section refer to the final sample that we use to estimate Equation (1) below and its variations.

[9]While this may appear to be a relatively small number, it is important to recognize that the active selection of, monitoring of, 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 tends to be small.

[10]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 38.6 bn DKK in debt and loans of Danish non-financial companies. Therefore, these entities are much more active as equity rather than debt investors. Danish pension funds and insurance companies hold 15.7% of the total equity of non-financial companies held by domestic financial corporations and only 2.1% of debt and loans. Additional institutional details of the Danish pension funds are provided in the online Appendix A.1.

[11]Due to confidentiality restrictions that prevent the identification of individual funds, we are unable to provide more detailed information on the pension funds in our sample.

found in Table 1. We show statistics for four different sub-samples: (i) all firm-year observations within the common support, (ii) firm-year observations with pension fund investment within the common support, equivalent to receiving a pension fund investment in the previous year (year $t-1$), (iii) firm-year observations without pension fund investment within the common support, and (iv) firm-year observations without pension fund investment outside the common support and therefore outside our estimation sample. Focusing on the second sub-sample, we can also describe two other variables related to pension fund investment: (a) investment intensity, which is equal to the aggregate share of a firm owned by all domestic pension funds together, and (b) investment length, captured by the number of consecutive years (up to and including the previous year) of pension fund investment in the firm. We observe that domestic pension funds invest on average for approximately 4 consecutive years and hold an aggregate stake of approximately 12% in a firm, conditional on investing in the firm in period t.

The second panel of Table 1 reports key characteristics 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. 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 the larger firms (Ferreira and Matos, 2008). Pension funds also tend to invest in slightly older firms: the average age of treated firms exceeds that of untreated firms by approximately two-thirds of a year. On average, pension funds start to invest in a firm in its 22nd 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). Note that the differences between treated and non-treated firms are reduced when we focus on our main sample, where the common support condition is enforced, particularly in terms of productivity, capital stock, age, and export status.

In addition to these firm characteristics, several features of the investment data itself deserve attention. A large share (42%) of firms receiving a pension fund investment do so in 2003, the first year for which we observe pension fund holdings. Consequently, the variable measuring investment duration is mechanically left-censored, since we cannot observe investments prior to 2003. Right-censoring also arises for investments that continue through the end of the sample period. For 54% of treated firms, the first observed investment coincides with the first year the firm appears in the sample, again reflecting left-censoring. We also record 118 instances of complete divestment, defined as a situation where at least one pension fund invests in a firm in year $t-1$ but none invest in year t. Finally, Table B.1 in the online Appendix B shows the distribution of firms across NACE Rev. 2 1-digit industries. Pension fund investments are clearly concentrated in manufacturing, which accounts for 57% of all treated firms.

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 (Della Croce et al., 2011; Beyer et al., 2014). Pension funds collect contributions from workers today and pay out retirement income decades later, creating long-term liabilities. This gives them strong incentives to hold assets that generate

Table 1: Descriptive Statistics

Variable	Definition	All		Firms with PFI		Firms without PFI (matched)		Firms without PFI (unmatched)	
Pension Fund Investment Variables									
$DPFI_{ij,t-1}$	dummy = 1 if a pension fund invested in the firm	0.015	(0.121)	1.000	(0.000)				
$Length_{ij,t-1}$	duration of current episode of pension fund investment (years)	0.059	(0.598)	3.946	(2.947)				
$Intensity_{ij,t-1}$	total ownership by domestic pension funds (%)	0.184	(2.457)	12.395	(15.956)				
Firm Variables									
Output/worker	output per worker (log)	7.449	(0.702)	7.513	(0.666)	7.448	(0.702)	7.192	(0.701)
VA/worker	value added per worker (log)	6.316	(0.399)	6.412	(0.458)	6.314	(0.398)	6.251	(0.424)
Value added	(log)	10.137	(1.097)	10.969	(0.989)	10.124	(1.094)	9.680	(1.020)
Labour	number of full-time employees (log)	3.821	(0.968)	4.557	(0.895)	3.810	(0.965)	3.429	(0.876)
Capital	fixed capital (log)	9.228	(1.572)	10.210	(1.532)	9.213	(1.568)	8.432	(1.855)
Intermediary inputs	(log)	10.750	(1.382)	11.566	(1.174)	10.738	(1.382)	9.982	(1.397)
Age	firm age (years)	24.950	(18.952)	25.600	(16.640)	24.941	(18.984)	18.434	(15.136)
Capital Intensity	capital stock per worker (log)	5.407	(1.193)	5.653	(1.248)	5.403	(1.192)	5.002	(1.504)
Listed	1 if firm is listed	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
$Export_{ijt-1}$	1 if the firm exports	0.624	(0.484)	0.898	(0.302)	0.620	(0.485)	0.437	(0.496)
Observations		58,319		893		57,426		41,919	

Notes: All descriptive statistics are calculated as averages over the sample period (2003-2019). 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 pension fund investment, equivalent to receiving a pension fund investment in the previous year (year $t-1$), (iii) firm-year observations without pension fund investment and with enforcement of the common support restriction, and (iv) firm-year observations without pension fund investment and without enforcement of the common support restriction. Values for subsample (ii) are reported conditional on the firm receiving a pension fund investment in the previous year $t-1$.

returns over correspondingly long horizons. Most Danish pension funds are defined contribution, while some are defined benefit.[12] Defined benefit funds promise a specific payout to retirees, placing the investment risk on the fund itself. To manage this risk, they typically hedge their long-term liabilities through fixed-income instruments and derivatives, rather than through their equity investments. The remainder of their portfolios is then largely allocated to equity, which provides a higher expected return over long periods. Defined contribution funds, where the investment risk is borne by the participant rather than the fund, have even fewer constraints on equity allocation, since there is no fixed payout obligation to hedge against. Crucially, regardless of fund type and irrespective of hedging needs, both defined contribution and defined benefit pension funds can afford to hold equity investments for extended periods, as the bulk of their participants are in the midst of their working life and will not require payouts for many years. We therefore expect pension funds, both defined contribution and defined benefit, to adopt longer investment horizons than other investors, allowing them to reap additional returns from patient, long-term equity holdings.

Empirical evidence supports the notion that pension funds typically have a longer investment horizon than other institutional investors (Döring et al., 2021; Cella et al., 2013; Harford et al., 2018; Cremers and Pareek, 2016). Our data confirm this trend. Table B.2 in the online Appendix B 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 either their 6-digit or 3-digit (DB07) sector code (in case of insurance companies). First, Panel A of Table B.2 in the online Appendix B reports the mean invest-

[12] Danish occupational pensions are for the most part defined contribution (*bidragsdefinerede*). Traditional defined benefit schemes (*ydelsesdefinerede*), primarily civil servant pensions, account for only approximately 1.4% of total pension assets, and guaranteed defined contribution schemes constitute only a minor share of total pension liabilities (Danmarks Nationalbank, 2025).

ment horizon of each investor group, conditional on investing in firm i at time $t-1$, as well as the difference between other investors and the average investment horizon of pension funds, and the p-value of a simple difference-in-means t-test. On average, pension funds invest in a firm for 0.7 years longer than banks do. While this difference may seem rather small, it represents approximately 20% of the mean investment horizon of pension funds, making it relatively important.[13] Our data show that among domestic investors, pension funds have a longer investment horizon than all other sectors except for non-financial holding companies.[14] Moreover, the differences in the length of the investment horizon between pension funds and other investor types are statistically significant for all sectors. Second, Panel B of Table B.2 shows that prior to divestment, pension funds invested in firms for a larger number of consecutive years than any other investor type.[15] Most of these differences are statistically significant at the 1% level. Third, 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.

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

[14] 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; thus, it is not surprising that they have a long investment horizon.

[15] 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-censored, as investment by an investor type might continue after 2019 or the firm exits the sample due to our sampling conditions. The issue of right-censoring is especially relevant for pension funds, which may be less likely than other investors to have terminated their investments in 2019.

4 Structural Productivity Estimation

To estimate firm productivity and relate it to pension fund investment, we follow the structural production-function literature and recover total factor productivity (TFP) as the residual from a Cobb–Douglas production function in value added, capital, and labor. Using TFP instead of labor productivity is particularly important because pension fund investments may raise firms' capital input, and we aim to isolate productivity changes that are not mechanically driven by input variation.

A central challenge in estimating productivity is the simultaneity between firms' input choices and their expectations about productivity. We address this using the control-function approach of Ackerberg et al. (2015) (ACF), which employs intermediate inputs as a proxy for unobserved productivity shocks. The method proceeds in two stages.

First stage. The log of output (y) of firm i in industry j in period t is generated by the production function:

$$y_{ijt} = \beta_k k_{ijt} + \beta_l l_{ijt} + \omega_{ijt} + \varepsilon_{ijt},$$

where k_{ijt} denotes the log of capital, l_{ijt} the log of labor, ω_{ijt} firm productivity observed by the firm but not by the econometrician, and ε_{ijt} an i.i.d. shock or measurement error. Intermediate material inputs m_{ijt} do not enter the production function directly but are used as a control variable for ω_{ijt}.

Under standard ACF assumptions, material demand is a function of capital, labor, and productivity and can be inverted to express productivity (ω_{ijt}) as a function of ($k_{ijt}, l_{ijt}, m_{ijt}$). Substituting this expression into the production function and augmenting it with year-fixed effects κ_t yields

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

where $h(\cdot)$ is a composite function that subsumes the linear input terms and productivity, κ_t denotes year fixed effects and ε_{ijt} is an i.i.d. shock or measurement error. In the first stage, we approximate $h(\cdot)$ with a flexible polynomial in $(k_{ijt}, l_{ijt}, m_{ijt})$, separately for each industry j, i.e., for each of the DB07 36 industries.[16] We then define $\hat{h}_{ijt}$ as the predicted output net of year-fixed effects. The predicted output from the first stage $\hat{h}_{ijt}$ is then used to identify the input elasticities in the second stage.

Second stage and productivity law of motion. In the second stage, we recover the input elasticities (β_k, β_l) by exploiting the assumed law of motion for productivity. Following De Loecker (2013) and related work, we model productivity as evolving according to a first-order Markov process that may be shifted by past pension fund investment, $PFI_{ij,t-1}$:

$$\omega_{ijt} = \rho\omega_{ij,t-1} + \gamma PFI_{ij,t-1} + \xi_{ijt}.$$

This specification allows pension fund investment to influence how productivity evolves over time, rather than entering directly as a production input, and conditions on past productivity to mitigate concerns about selection into investment. Since

$$\omega_{ijt} = \hat{h}_{ijt} - \beta_k k_{ijt} - \beta_l l_{ijt},$$

[16] More information on the Danish classification of industries can be found here: https://www.dst.dk/da/Statistik/dokumentation/nomenklaturer/db07

substituting into the law of motion yields the empirical second-stage equation:

$$\hat{h}_{ijt} = \alpha_j + \beta_k k_{ijt} + \beta_l l_{ijt} + \rho \left(\hat{h}_{ij,t-1} - \beta_k k_{ij,t-1} - \beta_l l_{ij,t-1} \right) + \gamma PFI_{ij,t-1} + \xi_{ijt}. \qquad (1)$$

Equation (1) is therefore the empirical implementation of the productivity law of motion, rewritten in terms of predicted output and including industry fixed effects α_j. The coefficient of interest, γ, measures how past pension fund investment is associated with subsequent productivity, conditional on past productivity and inputs. We estimate Equation (1) via GMM using standard ACF timing assumptions and instrument sets. A detailed exposition of the identification strategy, timing structure, and the complete two-step estimation procedure is provided in Appendix A.4.

5 Empirical Analysis

This section reports and discusses our empirical results. Unless explicitly noted otherwise, all results are based on the sample of unlisted firms.

5.1 Event Study

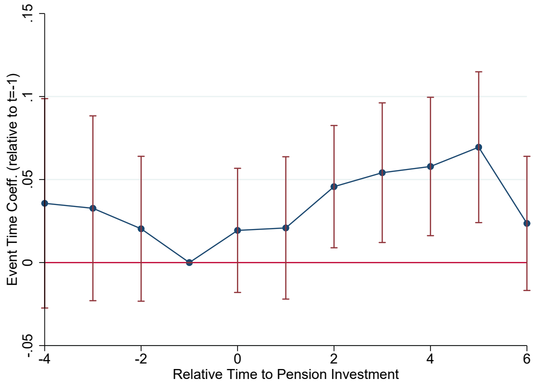
Before presenting the results obtained from the structural estimation of the production function, we take an event study approach that allows us to check for differential pre-trends, i.e., to assess whether, before the event of pension fund investment occurs, firms eventually treated with a pension fund 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 and D'Haultfœuille, 2024; 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. Figure 1 presents the relationship of a pension fund investment with two measures of firm productivity, output per worker and value added per worker, using the sample where the common support condition is enforced.[17] First we notice 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).[18] However, we do observe a positive association with productivity that persists for a number of years following the event date, as shown in the two figures. Online Appendix C shows that the event of a pension fund investment is associated with an increase in firms' sales and value added and a decrease (although insignificant) in the number of employees. Therefore, the positive correlation with output per worker and value added per worker are a combination of an effect on output/value added and an effect on employment, and the structural estimation approach presented in the next section will control for the change in employment to estimate the association of pension fund investment with productivity. Furthermore, the same event is associated with a positive increase in firms' investments. The fact that capital expenditures increase following pension fund investment events is consistent

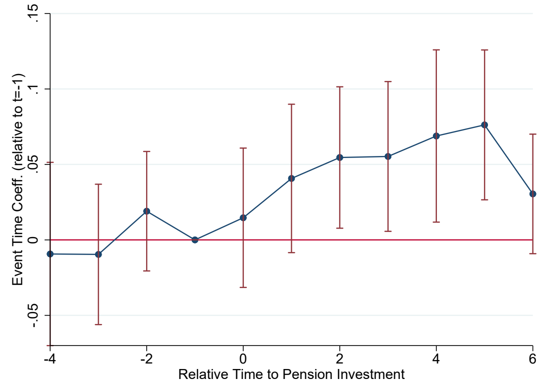
[17]The event study analysis is based on these two straightforward measures of firm productivity rather than on TFP derived from the structural estimation for two reasons. First, our goal in this setting is to assess the selection hypothesis by testing for differential pre-trends in an event study framework, which can be done only with conventional productivity measures. Second, the theoretical justification for extracting the productivity term from the production function and using it as the dependent variable in a separate regression is not straightforward (Ackerberg et al., 2015).

[18]We also do not find any evidence of differences in pre-trends using the estimator proposed by de Chaisemartin and D'Haultfœuille (2024).

with both the "supply-of-financing" and the "long-term commitment" channels highlighted in Section 2 above.[19]

Figure 1: Event Study Results





(a) Output per Worker

(b) Value added per Worker

Notes: The outcome variable is the log of output or value added per worker. Year 0 is the first year of pension fund investment. 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 and capital intensity. We also include year-by-(DB07-36) industry-fixed effects.

5.2 Main Results

Table 2 presents the results for the model in which the pension fund investment is included in Equation (1) through a dummy variable. For convenience, we report the coefficient estimates of the pension fund investment variable and the related standard errors multiplied by 100. Column 1 shows estimates for the case in which the law of motion of the exogenous productivity process is specified without the pension fund investment variable. Column 2 introduces the pension fund dummy in the specification. Column 3 restricts the pension fund investment dummy to take a value of 1 only if the aggregate holding by all Danish

[19] 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 an alternative output variable to measure productivity, where 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; 2) include the share of R&D workers among the control variables; or 3) omit all control variables from regressions. Moreover, our findings remain unaltered when we exclude pension fund investments that last for fewer than five consecutive years. All these additional results are reported in Appendix C.

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. Previous literature found that export status is important in the estimation of productivity (De Loecker, 2013). Column 4 therefore reports the results including a dummy in Equation (1) that takes 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 and of the autocorrelation coefficient ρ are in the range of estimates in previous studies (Fox and Smeets, 2011; Bøler et al., 2015).[20] We observe a positive and significant coefficient on the pension fund investment variable in all specifications. Receiving a pension fund investment in the previous year is associated with an increase in productivity ranging from 3.4% to 4.7%, depending on the specification. The coefficient is stronger 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 be an indication of the relevance of the "supply-of-financing channel", that we will discuss more extensively in the next section. 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 conditions on past productivity. In this way, we attenuate concerns related to selection driven by heterogeneity, particularly the possibility that pension funds select firms based on their productivity. Even after accounting for this potential source of selection, we find a positive and statistically significant association between pension fund investment and firm productivity. While conditioning on past productivity mitigates selection

[20] We report the results from the first stage in Table C.10 in the Online Appendix C.

concerns, we do not interpret these estimates as causal.

Furthermore, to assess the sensitivity of our main results to omitted unobserved variables, we apply the approach described in Oster (2019). 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 (1) 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 the notation found in Oster (2019)) equals 1. As reported at the bottom of Table 2, we obtain δ ratios ranging from approximately 12 to 15 in the estimation sample, which are well above the value of 1 usually seen as an upper bound for selection on unobservables. Under the assumptions of the framework described in Oster (2019), this suggests that a substantial degree of selection on unobserved factors would be required to fully account for the estimated association. While this exercise does not rule out all forms of endogeneity, it provides reassurance that omitted variable bias is unlikely to fully drive our main results.

Another concern with the results presented in Table 2 is that the positive association between pension fund investment and productivity may be fully driven by a change in input and output prices. If pension fund investments lead, for example, to higher output prices and/or 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.[21] The event study analysis reported in Figures C.6 and C.7 of the online Appendix C 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

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.956***	0.955***	0.955***	0.952***
	(0.006)	(0.006)	(0.006)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.079***	0.077***
	(0.005)	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}$		3.905***	4.771***	3.410**
		(1.471)	(1.584)	(1.476)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
Export$_{it-1}$	No	No	No	Yes
δ for $DPFI_{ij,t-1} = 0$		14.943	15.056	11.912
Autocorrelation ρ	0.530 (0.000)	0.530 (0.000)	0.531 (0.000)	0.531 (0.000)
Obs.	58,319	58,319	58,319	58,319
Obs. PF	893	893	596	893
# Firms	10,308	10,308	10,308	10,308
# Firms PF	272	272	201	272

Notes: This table presents the results from the estimation of Equation (1). $DPFI_{ij,t-1}$ is a dummy that takes a value of 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its association with productivity. The Autocorrelation row reports the estimated ρ with its p-value in parentheses. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Column 3, $DPFI_{ij,t-1}$ equals 1 if the aggregate holding of all pension funds in firm i in industry j in year $t-1$ was at least equal to 5%. In Column 4, we include a dummy equal to 1 if firm i in industry j is an exporter in year $t-1$. The coefficient δ for $PFI_{ij,t-1} = 0$ 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 at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

[21] The price analysis uses product-level data from Statistics Denmark (DST). Information on firms' input prices is drawn from VARK (Manufacturers' Purchases of Goods and Services), which records purchases of goods and services used in production at the product level. Output prices are obtained from VARS (Industriens salg af varer), which contains detailed data on firms' sales of manufactured products, including values and quantities. These data allow us to construct firm-level measures of average input and output prices for a representative sample of manufacturing firms.

5.3 Economic Mechanisms

In the previous section we show that firms' productivity correlates with the presence of pension fund investment. In this section we provide additional results to investigate plausible economic mechanisms behind this positive association.

5.3.1 The Supply-of-Financing Channel

First, we investigate whether the size of the pension fund investment matters by defining the pension fund investment in Equation (1) 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 intensity is associated with a TFP increase of approximately 0.1%. The significance of $Intensity_{ij,t-1}$ suggests a potential relevance of the "supply-of-financing channel", as more supply of fund capital is associated with a larger productivity increase. Another channel potentially suggested by this result is that a larger equity stake gives more control over the management of the target company, which could lead to higher productivity gains. A channel where, for instance, the CEO is fired and replaced by a more skilled CEO seems less relevant based on the fact that in fewer than 4% of observed cases of pension fund investments in our sample the stake is above 50%, while in 85% of the observed cases the total stake held by pension funds in the firm is at most 20%. However, the possibility cannot be excluded that, as equity stakeholders and potential board members, pension funds provide firms' management with valuable (strategic) advice. Note that the estimated coefficients on $Intensity_{ij,t-1}$ reported in Table 3 combine the effect due to the extensive margin (i.e., receiving a pension fund investment at all) with the one induced by the intensive margin (i.e., the size of the investment). Unfortunately, likely due to a limited number of treated observations, we lack the statistical power to distinguish between these two effects, although the signs of the estimated coefficients are as expected when both the extensive and intensive margin variables are included in the same specification.[22] Therefore, we have to interpret these results with this important caveat and also treat our interpretation on the implied channels as suggestive evidence.

Table 3: Productivity Estimates: Pension Fund Investment Intensity

	(1)	(2)	(3)
Elasticity of Labor (β_l)	0.956***	0.956***	0.952***
	(0.006)	(0.006)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.077***
	(0.004)	(0.004)	(0.004)
$Intensity_{ij,t-1}$	0.138*	0.134*	0.128*
	(0.082)	(0.080)	(0.070)
Industry FE	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	Yes	No
$\text{Export}_{ij,t-1}$	No	No	Yes
Obs.	58,319	58,319	58,319
Obs. PF	893	596	893
# Firms	10,308	10,308	10,308
# Firms PF	272	201	272

Notes: This table presents results from the estimation of Equation (1). $Intensity_{ij,t-1}$ is the aggregate share of firm i (in percent) held by domestic pension funds in industry j in year $t-1$. Coefficient estimates and standard errors for $Intensity_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $Intensity_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Column 2, $Intensity_{ij,t-1}$ is equal to 0 if the aggregate holding of all domestic pension funds in firm i in industry j at time $t-1$ is less than 5%. In Column 3, we include a dummy taking value 1 if firm i in industry j 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 in at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

[22] These additional results are reported in Online Appendix C (Table C.11).

An additional way to test the supply-of-financing channel is to examine whether the association is stronger for firms facing tighter financial frictions. To this end, we include interactions between pension fund investment and proxies for liquidity constraints. We measure liquidity constraints in two ways: (i) whether a firm's long-term-debt-to-assets ratio in its first sample year is above the 75th percentile, and (ii) whether the ratio of assets minus inventories to liabilities in its first sample year is below the 25th percentile. As shown in Columns 1 and 2 of Table 4, the coefficients on these interaction terms are positive, consistent with the hypothesis that pension fund investment may alleviate financial constraints, but they are not statistically significant. Thus, while the signs of the interactions point into the expected direction and are consistent with the hypothesis that low-liquidity firms may benefit relatively more from pension fund investment, the evidence remains at most modest.[23]

While unlisted firms may face tight financial constraints because they have limited access to external financing, this should be less of a concern for listed firms, ceteris paribus. To further support the plausibility of a supply-of-financing channel, in the last column of Table 4 we re-run the main analysis focusing solely on listed firms.[24] The results suggest that the correlation between pension fund investment and productivity is negative for listed firms. A plausible explanation is that pension fund investment decisions in listed firms may be subject to external pressures due to high public or political exposure, which can lead to investment strategies that are not fully aligned with maximizing shareholder value (Jiao and Ye, 2013; Andonov et al., 2018). However, the negative coefficient is not statistically significant. Overall, these estimates provide only suggestive evidence that listed firms do not

[23] Using a high long-term-debt ratio as one of our proxies also serves to control for the effect of debt financing, given that our pension fund investment measure captures only equity holdings.

[24] We define a firm as listed if it issued an equity instrument on the Copenhagen Stock Exchange during the sample period. We further apply a business group mapping using the KONC register: if any firm in a business group is listed in a given year, all firms in the group are defined as listed in that year.

benefit from pension fund investment. At the same time, the results are consistent with the hypothesis that pension fund investment raises productivity through the supply-of-financing channel among unlisted firms, which tend to face tighter financing constraints and have fewer alternative sources of external capital.[25]

Table 4: Productivity Estimates: Financial Constraints and Listed Firms

	Whole sample	Unlisted firms	Listed firms
	(1)	(2)	(3)
Elasticity of Labor (β_l)	0.945***	0.972***	0.777***
	(0.007)	(0.007)	(0.081)
Elasticity of Capital (β_k)	0.086***	0.069***	0.134**
	(0.005)	(0.005)	(0.054)
$DPFI_{ij,t-1}$	5.021**	3.339*	-1.097
	(2.051)	(1.727)	(14.973)
$Low\quad Liquidity_{ij}$	-5.978***	-2.889***	
	(0.539)	(0.588)	
$DPFI_{ij,t-1} \times Low\quad Liquidity_{ij}$	2.325	2.417	
	(3.082)	(3.649)	
Industry FE	Yes	Yes	Yes
Obs.	58,319	54,851	2,818
Obs. PF	893	777	798
# Firms	10,308	9,614	328
# Firms PF	272	240	148

Notes: This table presents the results from the estimation of the baseline specification of Equation (1), (see Column 2 of Table 2), adding the variable $Low\quad Liquidity_{ij}$, which in Column 1 (2) is a dummy equal to 1 if the ratio of total long-term debt to total assets (the ratio between assets minus inventories divided by liabilities) for firm i in industry j in the firm's base year is above (below) the 75th (25th) percentile of the distribution, and its interaction with $DPFI_{ij,t-1}$, 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 $DPFI_{ij,t-1}$, $Low\quad Liquidity_{ij}$ and their interaction are multiplied by 100. The coefficient estimates for $DPFI_{ij,t-1}$ and $Low\quad Liquidity_{ij}$ measure their correlation with productivity. Columns 1-3 include industry-fixed effects at the DB07 36-industry level. Column 3 restricts the sample to listed firms. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in at least one year. Finally, $^{*}\ = p < 0.1$, $^{**}\ = p < 0.05$, and $^{***}\ = p < 0.01$.

[25]This finding does not preclude the relevance of other channels. For example, unlisted and on average smaller firms may benefit more from engagement and from long-term financing commitments. These channels are examined in subsequent sections.

5.3.2 The Long-Term-Commitment Channel

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. Hence, we now investigate whether the holding period of a pension fund investment makes a difference by capturing the pension fund investment in Equation (1) with the variable $Length_{ij,t-1}$, which measures the number of consecutive years that firm i has received pension fund investment up to year $t-1$. Table 5 shows that an additional year of a pension fund investment is associated with a significant increase in productivity in the range of 0.5%-0.9% on average, depending on the specification.

Table 5: Productivity Estimates: Pension Fund Investment Length

	(1)	(2)	(3)
Elasticity of Labor (β_l)	0.956***	0.956***	0.952***
	(0.006)	(0.005)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.077***
	(0.004)	(0.004)	(0.004)
$Length_{ij,t-1}$	0.587**	0.933***	0.499**
	(0.279)	(0.324)	(0.220)
Industry FE	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	Yes	No
Export$_{ij,t-1}$	No	No	Yes
Obs.	58,319	58,319	58,319
Obs. PF	893	596	893
# Firms	10,308	10,308	10,308
# Firms PF	272	201	272

Notes: This table presents the results from the estimation of Equation (1). $Length_{ij,t-1}$ is the number of consecutive years that firm i in industry j received investment from any pension fund up to year $t-1$ included. Coefficient estimates and standard errors for $Length_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $Length_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Column 2, $Length_{ij,t-1}$ includes only the years when aggregate investment by domestic pension funds in the firm is at least 5%. In Column 3, we include a dummy equal to 1 if firm i in industry j 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 in at least one year in the sample. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

This finding is consistent with the potential presence of the "long-term-commitment channel". This is also in line with the event study, which provides suggestive evidence for a positive association with productivity not only in the first year of the investment but also some years after the investment starts. These results on the length variable should be interpreted with caution due to the following two caveats. First, like for the intensity results, the coefficient estimated on the variable $Length_{ij,t-1}$ captures the impact of both the extensive and intensive margin. Second, the $Length_{ij,t-1}$ variable may not fully reflect the true length of the firm's investment history due to truncation at the start of the sample period in 2003. This truncation introduces censoring, as some firms may have initiated investments prior to the sample period, leading us to observe only a portion of the full investment timeline. The implications of this censoring depend on whether the relationship between productivity and length is positive and convex or positive and concave. It may bias the estimated coefficients in Table 5 if the observed length is shorter than the true length since the effect of a longer duration could be inaccurately attributed to a shorter observed period. For example, if a firm has been invested in for 8 years but only 4 years are observed, then the estimated impact of the first additional observed year would correspond to the marginal effect of the fifth year, potentially overstating (if the relationship is convex) or understating (if concave) the per-year impact. However, it is unlikely that a convex relationship can exist over a long holding period, as productivity cannot become explosively large. Overall, potential truncation bias may affect the precision and interpretation of our estimates, and the results in Table 5 should be considered with this limitation in mind.

5.3.3 The Distinction between Direct and Indirect Investment and the Engagement Channel

We now re-estimate Equation (1) while distinguishing between direct and indirect pension fund holdings. To do so, we create two separate dummy variables, one for each investment type, and include both in the same regression. This specification allows us to examine whether the positive association between pension fund participation and firm productivity documented earlier is also present for indirect holdings, consistent with the possibility that pension funds may exert influence through intermediaries via which capital is channeled. Table B.5 in Online Appendix B reports descriptive evidence on the composition of indirect pension fund investment chains. Setting aside the two broad industry-level categories at the top of the table, which, by construction, encompass most of the more specific intermediary types, the table indicates that indirect ownership chains are frequently organized through holding companies, particularly non-financial holding companies, as well as investment companies.[26] These investor types are commonly associated with delegated monitoring, control rights, or active ownership structures, rather than with purely arm's length financial intermediation. By contrast, banks, insurance companies, and asset management firms, entities more typically linked to passive intermediation or contractual lending relationships, appear relatively less often in indirect pension fund ownership chains. While our data do not allow us to observe the operational role of these intermediaries directly, these statistics clarify the composition of ownership chains.

The first column of Table 6 shows that the estimated coefficient for the dummy representing direct pension fund investments is slightly smaller in size and less precisely estimated than the corresponding coefficient of indirect (intermediated) investments in the baseline specification. However, these estimates should be interpreted carefully. In our estimation sample, only about 4 percent of firms (12 firms) receiving pension fund capital are financed directly, whereas the vast majority (260 firms) receive funding through intermediaries. As a result, the absence of statistical significance for direct investments is likely driven by the limited number of such observations rather than by a lack of economic relevance. In the

[26] Additionally, when we focus on indirect pension fund investment, around 32% of such investments involve a pension fund investing in the firm through a subsidiary belonging to the same business group.

second column of the same table, we therefore explore differences resulting from how close pension funds are to their portfolio firms. Intermediated investments can occur through ownership chains of varying complexity, ranging from relatively simple arrangements with a single intermediary to multilayered setups with several intermediaries. To capture this, we construct a degree of separation measure for each ultimate owner–firm pair. Specifically, we multiply the investor's equity share by the number of intermediary links between the pension fund and the firm, defined as 1 for direct holdings (no intermediary), 2 for one intermediary, 3 for two, and so forth. We then aggregate these values across all pension fund investors to obtain a firm-level index in each year. Based on this index, firms with indirect pension fund investment are split into two groups: those with a low degree of separation (below the sample median) and those with a high degree of separation (above the median). The results, reported in the second column of Table 6, indicate that both types of indirect investment are positively correlated with productivity, but the estimated association is larger and statistically significant only for firms with a low degree of separation. This pattern suggests that pension funds are more closely linked to productivity improvements when the ownership chain is shorter, possibly because their investment priorities and governance practices reach the firm more directly. As the number of intermediaries increases, the estimated relationship becomes weaker, which may reflect greater monitoring difficulties or a dilution of pension funds' influence. In column (3), we merge direct holdings with indirect investments characterized by a low degree of separation to test whether proximity to the firm either through direct ownership or limited intermediation matters for performance. The results confirm that being closer to the firm has a larger and statistically significant association with productivity, consistent with the notion that tighter ownership links improve pension funds' ability to influence managerial behavior and improve firm performance.[27]

Table 6: Productivity Estimates: Direct and Indirect Investments

	(1)	(2)	(3)
Elasticity of Labor (β_l)	0.955***	0.955***	0.955***
	(0.006)	(0.006)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.079***
	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}(direct)$	3.258	3.250	
	(3.510)	(3.510)	
$DPFI_{ij,t-1}(indirect)$	3.958**		
	(1.557)		
$DPFI_{ij,t-1}(indirect\, and\, low\, separation)$		5.382***	
		(1.984)	
$DPFI_{ij,t-1}(direct\ plus\ indirect\, and\, low\, separation)$			5.088***
			(1.807)
$DPFI_{ij,t-1}(indirect\, and\, high\, separation)$		2.516	2.516
		(2.164)	(2.164)
Industry FE	Yes	Yes	Yes
Obs.	58,319	58,319	58,319
Obs. Indirect PF	825	825	825
Obs. Direct PF	66	66	66
Firms	10,308	10,308	10,308
Firms Indirect PF	260	260	260
Firms Direct PF	12	12	12

Notes: This table presents the results from the estimation of the baseline specification of Equation (1), (see Column 2 of Table 2), where we define the pension fund investment variables as follows. The dummy variable $DPFI_{ij,t-1}(indirect)$ takes the value one if at least one domestic pension fund is among the shareholders of firm i in period $t-1$ through intermediaries. The dummy variable $DPFI_{ij,t-1}(direct)$ takes the value one if at least one domestic pension fund is among the direct shareholders of firm i in period $t-1$. We define the degree of separation as the number of intermediary ownership layers between the pension fund and the firm. Firms with indirect investments are split at the median into $DPFI_{it-1}$(indirect, low separation) and $DPFI_{ij,t-1}$(indirect, high separation). Coefficient estimates and standard errors for all of the $DPFI_{ij,t-1}$ variables are multiplied by 100. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

[27] This indirect test for the engagement channel is also supported by some anecdotal evidence. A working group of the International Centre for Pension Management (ICPM, https://www.icpmnetwork.com/), which is 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 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 also 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.

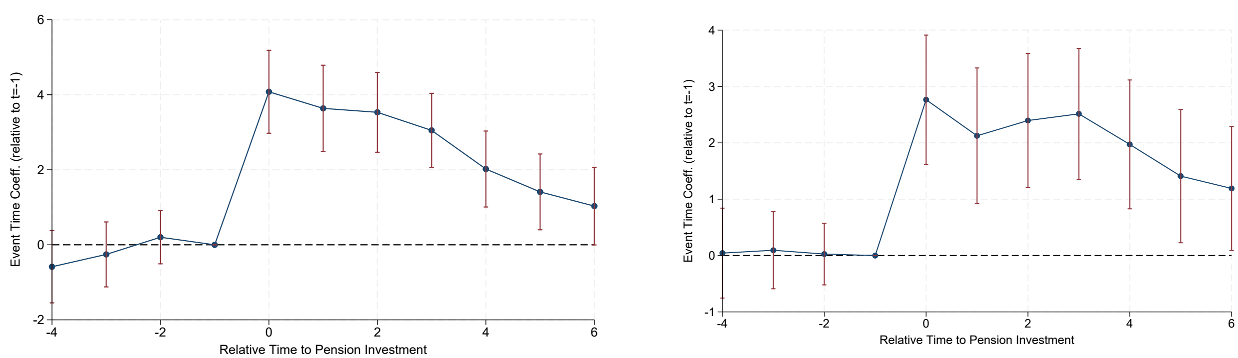
5.3.4 The Signalling Channel

A final mechanism that may contribute to the association between firm productivity and pension fund investment is a possible signalling channel. Pension funds are often viewed as reliable, long-horizon investors. Their entry into a firm's ownership structure could therefore be interpreted by some market participants as providing information about the firm's governance practices or longer-term prospects. If so, other investors might become more inclined to acquire equity stakes following pension fund involvement.

Figure 2 provides descriptive event-study evidence that is consistent with this possibility. Using the estimator of Sun and Abraham (2021), the figure plots the evolution of the additional number of equity owners (excluding the pension fund associated with the event) around the first year in which a firm receives a pension fund investment (panel a). Prior to the event, treated and untreated firms exhibit similar trends. After pension fund entry, the total number of additional owners increases by four on average and remains elevated in subsequent years. When focusing on additional pension funds that enter after the initial event, a slightly smaller increase is observed (panel b), indicating that the post-entry expansion of the investor base is driven especially by other pension funds.

Several explanations could underlie this pattern. One interpretation is that pension fund investment helps reduce information frictions by signalling that the firm has undergone some degree of financial or governance scrutiny. Another possibility is that the presence of a large, stable institutional owner reassures other investors about the credibility of the firm's governance. It is important to note, however, that although the number of owners rises after pension fund entry, our co-investment tests in the previous section indicate that other investor types are generally not correlated with productivity. The fact that the ownership increase is mainly attributable to additional pension funds alleviates potential tension with these findings, since pension funds are precisely the investor group for which we document a robust association with productivity. Moreover, the gradual entry of additional pension funds in the years following the initial investment event, taken together with the results in Section 5.3.2, which show that longer durations of pension fund investment are positively correlated with productivity, is consistent with a high degree of long-term commitment by the pension fund industry as a whole.

Figure 2: Total Number of Additional Investors



(a) Number of Add. Investors

(b) Number of Add. PF Investors

Notes: In the first panel, the outcome variable is the total number of additional firm's owners (excluding the pension fund associated with the event) relative to the moment of the first pension investment stake. The second panel focuses on additional pension funds entering as investors after the event. Year 0 is the first year of pension fund investment. The figure presents point estimates and 95% confidence intervals from an event-study specification using the estimator proposed by Sun and Abraham (2021). The specification includes the following controls: firm age and capital intensity. We also include year-by-industry fixed effects at the DB07 36-industry level.

6 Robustness and Heterogeneity Analysis

This section reports some robustness tests of our main findings and includes a heterogeneity analysis for the association between pension fund investment and firm productivity. We first show that co-investments by other financial sector investors do not drive our results. We then re-estimate our main specifications with a series of alternative approaches, including different matching strategies, production function estimators, and variable definitions. Finally, we examine whether the association varies across industries and firm characteristics.

6.1 The Role of Co-investments

One concern is that if pension funds consistently invest in firms jointly with other specific investors (such as private equity funds or insurance companies), interpreting the positive coefficients reported in the previous tables as effects on productivity exclusively attributable to pension fund investments could be misleading. We therefore augment our baseline specification from Column 2 of Table 2 by adding a dummy variable that captures investments in unlisted firms by any other financial party, and we report the results in Table 7.[28] It is important to note that the investor categories reported in Table 7 represent ultimate owners as identified by our ownership algorithm (the same algorithm used to identify pension funds). Entities that appear within ownership chains are treated as intermediate layers and are therefore not counted as owners in Table 7; such cases reflect "vertical" ownership relationships (via intermediaries), whereas Table 7 captures "horizontal" ownership situations in which multiple ultimate owners, such as pension funds and investment companies, co-own a firm.

The new estimates allow us to dismiss the hypothesis that the main channel through which firm productivity positively correlates with pension fund investment is the presence

[28] We construct this additional variable based on 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, fewer than 1% of the firms in our sample are foreign-owned.

of other investor types. Table 7 shows that, regardless of how we measure the other-investor dummy, the coefficient on the pension fund variable remains positive and statistically significant in all cases, with an estimated magnitude between 2 and 5%. At the same time, the results also reveal that some other investor types, such as investment companies and other financial intermediaries, exhibit a positive association with productivity as well. However, although certain other investor types exhibit positive coefficients, these estimates tend to be smaller than those for pension funds. This pattern is consistent with the descriptive evidence presented in Section 3.1, which shows that these investor groups, like pension funds, tend to remain invested in firms for several consecutive years.[29] Specifically, pension funds, investment companies, and other financial intermediaries remain invested for roughly four consecutive years, a longer period than asset managers, banks, venture companies, and capital funds. This long-term investment approach, as highlighted in Section 5.3.2, combined with the relatively substantial size of pension fund investments discussed in Section 5.3.1, appears to be an important mechanism explaining why pension funds exhibit a particularly strong and robust association with firm productivity. This pattern aligns with the idea that short-term or more volatile investment strategies do not provide firms with the financial stability and governance continuity necessary to foster productivity improvements. Finally, when we replicate this analysis for the sample of listed firms, the results of which are reported in Online Appendix Table C.3, the coefficients on both the pension fund and other investor-type dummies are not statistically significant. This finding is consistent with our earlier result that the positive relationship between pension fund investment and productivity is confined to unlisted firms.

[29] To comply with the DST data disclosure policy, Table B.2 provides a slightly more aggregated classification of other investors.

Table 7: Productivity Estimates: Including Other Investors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Elasticity of Labor (β_l)	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***	0.955***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***	0.079***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}$	4.142***	4.136***	4.814***	4.152***	3.596**	4.127***	2.984**	3.630**	3.421**	4.484***	2.253*	4.054**	3.916**
	(1.412)	(1.459)	(1.709)	(1.423)	(1.661)	(1.534)	(1.500)	(1.429)	(1.513)	(1.699)	(1.350)	(1.735)	(1.588)
$Other_{ij,t-1}$	-0.465	-0.455	-2.200	-0.646	0.708	-0.731	1.698*	3.197	1.733**	-1.152	2.022*	-1.183	-1.689
	(0.367)	(0.383)	(1.747)	(0.461)	(0.831)	(0.543)	(0.900)	(3.244)	(0.880)	(1.901)	(1.181)	(2.307)	(2.910)
Obs.	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319
Obs. PF	893	893	893	893	893	893	893	893	893	893	893	893	893
# Firms	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308
# Firms PF	272	272	272	272	272	272	272	272	272	272	272	272	272
Obs. other	23,755	23,688	539	21,635	2,031	20,441	2,396	110	2,048	580	1,862	146	43
# Firms other	5,122	5,112	178	4,783	598	4,579	667	69	584	179	545	56	17
Obs. both	804	799	327	662	386	573	479	72	261	407	547	99	-
# Firms both	252	250	119	218	136	198	168	46	108	143	170	44	-

Notes: This table presents the results from the estimation of Equation (1), the baseline variant in Column 2 of Table 2, adding a dummy for domestic investors that are not pension funds. $DPFI_{ij,t-1}$ is a dummy equal to 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. $Other_{ij,t-1}$ 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 sector, according to the 6 digit DB sector classification, invested in firm i in industry j in year $t-1$. This dummy takes value 1 according to the following. 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 $DPFI_{ij,t-1}$ and $Other_{ij,t-1}$ are multiplied by 100. The coefficient estimates of $DPFI_{ij,t-1}$ and $Other_{ij,t-1}$ measure their associations with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in at least one year. 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. Cells with fewer than 10 observations are omitted to comply with DST data disclosure policy. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

6.2 Further robustness analysis

We begin by examining the sensitivity of our results to the way we construct the matched sample. Specifically, we re-estimate the propensity scores using a random forest model to create a sample with common support. Unlike the logit model used for propensity score estimation in the main analysis, the random forest is a non-parametric ensemble learning method well-suited for capturing non-linear relationships and complex interactions among covariates. As in the main analysis, we estimate the random forest model separately for each year and industry pair. For each pair, the dataset is split into training and testing subsets, with 70% of the observations allocated to the training set and 30% to the testing set.[30] To improve the reliability of the propensity score estimation, the model is configured to grow 1,000 trees per forest, and the hyper-parameter governing the number of variables randomly sampled as candidates at each split is tuned using a grid search combined with 10-fold cross-validation. Finally, we validate the resulting propensity scores on the testing set to ensure predictive accuracy.[31] In the second check, we construct a sample by applying a more stringent common support condition than the one used in the main analysis. Specifically, instead of defining the overlap of the propensity score distributions for treated and non-treated observations based on the minimum propensity score for treated observations and the maximum for non-treated observations, we use the 5th and 95th percentiles of the propensity score distribution, respectively. Note that this adjustment significantly reduces the sample size, shrinking it from approximately 58,000 to nearly 23,000 observations. In

[30] During this partitioning process, we ensure that the dummy variable of pension fund investments is well-represented in both subsets by employing stratified sampling. This approach preserves the distribution of treated and untreated observations across the training and testing sets.

[31] Note that this approach is computationally and data demanding, and the propensity score cannot be estimated for all observations; as a result, the final sample used to estimate the production function decreases from approximately 58,000 to 38,000 firm-year observations.

the last check, we re-estimate the production function using the same sample as in the main analysis but apply inverse probability weights to both stages of the production function estimation (Imbens and Wooldridge, 2009). This approach internalizes the propensity score directly into the estimation of coefficients of interest. The inverse probability weights, calculated based on the propensity scores, assign greater importance to non-treated observations and less importance to treated observations during estimation. The results of these three checks, reported in Table 8, are very similar to the main results discussed in the previous section.

Second, the last column of Table 8 presents results from excluding firms without ownership information. Our baseline uses all Danish firms as the control group, although ownership data exist only for firms partly owned by other firms, of which those receiving pension fund investment are a subset. To ensure that missing ownership data do not drive our results, we re-estimate the baseline model on a restricted sample that excludes firms without ownership information. The coefficients on pension fund investment become slightly larger, but the overall conclusions remain unchanged.

Table 8: Productivity Estimates: Alternate Matching Strategies

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.870***	0.893***	0.975***	0.926***
	(0.009)	(0.008)	(0.017)	(0.007)
Elasticity of Capital (β_k)	0.105***	0.080***	0.051***	0.092***
	(0.007)	(0.005)	(0.014)	(0.005)
$DPFI_{ij,t-1}$	3.457*	3.980**	4.778***	4.966***
	(1.990)	(1.720)	(2.958)	(1.511)
Industry FE	Yes	Yes	Yes	Yes
Obs.	38,734	23,060	58,319	42,066
Obs. PF	649	416	893	887
Firms	8,070	5,733	10,308	7,753
Firms PF	207	141	272	271

Notes: This table presents the results from the estimation of the baseline specification of Equation (1), (see Column 2 of Table 2). The first column presents the results from the estimation of Equation (1) using a common support constructed with a propensity score estimated from a random forest model. The second column presents the results from the estimation of Equation (1) using a sample based on the 5th and 95th percentile of the propensity scores distribution for respectively non-treated and treated observations as boundaries for the common support condition. The third column presents the results from the estimation of Equation (1) using the main sample and inverse probability weights calculated with the estimated propensity scores. The fourth column includes in the sample only firms with ownership data. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level with the only exception of Column 2 where we use the 1-digit classification. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Third, we re-estimate the production function using the approach of Olley and Pakes (1996), augmenting the law of motion with the dummy variable capturing pension fund investments.[32] This approach explicitly models firm attrition in the estimation of the production function. The results, presented in Table C.1 in the online Appendix C, confirm the robustness of our findings.[33]

Fourth, we present the results obtained from a gross-output production function, which

[32] We identify attrition by determining whether a firm ID disappears from our sample.

[33] Sample truncation, caused by using investments in Olley and Pakes (1996) as a proxy variable, reduces the sample size by nearly half compared to the main sample, which implies that some statistical power is lost. In contrast, this issue does not arise in ACF, where intermediate material inputs, being a less lumpy variable than investments, are used as a proxy.

cannot be identified using the standard ACF approach. Table C.2 in the online Appendix C reveals that our findings and interpretations remain generally robust and with similar magnitudes and significance when employing a gross-output-based production function instead of a value added based one, using the methodology developed by Gandhi et al. (2020).[34]

We close this section with a few additional robustness checks. First, we exclude firms whose share capital increased in any sample year. A firm that undertakes a capital increase 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 association between productivity and pension fund investment. However, excluding these firms confirms our baseline results, with positive and highly significant coefficients in all specifications (Table C.4 of the online Appendix C). Second, our results remain unaffected if we approximate the function $h(.)$ in the first-stage of the production function[35] by a third-degree polynomial in labor, capital, intermediary inputs, average wage, and investment rate (following Fan et al., 2022) (Table C.5 of the online Appendix C). Third, 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 (Table C.6 of the online Appendix C). Finally, for completeness, we also report the main results obtained from the unmatched sample (Table C.7 in the online Appendix C), which tend to be slightly stronger than the ones estimated from the matched sample.

[34] Following the authors' guidance, we modify their code to allow for an endogenous Markov process for productivity, incorporating our pension fund investment variable.

[35] See equation 7 in online Appendix A.4.

6.3 Heterogeneity analysis

In the online Appendix C, we also present a heterogeneity analysis examining whether the association between productivity and pension fund investment varies across industries and firm characteristics. When re-estimating the production function separately by 1-digit industry, we find that the coefficient on pension-fund investment is generally positive, although statistical significance is limited by the small number of treated observations within most sectors (see Table C.8 of the online Appendix C). Manufacturing stands out as the only industry with a statistically significant effect, consistent with the importance of long-term capital and governance benefits in a highly capital-intensive sector. Additional heterogeneity analyses based on firm size, age and labor productivity in the base year, i.e., the first year a firm appears in the sample, reveal that smaller firms benefit slightly more from pension fund investment, which is consistent with a supply-of-financing channel, while firm age does not influence the association between productivity and pension fund investment (see Table C.9 of the online Appendix C). Moreover, the positive and significant association persists even after controlling for high initial productivity, suggesting that it is not driven by pension funds selecting already more productive firms, which is consistent with the event study evidence.

7 Discussion and Conclusion

Among various initiatives to boost productivity, this paper examines whether equity investments channeled through funded pension schemes are associated with increases in firm productivity. In recent decades, funded pension savings have grown substantially across the globe, and countries with high levels of pension savings relative to GDP typically top international rankings 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 remains largely unresolved 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 their implications for the wider economy.

We combine high-quality Danish register data with a detailed database on the domestic shareholders of Danish unlisted firms that we construct. Our estimates suggest a quantitatively large, positive association between firm productivity and pension fund investment, with an average magnitude of 3–5%. This outcome, achieved despite the complex ownership structure in our database, supports our hypothesis that pension fund investments are related to productivity differences among unlisted firms. As explained in the data section, we can identify the ultimate owners of firms only by relying on numerous assumptions, inevitably introducing some unintended "measurement error" in how ownership power is distributed. In our view, this complexity further corroborates our main hypothesis. In fact, despite these challenges in accurately determining firms' ultimate owners, the positive coefficient on our pension fund variable is highly robust across a wide range of refinement analyses. It remains, for example, when we control for whether a firm exports and when we account for other domestic investors from the financial industry.

We also find suggestive evidence that the productivity association is stronger when pension funds hold larger stakes and have longer investment horizons in the firm. The former result suggests a role for the "supply-of-financing channel", while the latter emphasizes the "long-term-commitment channel". Moreover, we observe that the association is stronger when pension funds are closer to the owned firm in the ownership chain, consistent with an "engagement channel" in which more proximate owners can exercise greater oversight. Finally, we find indicative evidence of a signalling channel: after a pension fund enters a firm's ownership structure, the number of other investors (especially other pension funds) increases. This pattern is consistent with pension fund involvement sending a positive signal about the firm's quality and governance, thereby attracting additional investors and broadening the ownership base. A refinement analysis focusing on listed firms shows that the association between productivity and pension fund investment is present only for unlisted firms. This pattern is consistent with the supply-of-financing channel, as unlisted firms typically face tighter financing constraints and have fewer alternative sources of external capital, and with the notion that listed firms' greater public visibility and exposure to external (including political) pressures may limit the scope for pension funds' influence. At the same time, this finding does not preclude the relevance of other mechanisms, such as engagement or long-term commitment, which may be particularly important for unlisted and, on average, smaller firms.

These results also speak to a gap in the existing literature on institutional ownership and firm performance. Prior work has documented positive associations between institutional ownership and productivity-related outcomes (such as innovation), but these findings come mainly from listed firms (Aghion et al., 2013) or from studies of PE and VC investors, who improve performance through active operational control (Chemmanur et al., 2011; Davis et al., 2014; Bernstein et al., 2017). Pension funds have received comparatively little attention in this literature, despite differing from both broad institutional investors and PE/VC funds in important ways. Our results complement these prior findings by showing that pension funds, investors with longer horizons and a less interventionist mode of engagement,[36] are positively associated with productivity, but only among unlisted firms. The key distinction is that, for unlisted firms, external equity capital is scarce and the pool of potential equity providers is small. In this environment, the entry of a large, patient investor can relax financing constraints, provide stability, and, as our evidence on ownership proximity suggests, contribute to governance in ways that would be redundant in listed markets where multiple institutional investors are already present (Brav et al., 2008; McCahery et al., 2016) and alternative capital sources abundant.

Our study provides tentative leads for policies aimed at increasing firms' productivity. This is particularly important in an era in which potential GDP growth has gradually fallen across many industrialized countries, raising the question of how such developments might be reversed. At the same time, many developed countries face the need to reform their pension systems in light of population ageing, while emerging and developing economies confront the dual challenge of promoting economic development and designing sustainable pension systems for a growing population. These considerations make the challenge of boosting productivity growth even more pressing. Moreover, the global trend toward greater reliance on funded pensions increases the relevance of understanding how pension funds interact with the real economy. Against this backdrop, our micro-level results, although derived from a single-country context with a highly-developed pension system, may offer suggestive insights

[36] Unlike PE and VC funds, which typically acquire controlling stakes, restructure operations, and replace management, pension funds generally do not seek operational control. Their influence tends to be indirect: by providing stable, long-horizon capital, exercising governance through ownership proximity, and signalling firm quality to attract additional investors.

for policymakers considering the broader macroeconomic implications of funded pension systems.

Specifically, a positive association between pension fund investment and firm productivity provides indicative support for the idea that funded pension schemes could, under certain institutional conditions, contribute to productivity improvements. However, given that our study is set in Denmark, where data quality is exceptional and pension institutions are particularly well developed, caution is needed when extrapolating these findings to countries with different institutional frameworks. To the extent that any productivity increase is driven by pension funds' long-term financing commitment, our results may also be viewed as suggestive of the potential importance of policies that avoid premature liquidation of pension savings, such as restrictions on early withdrawals.[37] Likewise, policies aimed at increasing pension savings, such as tax incentives for contributions, could, in settings with similar institutional features, support domestic investment and productivity. At the same time, our findings should not be interpreted as implying that pension funds should concentrate their portfolios domestically; rather, we document empirical relationships for the subset of domestic investments that can be observed in our data.

[37] 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.

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Appendices: Not For Publication

A.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 the GDP. These assets, including those of public sector employees, are managed by private 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, which are often obtained as private equity, for example, directly from the founder or another party. They can be either passive investors, as would be the case if they merely invest in a stock market index, or active investors to the extent that they also directly engage with the firm's management and its decisions.

Anecdotal evidence gathered within the working group of the International Centre for Pension Management suggests that when pension funds select firms to invest in, their decisions are influenced by a combination of strategic evaluation and the potential for enhancing productivity. Pension funds may target companies where their intervention could unlock growth and productivity that would otherwise remain unattainable. They are also likely to invest in firms that benefit from long-term investment, thereby aligning with the funds' liability durations and investment horizons. These firms often participate in substantial projects, such as infrastructure or technology, which require a prolonged period to realize returns. An important case supporting this observation is Pension Danmark's investment in a Danish clean-tech firm. This investment demonstrates how pension funds deploy capital to foster innovation and support emerging technologies that align with broader societal goals, such as sustainability and climate change mitigation. The firm benefits from Pension Danmark's long-term investment horizon, which is crucial for developing its technology to commercial viability (Beetsma et al., 2024).

A.2 Common Support

To address the fact that firms in the control group tend to differ, on average, in observable characteristics (such as size and value added) from treated firms, we construct a matched sample using a propensity score approach. The sample obtained with this method serves as our main sample for both the event study analysis and the structural estimation results. First, we estimate the probability of a firm receiving a pension fund investment by running a logit regression of the dummy variable $DPFI_{ijt}$ on value added, capital and size (number of employees), where all explanatory variables are measured at *time* $t-1$, separately by industry and year.[38] We then drop firms with propensity scores that lie outside the common support. Specifically, we exclude observations where the propensity score is below the minimum value calculated for treated firms and those where the propensity score exceeds the maximum

[38] Using base year values instead of one-period lags yields very similar results. Similar results are also obtained by using value added per employee and capital per employee as controls.

value calculated for non-treated firms. In this way, we exclude from the treated group firms that have a very high probability of receiving pension fund investment on the basis of, for example, their productivity, as well as firms that are very unlikely to receive this type of investment. We therefore include in the final matched sample only firms in the treated and control groups with a comparable chance of receiving pension fund investment. As a refinement, we go a step further and also weight the results by propensity scores using an inverse probability weighting approach in Section 6. Furthermore, while the specification for the propensity score is very parsimonious, estimating it separately for each industry-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. There, we also present the distribution of estimated propensity scores for treated and non-treated firms before enforcing the common support requirement. While trimming increases comparability by excluding 37,000 observations from a sample of approximately 115,000, some residual differences remain. In Section 6, we further restrict the sample to firms within the 5th–95th percentiles of the propensity score distribution resulting in the exclusion of 90,000 observations from the original sample, and find that the estimated coefficients remain qualitatively similar to the main results.

A.3 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.3.1 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 15th 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.[39] 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 duplicate observations:

   (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

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

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

Table A.1: Timing Example

Original Data:

Owner	Owned	1lYear	1lDelivery	1lStake
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.3.2 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.3.3 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.[40]

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.3.4 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

[40]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.

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 6% 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.3.5 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.3.6 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

5p20.225em—First round of iteration:	5p20.225emSecond round of iteration:								
1p4.045emOwner	1p4.045emOwned	Year	Stake	1p4.045em—Level	1p4.045emOwner	1p4.045emOwned	1p4.045emYear	1p4.045emStake	1p4.045emLevel
1p4.045emB	1p4.045emA	1l2010	1l33	1l—1	1p4.045emB	1p4.045emE	1c2010	1l33	1l2
1p4.045emC	1p4.045emA	1l2010	1l33	1l—1	1p4.045emC	1p4.045emE	1c2010	1l33	1l2
1p4.045emD	1p4.045emA	1l2010	1l33	1l—1	1p4.045emD	1p4.045emE	1c2010	1l33	1l2
1p4.045emE	1p4.045emA	1l2010	1l100	1l—1					

5p20.225emFinal Data:

Owner	Owned	1p4.045emYear	1p4.045emStake	1p4.045emLevel
B	A	2010	33	1
C	A	2010	33	1
D	A	2010	33	1

A.3.7 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.

A.4 Structural Productivity Estimation

This section describes the methodology used to shed light on the empirical relationship between pension fund investment and firm productivity. 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 the 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:

$$y_{ijt} = \beta_k k_{ijt} + \beta_l l_{ijt} + \omega_{ijt} + \varepsilon_{ijt} \tag{2}$$

where lower case letters denote logs and y_{ijt} is the value added of firm i in industry j at time t, k_{ijt} is its capital stock and l_{ijt} is its labor input.[41] Furthermore, ε_{ijt} is an i.i.d. unobservable

[41] 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 industry-specific deflators published by Statistics Denmark.

shock to production (or a measurement error), while ω_{ijt} 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.[42] 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_{ijt}, k_{ijt}) and ω_{ijt} 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_{ijt}.[43] 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 the recent literature (Bøler et al. (2015); Fan et al. (2022); Doraszelski and Jaumandreu (2013); Maican et al. (2022)), and estimate the impact of a pension fund investment by using a control function approach in two steps. 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 otherwise bias the estimation of productivity. De Loecker (2013) finds that controlling for this type of 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

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

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

expenditure choices (Bøler et al., 2015; Fan et al., 2022; De Loecker, 2013; Doraszelski and Jaumandreu, 2013; 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 (2), we assume the following:

$$E\left(\varepsilon_{ijt} \mid l_{ijt}, k_{ijt}, m_{ijt}, l_{ij,t-1}, k_{ij,t-1}, m_{ij,t-1}, ..., l_{ij1}, k_{ij1}, m_{ij1}\right) = 0 \tag{3}$$

where m refers to our proxy variable (intermediate material inputs). We abstract from serial dependence in the pure shock term, hence past values of ε_{it} are not included in the conditioning set. Furthermore, we restrict the dynamics of the productivity process as follows:

$$E\left(\omega_{ijt} \mid \omega_{ij,t-1}, \omega_{ijt-2}, ..., \omega_{ij1}\right) = E\left(\omega_{ijt} \mid \omega_{ij,t-1}\right) = g\left(\omega_{ij,t-1}\right) \tag{4}$$

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 $t-1$, which means that 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:

$$m_{ijt} = f(k_{ijt}, l_{ijt}, \omega_{ijt}) \tag{5}$$

Moreover, following the standard assumption in the literature that the material demand function is strictly monotonic in the productivity shock ω_{ijt} , we can invert the function in (5) to obtain ω_{ijt} as a function of k_{ijt}, l_{ijt} and m_{ijt}:

$$\omega_{ijt} = \tilde{h}(k_{ijt}, l_{ijt}, m_{ijt}) \tag{6}$$

We plug $\tilde{h}\,(.)$ into production function (2) and augment the resulting expression with year-fixed effects κ_t, to obtain the following:

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

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, i.e., to separate ω_{ijt} from ε_{ijt}. We operationalize this first stage by approximating $h(.)$ with a second-degree polynomial of capital, labor and intermediate inputs with full interaction terms and estimating the resulting equation via OLS.[44] In order to allow for heterogeneity in production technology and demand across industries, we estimate (7) separately for each industry j, i.e., for each of the DB07 36

[44] The results are unaffected when we use an alternative specification of the first stage – see the discussion of robustness in Section 5 below.

industries.[45] We then define $\hat{h}_{ijt}$ as the predicted output net of year-fixed effects. The predicted output from the first stage $\hat{h}_{ijt}$ is then used to identify the input elasticities in the second stage.

To obtain the second-stage estimation equation, we assume that productivity ω_{ijt} 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 De Loecker (2013); Bøler et al. (2015); 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_{ijt} over time. We prefer this approach to the inclusion of pension fund investment directly as an input in the production function (2) since Equation (2) expresses output solely as a function of the physical inputs. Moreover, 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 therefore assume that productivity ω_{ijt} depends on firm i receiving a pension fund investment through the following law of motion:

$$\omega_{ijt} = \rho\omega_{ij,t-1} + \gamma PFI_{ij,t-1} + \xi_{ijt} \tag{8}$$

where $PFI_{ij,t-1}$ denotes a pension fund investment in firm i in industry j at time $t-1$.

[45] More information on the Danish classification of industries can be found here: https://www.dst.dk/da/Statistik/dokumentation/nomenklaturer/db07

Furthermore, ξ_{ijt} is an idiosyncratic error term uncorrelated with the other right-hand-side variables and any other information at time $t-1$ and earlier.[46] Note that the conditional expectation of ω_{ijt} in (5) now becomes a function of its lag and $PFI_{ij,t-1}$.

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

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

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

$$\hat{h}_{ijt} = \alpha_j + \beta_k k_{ijt} + \beta_l l_{ijt} + \rho\left(\hat{h}_{ij,t-1} - \beta_k k_{ij,t-1} - \beta_l l_{ij,t-1}\right) + \gamma PFI_{ij,t-1} + \xi_{ijt} \tag{10}$$

where we have added the constant α_j, which is allowed to vary across industry j, i.e., for each of the DB07 36 industries, to arrive at the empirical specification. We estimate (10) by the generalized method of moments (GMM).[47] Following the standard ACF approach, we use k_{ijt} and $l_{ij,t-1}$ as instruments. Since $\hat{h}_{ij,t-1}$, $k_{ij,t-1}$, k_{ijt} and $PFI_{ij,t-1}$ are determined at time $t-1$ or earlier, they are orthogonal to the error term ξ_{ijt} and can be used to form the

[46] $PFI_{ij,t-1}$ and earlier pension fund investment therefore indirectly enter the production function (2) through ω_{ijt}. 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.

[47] For the identification of the production function elasticities, our approach requires variation in these inputs conditionally on ω_{ijt}. Stated differently, our approach requires either exogenous input price differences across firms or differences in input dynamics across firms. However, we obtain similar results 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.

necessary moment conditions. Labor l_{ijt}, however, is chosen after $t-1$, given our timing assumptions, so we instrument it with $l_{ij,t-1}$. Finally, we allow the constant α_j to vary by industry by including industry dummies, one for each of the DB07 36 industries, using these dummies as their own instruments. The instrument set thus contains $l_{ij,t-1}$, $\hat{h}_{ij,t-1}$, k_{ijt}, $PFI_{ij,t-1}$ and the industry dummies.

The coefficient γ in Equation (10) captures the association of a past pension fund investment with firm productivity. We identify this coefficient in the second stage by exploiting variation in past pension fund investment $PFI_{ij,t-1}$ conditional on lagged productivity $\omega_{ij,t-1}$. 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 coefficient of interest directly from the law of motion of productivity as we do allows us to control for past productivity and to attenuate more explicitly the issue of selection.

Appendix B Additional Statistics

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

Sector	Firms with PFI	Firms without PFI
Manufacturing	159	2,791
Construction	17	1,463
Wholesale and retail trade; repair of motor vehicles and motorcycles	41	3,562
Transportation and storage	–	700
Information and communication	33	561
Real estate activities	–	88
Professional, scientific and technical activities	16	801
Administrative and support service activities	–	487
Total	**272**	**10,453**

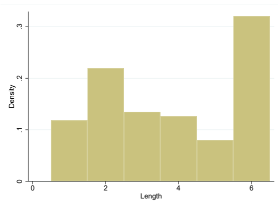
Notes: This table illustrates the industry distribution among firms in the sample. Since a firm is treated if it received a pension fund investment in the previous year, this table splits the sample into firms that are treated at least once over the sample period (left Column) and firms that are never treated (right Column). PFI denotes pension fund investment. Cells with fewer than 10 observations are omitted (–) to comply with DST data disclosure policy.

Table B.2: Investment Length: Pension Funds and Other Investors

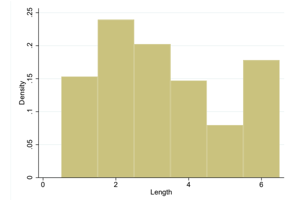
Investor sector	**N**	**Mean** $\boldsymbol{Length_{ijt-1}}$	**Difference**	**Difference p-value**
Panel A				
Pension funds	1,587	4.50	.	.
Banks, savings banks and cooperative banks	665	3.78	0.72	0.00
Financial holding companies	2,426	3.71	0.80	0.00
Non-financial holding companies	23,718	5.11	-0.61	0.00
Investment associations	162	2.06	2.44	0.00
Investment companies	2,555	4.18	0.32	0.00
Venture companies and capital funds	688	3.55	0.95	0.00
Other financial intermediation except insurance and pension insurance	2,361	4.16	0.34	0.00
Asset management	55	3.40	1.10	0.01
Insurance companies	187	2.99	1.51	0.00
Panel B				
Pension funds	237	4.65	.	.
Banks, savings banks and cooperative banks	163	3.80	0.86	0.01
Financial holding companies	364	3.15	1.50	0.00
Non-financial holding companies	1,390	4.29	0.36	0.11
Investment associations	74	2.35	2.30	0.00
Investment companies	373	3.67	0.99	0.00
Venture companies and capital funds	123	4.21	0.44	0.19
Other financial intermediation except insurance and pension insurance	367	3.61	1.04	0.00
Asset management	10	2.20	2.45	0.02
Insurance companies	58	2.72	1.93	0.00

Notes: This table reports the average value of the investment length variable ($Length_{it-1}$), for pension funds, the six-digit investor sectors and insurance companies (three-digit sector). It also shows the difference in mean investment length between pension funds and each investor sector, together with the p-values from two-sample t-tests comparing each sector to pension funds. Panel A refers to the whole sample and includes all cases in which at least one investor from the sector holds an equity stake in firm i at time $t-1$. Panel B instead focuses on cases of complete (terminated) investments by restricting attention to divestments, defined as at least one investor from the sector holding an equity stake in firm i at time $t-1$ but no longer investing in the same firm in period t.

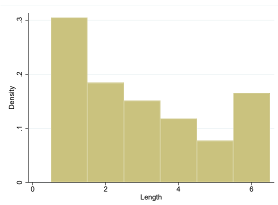
Figure B.1: Distribution of the Investment Length



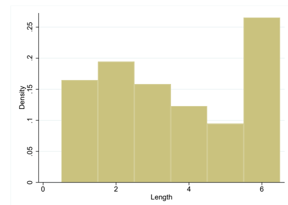
(a) Pension Funds



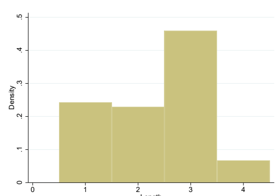
(b) Banks, savings banks and cooperative banks



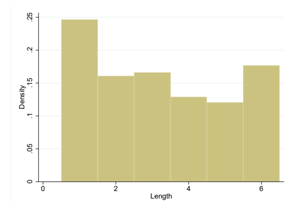
(c) Financial holding companies



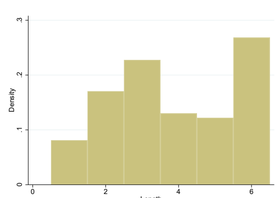
(d) Non-financial holding companies



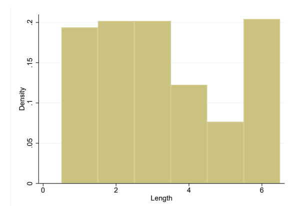
(e) Investment associations



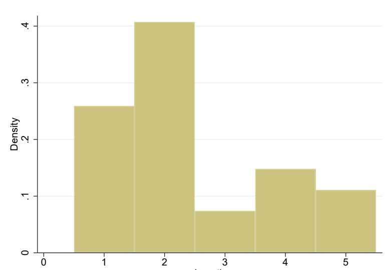
(f) Investment companies



(g) Venture companies and capital funds



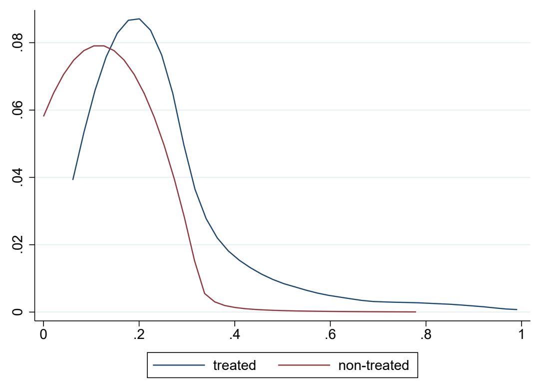
(h) Other financial intermediation except insurance and pension insurance



(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.2). 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.2) due to a very low number of observations.

Figure B.2: Propensity score distribution for treated and non-treated firms



Notes: The propensity scores for treated and non-treated firms are estimated using the procedure described in Section 7. Y-axis is the kernel density of propensity scores for treated vs. non-treated firms. X-axis is the propensity score.

Table B.3: Descriptive Statistics Matching Variables

		Firms with PFI	**Firms without PFI**	**Firms without PFI (outside common support)**
Value added	(DKK, log)	10.748	9.977	9.531
		(1.102)	(1.062)	(1.073)
Capital	fixed assets (DKK, log)	9.825	9.030	8.571
		(1.789)	(1.645)	(1.907)
Labour	number of full-time employees (log)	4.334	3.880	3.410
		(1.029)	(0.943)	(0.910)
Observations		3,481	74,019	37,111

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 Section 4.

Table B.4: Descriptive Statistics for Listed Firms

		Listed Firms	
Variable	**Definition**	**Mean**	**Sd**
Pension Fund Investment Variables			
$DPFI_{ij,t-1}$	dummy = 1 if a pension fund invested in the firm	0.334	(0.472)
$Length_{ij,t-1}$ (*)	duration of current episode of pension fund investment (years)	1.814	(3.221)
$Intensity_{ij,t-1}$ (*)	total ownership by domestic pension funds (%)	3.003	(5.494)
Firm Variables			
Output/worker	output per worker (DKK, log)	7.809	(0.835)
VA/worker	value added per worker (DKK, log)	6.537	(0.478)
Value added	(DKK, log)	11.820	(1.116)
Labour	number of full-time employees (log)	5.284	(1.076)
Capital	fixed capital (DKK, log)	11.169	(1.683)
Intermediary inputs	(DKK, log)	12.539	(1.425)
Age	firm age (years)	29.351	(20.339)
Capital Intensity	capital stock per worker (DKK, log)	5.886	(1.272)
Export	1 if the firm exports	0.825	(0.380)
Observations		2,818	

Notes: All descriptive statistics are calculated as averages over the sample 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 the sample with listed firm-year observations. (*) Values are reported conditional on the firm receiving a pension fund investment in at least one year.

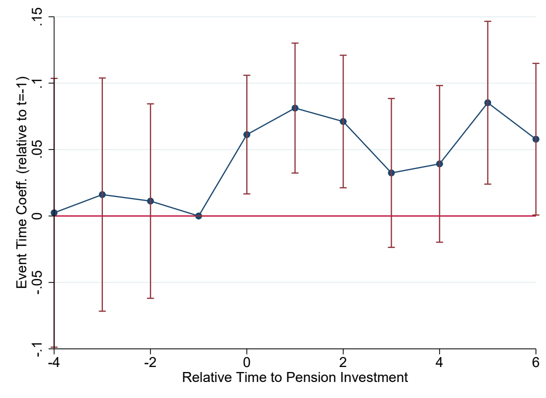
Table B.5: Intermediary Types Appearing in Indirect Pension Fund Investment Chains

Intermediary Type	**Share of Indirect Investments**
Any domestic financial investor (excluding pension funds)	0.90
Banking and financing activities, except insurance and pensions	0.90
Banks, savings banks and cooperative banks	0.53
Holding companies	0.25
Financial holding companies	0.37
Non-financial holding companies	0.76
Investment associations and investment companies	0.02
Money market associations	0.27
Investment companies	0.65
Venture companies and capital funds	0.04
Other financial intermediation except insurance and pension insurance	0.00
Insurance companies	0.00
Asset management	0.15

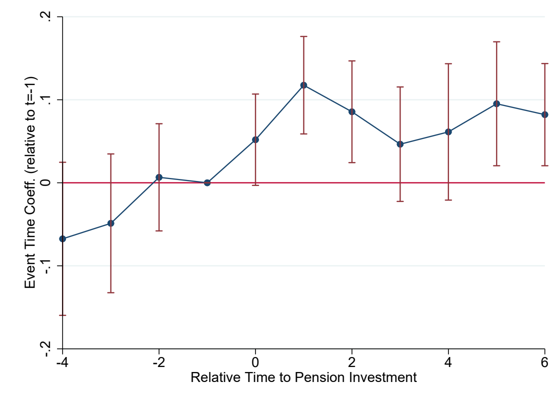
Notes: The reference sample for this table includes only indirect pension fund investment. For each intermediary type, the table reports the fraction of investment chains that contain at least one intermediary of that type at any layer of the ownership structure. The first row ("Any domestic financial and non-financial investor, excluding pension funds") is a broad aggregate category and by construction encompasses all intermediary types reported in the panel below. The second row ("Banking and financing activities, except insurance and pensions") is a sector-level aggregate and includes only intermediaries engaged in banking and financial activities, excluding insurance and pension-related entities. Shares do not sum to one because multiple intermediary types may appear within the same chain.

Appendix C Additional Results

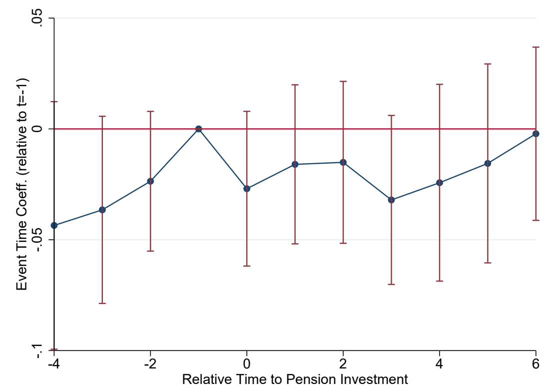
Figure C.1: Event Study Results, Output, Value Added, Labor and Investments



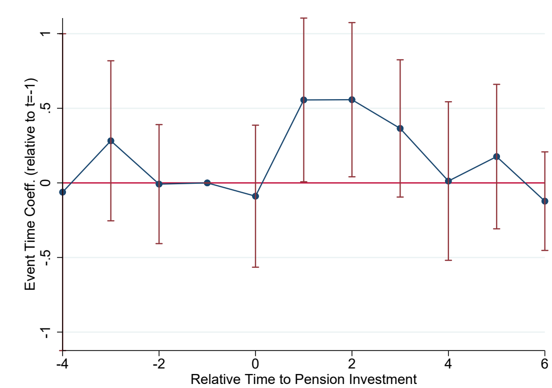
(a) Output



(b) Value Added



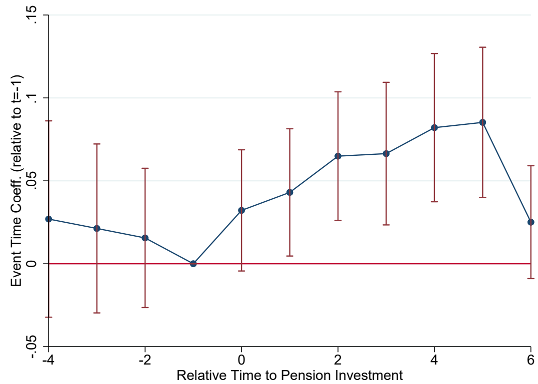
(c) Labor (employees)



(d) Investments

Notes: In the first panel, the outcome variable is the log of output (sales) in a given year. In the second panel, the outcome variable is the log of value added in a given year. In the third panel, the outcome variable is the log of number of employees in a given year. In the fourth panel, the outcome variable is the log of investments in a given year, where investments are calculated as the difference in capital stock between two consecutive years. Year 0 is the first year of pension fund investment. 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 and capital intensity. We also include year-by-(DB07-36)industry fixed effects.

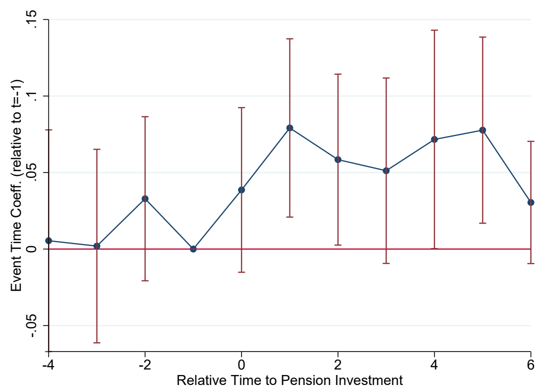
Figure C.2: Event Study Results, Alternative Measure of Output



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

Notes: The outcome variable is the log of 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. Year 0 is the first year of pension fund investment. 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 and capital intensity. We also include year-by-(DB07-36)industry fixed effects.

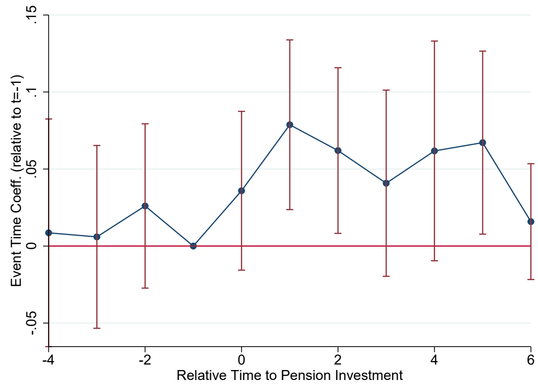
Figure C.3: Event Study Results, Specification without Control Variables



(a) Value added per Worker

Notes: The outcome variable is the log of value added per worker. Year 0 is the first year of pension fund investment. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). We also include year-by-(DB07-36)industry fixed effects.

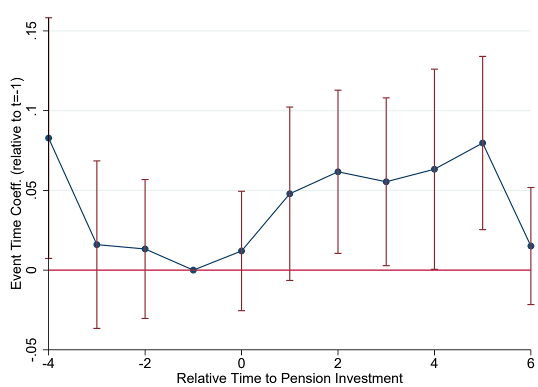
Figure C.4: Event Study Results, Controlling for the Share of R&D Workers



(a) Value added per Worker

Notes: The outcome variable is the log of value added per worker. Year 0 is the first year of pension fund investment. This figure presents point estimates and 95% confidence intervals of an event study specification using the estimator proposed by Sun and Abraham (2021). We add to the control variables the share of R&D workers. We also include year-by-(DB07-36)industry fixed effects.

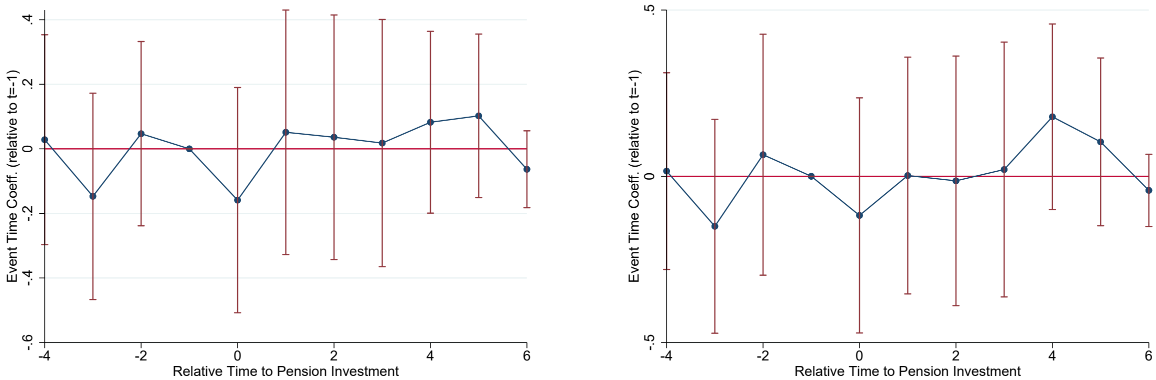
Figure C.5: Event Study Results, Excl. Short Investments



(a) Value added per Worker

Notes: The outcome variable is the log of value added per worker. Year 0 is the first year of pension fund investment. 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 following controls enter the specification: firm age, a dummy for the firm being listed in the base year and capital intensity. We also include year-by-(DB07-36)industry fixed effects.

Figure C.6: Event Study Results, Output Price

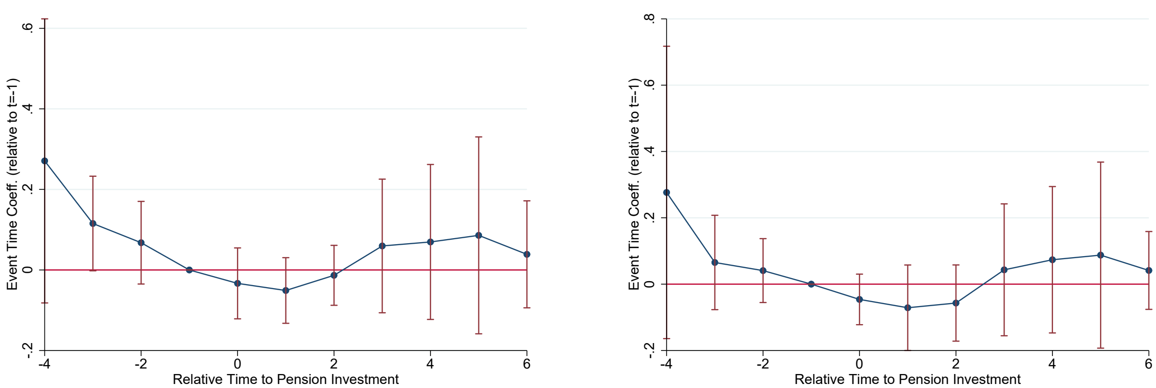


(a) Av. Output Price

(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. Year 0 is the first year of pension fund investment. 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 and capital intensity. We also include year-by-(DB07-36)industry fixed effects.

Figure C.7: 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. Year 0 is the first year of pension fund investment. 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 and capital intensity. We also include year-by-(DB07-36)industry fixed effects.

Table C.1: Productivity Estimates using Olley and Pakes (1996): Pension Fund Dummy

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.935***	0.935***	0.935***	0.935***
	(0.004)	(0.004)	(0.004)	(0.004)
Elasticity of Capital (β_k)	0.125***	0.125***	0.125***	0.104***
	(0.013)	(0.013)	(0.013)	(0.009)
$PFI_{ij,t-1}$		4.382**	7.268***	4.820**
		(2.183)	(2.624)	(2.146)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
Export$_{ij,t-1}$	No	No	No	Yes
Obs.	24,294	24,294	24,294	24,294
Obs. PF	364	364	242	364
# Firms	6,277	6,277	6,277	6,277
# Firms PF	154	154	108	154

Notes: This table presents the results from the estimation of the production function using the approach developed by Olley and Pakes (1996). $DPFI_{ij,t-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 3, $DPFI_{ij,t-1}$ equals 1 if the aggregate holding of all pension funds in firm i in industry j in year $t-1$ was at least equal to 5%. In Column 4, we include a dummy equal to 1 if firm i in industry j 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 at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.2: Productivity Estimates Based on Gross-Output: Pension Fund Dummy

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.346***	0.342***	0.342***	0.342***
	(0.006)	(0.006)	(0.005)	(0.006)
Elasticity of Capital (β_k)	0.030***	0.028***	0.028***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
Elasticity of Intermediate Input (β_m)	0.722***	0.724***	0.724***	0.724***
	(0.018)	(0.039)	(0.003)	(0.002)
$PFI_{ij,t-1}$		4.772**	4.870*	4.868*
		(2.244)	(2.712)	(2.957)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
$\text{Export}_{ij,t-1}$	No	No	No	Yes
Obs.	58,152	58,125	58,125	58,125
Obs. PF	731	731	496	731
Firms	8,197	8,197	8,197	8,197
Firms PF	214	214	156	214

Notes: This table presents the results from the estimation of the production function using the approach developed by Gandhi et al. (2020). $DPFI_{ij,t-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 3, $DPFI_{ij,t-1}$ equals 1 if the aggregate holding of all pension funds in firm i in industry j in year $t-1$ was at least equal to 5%. In Column 4, we include a dummy equal to 1 if firm i in industry j 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 at least one year. Finally, $^{*}\ = p < 0.1$, $^{**}\ = p < 0.05$, and $^{***}\ = p < 0.01$.

Table C.3: Productivity Estimates: Including Other Investors, Sample of Listed Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Elasticity of Labor (β_l)	0.776***	0.776***	0.777***	0.777***	0.777***	0.777***	0.777***	0.777***	0.777***	0.777***	0.780***	0.777***	0.777***
	(0.043)	(0.043)	(0.047)	(0.041)	(0.048)	(0.040)	(0.047)	(0.047)	(0.047)	(0.047)	(0.052)	(0.046)	(0.046)
Elasticity of Capital (β_k)	0.135***	0.135***	0.133***	0.134***	0.133***	0.133***	0.133***	0.133***	0.133***	0.134***	0.133***	0.133***	0.133***
	(0.042)	(0.042)	(0.044)	(0.041)	(0.044)	(0.041)	(0.045)	(0.044)	(0.045)	(0.044)	(0.047)	(0.043)	(0.044)
$DPFI_{ij,t-1}$	-0.183	-0.314	-1.478	-1.065	-0.711	-1.177	-0.737	-1.008	-0.787	-0.957	1.408	-0.734	-1.224
	(0.475)	(0.786)	(1.120)	(0.971)	(1.266)	(1.126)	(0.390)	(0.961)	(0.836)	(1.544)	(1.320)	(1.724)	(1.141)
$Other_{ij,t-1}$	-7.150	-5.827	3.941	-0.302	-3.902	0.686	-2.322	-5.160	-2.106	-1.742	-9.937	-10.779	-
	(10.076)	(26.203)	(16.677)	(6.122)	(7.759)	(7.450)	(8.704)	(22.968)	(3.393)	(8.801)	(25.125)	(22.651)	-
Obs.	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818	2,818
Obs. PF	798	798	798	798	798	798	798	798	798	798	798	798	798
# Firms	328	328	328	328	328	328	328	328	328	328	328	328	328
# Firms PF	148	148	148	148	148	148	148	148	148	148	148	148	148
Obs. other	1,979	1,944	136	1,608	235	1,531	490	78	396	115	503	40	12
# Firms other	289	286	50	253	79	246	108	35	86	31	129	14	-
Obs. both	631	625	82	509	108	498	207	39	177	64	282	27	-
# Firms both	124	122	37	111	46	104	50	21	43	17	69	-	-

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 for the sample of listed firms. $DPFI_{ij,t-1}$ is a dummy equal to 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. $Other_{ij,t-1}$ 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 sector, according to the 6 digit DB sector classification, invested in firm i in industry j in year $t-1$. This dummy takes value 1 according to the following. 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 on $Other_{ij,t-1}$ omitted due to DST disclosure). Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ and $Other_{ij,t-1}$ are multiplied by 100. The coefficient estimates of $DPFI_{ij,t-1}$ and $Other_{ij,t-1}$ measure their correlations with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in at least one year. 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. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.4: Productivity Estimates: Excluding Firms with Capital Increases

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.964***	0.964***	0.964***	0.960***
	(0.007)	(0.007)	(0.007)	(0.007)
Elasticity of Capital (β_k)	0.076***	0.076***	0.076***	0.074***
	(0.005)	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}$		4.756**	4.891**	4.473**
		(2.258)	(2.053)	(2.208)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
Export$_{ij,t-1}$	No	No	No	Yes
Obs.	44,048	44,048	44,048	44,048
Obs. PF	508	508	361	508
# Firms	8,436	8,436	8,436	8,436
# Firms PF	169	169	128	169

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. $DPFI_{ij,t-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in industry j at time $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 3, $DPFI_{ij,t-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i in industry j at time $t-1$ was at least equal to 5%. In Column 4, we include a dummy taking value 1 if firm i in industry j 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 at least one year. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Productivity Estimates: Alternative First-Stage Polynomial

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.962***	0.961***	0.961***	0.953***
	(0.007)	(0.007)	(0.007)	(0.007)
Elasticity of Capital β_k	0.080***	0.080***	0.080***	0.075***
	(0.005)	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}$		5.102**	6.352**	3.874*
		(2.234)	(2.748)	(2.228)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
$\text{Export}_{ij,t-1}$	No	No	No	Yes
Obs.	57,692	57,692	57,692	57,692
Obs. PF	889	889	592	889
# Firms	10,230	10,230	10,230	10,230
# Firms PF	271	271	200	271

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 labor, capital, intermediary inputs, average wage and the investment rate (following Fan et al. (2022)). $DPFI_{ij,t-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in industry j at time $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 3, $DPFI_{ij,t-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i in industry j at time $t-1$ was at least equal to 5%. In Column 4, we include a dummy taking value 1 if firm i in industry j 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 at least one year. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: Productivity Estimates: Alternative Definition of Capital

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	1.000***	1.000***	1.000***	0.994***
	(0.005)	(0.005)	(0.005)	(0.005)
Elasticity of Capital (β_k)	0.040***	0.040***	0.040***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)
$DPFI_{ij,t-1}$		4.320***	5.215***	3.689**
		(1.613)	(1.790)	(1.584)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
Export$_{ij,t-1}$	No	No	No	Yes
Obs.	57,692	57,692	57,692	57,692
Obs. PF	889	889	592	889
# Firms	10,230	10,230	10,230	10,230
# Firms PF	271	271	200	271

Notes: This table presents results from the estimation of Equation (10) with k_{ijt} defined as the log book value of fixed assets (instead of calculated through the perpetual inventory method as in the main results). $DPFI_{ij,t-1}$ 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 $DPFI_{ij,t-1}$ are multiplied by 100. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, clustered by firm, with 200 replications in parentheses. In Column 3 $DPFI_{ij,t-1}$ takes value 1 if the aggregate holding of all domestic pension funds in firm i in industry j at time $t-1$ was at least equal to 5%. In Column 4, we include a dummy taking value 1 if firm i in industry j 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 at least one year. Finally, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: Productivity Estimates: Pension Fund Dummy (Unmatched Sample)

	(1)	(2)	(3)	(4)
Elasticity of Labor (β_l)	0.952***	0.952***	0.952***	0.948***
	(0.005)	(0.005)	(0.005)	(0.005)
Elasticity of Capital (β_k)	0.084***	0.084***	0.084***	0.082***
	(0.004)	(0.004)	(0.004)	(0.004)
$DPFI_{ij,t-1}$		4.262***	5.386***	3.760***
		(1.308)	(1.592)	(1.301)
Industry FE	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	No	Yes	No
Export$_{ij,t-1}$	No	No	No	Yes
Obs.	99,189	99,189	99,189	99,189
Obs. PF	1,233	1,233	816	1,233
# Firms	14,591	14,591	14,591	14,591
# Firms PF	386	386	278	386

Notes: This table presents the results from the estimation of Equation (10). $DPFI_{ij,t-1}$ is a dummy that takes a value of 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Column 3, $DPFI_{ij,t-1}$ equals 1 if the aggregate holding of all pension funds in firm i in industry j in year $t-1$ was at least equal to 5%. In Column 4, we include a dummy equal to 1 if firm i in industry j 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 at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.8: Productivity Estimates by Industry

	Manufacturing	Construction	Wholesale	Transport
Elasticity of Labor (β_l)	0.954***	0.966***	0.986***	0.838*
	(0.008)	(0.010)	(0.011)	(0.483)
Elasticity of Capital (β_k)	0.093***	0.081***	0.056***	0.163
	(0.005)	(0.006)	(0.008)	(0.238)
$DPFI_{ij,t-1}$	3.643**	3.983	5.684	–
	(1.756)	(4.112)	(5.086)	–
Obs.	18,507	7,626	23,348	615
Obs. PF	531	58	130	–
# Firms	2,953	1,597	3,689	437
# Firms PF	160	19	43	–
	Inform. & Com.	Real Estate	Prof. Service	Other Service
Elasticity of Labor (β_l)	1.004***	0.763***	1.006***	0.752***
	(0.019)	(0.059)	(0.023)	(0.020)
Elasticity of Capital (β_k)	0.020*	0.351***	0.017	0.157***
	(0.010)	(0.045)	(0.017)	(0.011)
$DPFI_{ij,t-1}$	0.681	–	–	–
	(2.685)	–	–	–
Obs.	3,191	156	3,575	1,301
Obs. PF	86	–	–	–
# Firms	591	56	871	360
# Firms PF	29	–	–	–

Notes: This table presents the results from the estimation of the production function separately by one digit using the baseline specification of Equation (1), (see Column 2 of Table 2). $DPFI_{ij,t-1}$ 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 $DPFI_{ij,t-1}$ are multiplied by 100. The estimated coefficient of $DPFI_{ij,t-1}$ measures its correlation with productivity. Cells and results referring to fewer than 10 firms are omitted (-) to comply with Statistics Denmark's data disclosure policy. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. The line Obs. PF (# Firms PF) gives the number of observations (number of firms) with a pension fund investment in at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.9: Productivity Estimates: Heterogeneity Analysis

	Age			Size			$\frac{output}{worker}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_l	0.955***	0.955***	0.952***	0.948***	0.948***	0.946***	0.955***	0.955***	0.953***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
β_k	0.078***	0.078***	0.077***	0.079***	0.079***	0.077***	0.070***	0.070***	0.069***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
$DPFI_{ij,t-1}$	5.802**	5.097**	4.836*	2.438*	3.967***	2.056	2.448*	3.159**	2.131*
	(2.556)	(2.523)	(2.549)	(1.453)	(1.536)	(1.467)	(1.270)	(1.293)	(1.200)
$young_{ij}$	0.483	0.438	0.100						
	(0.447)	(0.448)	(0.440)						
$DPFI_{ij,t-1} \times young_{ij}$	-3.294	-0.563	-2.474						
	(3.079)	(3.373)	(3.053)						
$small_{ij}$				-2.054**	-2.011**	-1.736**			
				(0.863)	(0.861)	(0.856)			
$DPFI_{ij,t-1} \times small_{ij}$				7.862*	4.140*	7.322*			
				(4.476)	(2.319)	(4.434)			
$hlprod_{ij}$							17.391***	17.400***	17.055***
							(0.724)	(0.723)	(0.706)
$DPFI_{ij,t-1} \times hlprod_{ij}$							-0.601	-0.172	-0.589
							(2.724)	(2.822)	(2.715)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	Yes	No	No	Yes	No	No	Yes	No
Export$_{ij,t-1}$	No	No	Yes	No	No	Yes	No	No	Yes
Obs.	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319	58,319
Obs. PF	893	596	893	893	596	893	893	596	893
# Firms	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308	10,308
# Firms PF	272	201	272	272	201	272	272	201	272

Notes: This table presents interaction results using dummies for young firms ($young_{ij}$=1 if firm age in the base year is below the sample median), small firms ($small_{ij}$=1 if firm size in the base year is below the sample median), and labor productivity ($hlprod_{ij}$=1 if labor productivity in the base year is above the sample median). $DPFI_{ij,t-1}$ is a dummy taking a value of 1 if at least one domestic pension fund invested in firm i in industry j 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 correlation with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Columns 2, 5 and 8, $DPFI_{ij,t-1}$ equals 1 if the aggregate holding of all domestic pension funds in firm i in industry j 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 in industry j 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 at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.10: First Stage Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y
l	16.643**	6.647	-5.689	28.306	1.289	0.862	5.856	-7.740	22.236	-11.713	1.119	-2.076	5.855	7.393	26.505	-9.733**	-26.604	-0.411	48.579	-0.912	3.664
	(6.884)	(21.787)	(9.631)	(35.408)	(9.397)	(5.228)	(8.978)	(5.524)	(18.009)	(8.648)	(2.417)	(3.267)	(4.718)	(9.250)	(47.750)	(4.909)	(16.689)	(2.769)	(42.077)	(10.266)	(3.956)
l1m1	-3.284***	3.533	1.713	-7.479	-0.714	1.153	-0.378	1.195	-2.891	1.797	0.373	0.027	-0.149	-0.127	-9.371	2.340**	8.489**	-0.168	-11.621	0.268	-0.883
	(0.965)	(4.141)	(1.114)	(6.778)	(1.523)	(0.916)	(1.421)	(1.099)	(3.439)	(1.333)	(0.419)	(0.534)	(0.702)	(1.665)	(12.726)	(0.913)	(3.301)	(0.473)	(8.919)	(2.065)	(0.854)
l1k1	0.005	-3.395*	0.150	2.108	1.255	-0.963**	0.294	0.597	-0.616	0.546	-0.270	0.468*	-0.727	-0.533	5.487	0.155	-2.877*	0.789**	0.922	0.060	0.507
	(0.991)	(1.773)	(1.280)	(3.351)	(1.242)	(0.461)	(0.810)	(0.418)	(1.255)	(0.742)	(0.294)	(0.239)	(0.503)	(0.746)	(5.291)	(0.362)	(1.593)	(0.322)	(1.619)	(0.707)	(0.311)
l1m2	0.229***	-0.252	-0.031	0.590	0.028	-0.088	0.020	-0.102	0.123	-0.194**	-0.018	-0.022	0.020	-0.015	0.697	-0.141***	-0.563***	0.017	0.718	-0.050	0.045
	(0.066)	(0.263)	(0.069)	(0.424)	(0.088)	(0.056)	(0.088)	(0.073)	(0.220)	(0.080)	(0.025)	(0.028)	(0.042)	(0.091)	(0.914)	(0.049)	(0.204)	(0.028)	(0.489)	(0.106)	(0.046)
l1k2	0.110	0.057	0.085	0.022	-0.020	0.039	0.010	-0.069*	0.055	-0.119*	0.023	-0.031	0.059	0.030	-0.019	-0.040	0.009	-0.032	0.156	-0.058	-0.046*
	(0.084)	(0.152)	(0.083)	(0.210)	(0.073)	(0.040)	(0.057)	(0.036)	(0.119)	(0.063)	(0.025)	(0.020)	(0.037)	(0.058)	(0.261)	(0.033)	(0.094)	(0.022)	(0.195)	(0.053)	(0.027)
l2	-3.141*	-0.408	-1.900	-7.472	-0.940	0.067	-2.007	1.553*	-4.822	3.762**	-0.285	1.044	-1.286	-1.271	-5.495	0.963	5.566**	-0.455	-7.268	0.795	-0.521
	(1.662)	(4.786)	(2.053)	(8.138)	(1.440)	(1.067)	(1.733)	(0.912)	(3.451)	(1.603)	(0.457)	(0.649)	(0.836)	(1.567)	(8.878)	(0.822)	(2.773)	(0.468)	(6.281)	(1.412)	(0.561)
l2m1	0.554**	-0.674	0.173	1.096	0.257	-0.118	0.203	-0.167	0.785	-0.451**	-0.007	-0.060	0.117	0.064	0.939	-0.210	-1.350***	0.102	1.682	-0.113	0.118
	(0.215)	(0.714)	(0.229)	(1.207)	(0.211)	(0.140)	(0.219)	(0.149)	(0.544)	(0.225)	(0.075)	(0.093)	(0.109)	(0.255)	(1.540)	(0.134)	(0.487)	(0.073)	(1.159)	(0.277)	(0.107)
l2k1	0.215	0.505	0.172	0.656	-0.144	0.064	0.080	-0.202**	0.055	-0.373**	0.062	-0.139***	0.138	0.123	0.098	-0.058	0.099	-0.040	0.257	-0.108	-0.027
	(0.169)	(0.470)	(0.236)	(0.607)	(0.194)	(0.099)	(0.169)	(0.090)	(0.319)	(0.154)	(0.050)	(0.053)	(0.092)	(0.130)	(0.666)	(0.058)	(0.257)	(0.047)	(0.547)	(0.106)	(0.051)
l2m2	-0.030***	0.040	-0.006	-0.070	-0.008	0.009	-0.006	0.011	-0.034	0.028**	0.001	0.004	-0.006	0.000	-0.049	0.013*	0.074***	-0.004	-0.099	0.007	-0.006
	(0.011)	(0.039)	(0.012)	(0.059)	(0.011)	(0.007)	(0.011)	(0.009)	(0.030)	(0.012)	(0.004)	(0.004)	(0.006)	(0.012)	(0.089)	(0.006)	(0.026)	(0.004)	(0.065)	(0.014)	(0.005)
l2k2	-0.018*	-0.013	-0.011	-0.036	0.006	-0.003	-0.003	0.012**	-0.006	0.023**	-0.002	0.007**	-0.008	-0.005	-0.004	0.006	0.002	0.003	-0.038	0.009	0.002
	(0.010)	(0.029)	(0.012)	(0.035)	(0.010)	(0.006)	(0.010)	(0.006)	(0.021)	(0.010)	(0.004)	(0.003)	(0.006)	(0.009)	(0.045)	(0.005)	(0.015)	(0.003)	(0.039)	(0.008)	(0.004)
lkm	-0.183**	0.112	-0.181*	-0.385	-0.066	0.030	-0.065	0.079*	-0.026	0.199***	-0.029	0.031	-0.045	-0.018	-0.537	0.038	0.272**	-0.037	-0.283	0.096*	0.005
	(0.078)	(0.212)	(0.094)	(0.360)	(0.098)	(0.044)	(0.078)	(0.047)	(0.164)	(0.063)	(0.022)	(0.024)	(0.033)	(0.060)	(0.648)	(0.028)	(0.121)	(0.028)	(0.337)	(0.052)	(0.029)
k	13.631***	-11.277	1.639	6.343	4.046	2.572	-2.828	-3.362	-13.844	-15.643***	-1.034	-2.249	-2.408	-2.685	11.950	-0.158	14.425	0.888	17.762	6.405	1.348
	(5.261)	(9.033)	(8.879)	(18.502)	(8.829)	(2.839)	(8.698)	(4.759)	(17.618)	(5.039)	(2.280)	(1.950)	(4.681)	(5.844)	(48.916)	(2.661)	(10.847)	(2.407)	(24.509)	(4.072)	(2.059)
k1m1	-2.541**	3.303	-0.369	-1.330	-1.594	-0.253	0.814	0.270	2.010	3.050***	0.271	0.366	0.592	0.614	-2.393	-0.125	-1.647	-0.437	-4.426	-1.284	-0.341
	(1.029)	(2.114)	(1.910)	(3.342)	(1.887)	(0.589)	(1.842)	(0.973)	(3.536)	(1.035)	(0.501)	(0.356)	(0.873)	(1.131)	(9.284)	(0.524)	(2.504)	(0.538)	(5.131)	(0.792)	(0.409)
k1m2	0.149**	-0.199	0.055	0.044	0.111	0.012	-0.050	-0.019	-0.045	-0.189***	-0.007	-0.024	-0.018	-0.025	0.121	0.001	0.002	0.025	0.299	0.042	0.002
	(0.060)	(0.126)	(0.099)	(0.171)	(0.100)	(0.034)	(0.098)	(0.055)	(0.193)	(0.060)	(0.029)	(0.018)	(0.044)	(0.059)	(0.483)	(0.027)	(0.140)	(0.032)	(0.298)	(0.043)	(0.024)
k2	-1.029***	0.753	-0.072	-1.167	-0.027	-0.081	-0.054	0.447	1.048	1.128***	0.126	0.173	0.159	0.276	-1.910	0.228	-0.577	-0.043	-1.830	-0.265	-0.150
	(0.343)	(0.723)	(0.508)	(1.356)	(0.507)	(0.202)	(0.575)	(0.341)	(1.184)	(0.344)	(0.167)	(0.137)	(0.303)	(0.454)	(3.877)	(0.209)	(0.595)	(0.173)	(1.743)	(0.306)	(0.148)
k2m1	0.171***	-0.176	-0.009	0.218	0.035	0.007	-0.011	-0.057	-0.163	-0.205***	-0.029	-0.030	-0.038	-0.061	0.283	-0.028	0.082	0.020	0.384	0.065	0.042
	(0.060)	(0.137)	(0.099)	(0.215)	(0.099)	(0.038)	(0.112)	(0.066)	(0.223)	(0.062)	(0.033)	(0.023)	(0.054)	(0.081)	(0.665)	(0.038)	(0.128)	(0.034)	(0.343)	(0.057)	(0.026)
k2m2	-0.009***	0.010	-0.000	-0.007	-0.003	-0.001	0.002	0.003	0.005	0.011***	0.001	0.002	0.001	0.003	-0.009	0.001	-0.001	-0.001	-0.023	-0.003	-0.001
	(0.003)	(0.007)	(0.005)	(0.010)	(0.005)	(0.002)	(0.006)	(0.003)	(0.011)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)	(0.031)	(0.002)	(0.007)	(0.002)	(0.019)	(0.003)	(0.001)
m	18.916***	-23.087*	2.275	18.199	11.998	-2.023	-6.011	-2.725	-3.422	-19.218***	-1.854	-2.466	-2.555	-1.744	38.232	-4.296	-13.387	2.588	36.112	4.773	2.064
	(6.131)	(13.462)	(10.332)	(21.073)	(10.038)	(3.591)	(8.657)	(5.863)	(20.118)	(6.070)	(2.523)	(1.983)	(4.263)	(5.570)	(63.274)	(2.972)	(14.622)	(2.585)	(23.597)	(4.278)	(2.619)
m2	-1.092***	1.401*	-0.356	-1.044	-0.705	0.164	0.351	0.233	-0.018	1.270***	0.086	0.194*	0.082	0.118	-2.260	0.278*	1.219	-0.153	-2.215	-0.104	-0.045
	(0.386)	(0.842)	(0.579)	(1.225)	(0.584)	(0.224)	(0.479)	(0.348)	(1.151)	(0.371)	(0.148)	(0.106)	(0.229)	(0.319)	(3.697)	(0.164)	(0.898)	(0.159)	(1.478)	(0.238)	(0.153)
Obs.	2571	513	1897	455	1527	5779	1998	5014	496	3025	11508	28904	1405	1415	60	2690	405	4332	107	1186	2213
R2	0.954	0.911	0.939	0.882	0.937	0.915	0.917	0.929	0.944	0.921	0.925	0.883	0.936	0.919	0.974	0.917	0.889	0.926	0.875	0.892	0.884

Notes: This table presents the estimation of Equation (7) separately by DB07 36 industries. The specification of the first stage includes the second-degree polynomial of capital, labor and intermediate inputs with full interaction terms: y, k, l, and m denote, respectively, value added, capital stock, labor input and intermediate material inputs at the firm level in a given year t, where lower-case letters denote natural logarithms and subscripts "2" indicate the squared terms of the corresponding variables. Columns correspond to : (1) Manuf. of food, beverages, and tobacco; (2) Manuf. of textiles;(3) Manuf. of wood and paper; printing;(4) Manuf. of coke, refined petroleum, and chemical; (5) Manuf. of rubber, plastics; (6) Manuf. of basic metals and fabricated metal; (7) Manuf. of computer, electronic; (8) Manuf. of machinery and equipment; (9) Manuf. of transport equipment; (10) Other manufacturing; (11) Construction; (12) Wholesale and retail trade; repair of motor vehicles and motorcycles; (13) Transportation and storage; (14) Publishing and broadcasting activities; (15) Telecommunications; (16) and other information services; (17) Real estate activities; (18) Legal and accounting activities; (19) Archit. and engineering activities; (20) Scientific research and development; (21) Administrative and support service activities. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.

Table C.11: Productivity Estimates: Pension Fund Dummy and Investment Intensity

	(1)	(2)	(3)
Elasticity of Labor (β_l)	0.955***	0.955***	0.952***
	(0.006)	(0.006)	(0.006)
Elasticity of Capital (β_k)	0.079***	0.079***	0.077***
	(0.005)	(0.005)	(0.005)
$DPFI_{ij,t-1}$	3.512	3.525	2.918
	(1.977)	(1.911)	(1.938)
$Intensity_{ij,t-1}$	0.082	0.083	0.070
	(0.110)	(0.105)	(0.103)
Industry FE	Yes	Yes	Yes
$PFI_{ij,t-1} \geq 5\%$	No	Yes	No
Export$_{ij,t-1}$	No	No	Yes
Obs.	58,319	58,319	58,319
Obs. PF	893	596	893
# Firms	10,308	10,308	10,308
# Firms PF	272	201	272

Notes: This table presents results from the estimation of Equation (1). Note that this table estimates extensive and intensive margins simultaneously, to be read alongside Table 3. $DPFI_{ij,t-1}$ is a dummy that takes a value of 1 if at least one domestic pension fund invested in firm i in industry j in year $t-1$. $Intensity_{ij,t-1}$ is the aggregate share of firm i (in percent) held by domestic pension funds in industry j in year $t-1$. Coefficient estimates and standard errors for $DPFI_{ij,t-1}$ and $Intensity_{ij,t-1}$ are multiplied by 100. The estimated coefficients of $DPFI_{ij,t-1}$ and $Intensity_{ij,t-1}$ measures correlations with productivity. All specifications include industry-fixed effects at the DB07 36-industry level. Bootstrapped standard errors, which are clustered by firm with 200 replications, are reported in parentheses. In Column 2, $Intensity_{ij,t-1}$ and $DPFI_{ij,t-1}$ are equal to 0 if the aggregate holding of all domestic pension funds in firm i in industry j at time $t-1$ is less than 5%. In Column 3, we include a dummy taking value 1 if firm i in industry j 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 in at least one year. Finally, $^{*} = p < 0.1$, $^{**} = p < 0.05$, and $^{***} = p < 0.01$.