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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Pension funds’ carbon footprint and investment trade-offs*

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Abstract

With the adoption of the Paris Agreement in December 2015, better understanding of portfolio carbon dioxide (CO_2) exposures has become increasingly important for investors, regulators and society at large. In this paper we measure the portfolio carbon footprints (*CFP*s) of pension funds’ stock investments. We utilize security-by-security holdings of Dutch pension funds over the period 2009-2015 and combine this with firm-level CO_2 information to analyze the drivers of *CFP* at the portfolio level. The results show that pension funds face intricate trade-offs when aiming to reduce portfolio related CO_2 emissions: expected dividend yields are positively related to the carbon footprint while portfolios’ systematic risk (market beta) is negatively related to the carbon footprint. The dividend trade-off with carbon exposures only applies to well-funded pension funds and is driven to some extent by investments in energy and utility companies. For the period 2013-2015 pension funds which publicly disclose their carbon footprint tend to have relatively lower exposure to firm with high carbon emissions.

Keywords: carbon emissions, pension funds, institutional investors, socially responsible investment, climate change.
JEL classifications: G11, G23, H55, Q54, Q56.

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1 Introduction

In December 2015 world leaders signed the Paris Agreement on Climate Change and thereby committed themselves to significantly reducing carbon dioxide (CO_2) emissions. To achieve these goals, firms must reduce their carbon footprint (CFP). Similarly, many institutional investors have started to measure and publicly disclose the CFP of their investment portfolios with the aim of lowering the carbon emissions associated with their investments.[1]

Institutional investors are interested in their CFP for two main reasons. First, they act as "universal owners" because of long-term and diversified investment positions in a wide range of firms (Dimson et al., 2015). These assets under management face a trade-off between expected short-term gains from carbon-intensive businesses versus potential long-term benefits from a decarbonized economy. That is, institutional investors recognize the importance of fossil fuels for the near future, but are also confronted with environmental and regulatory risks associated with carbon-intensive investments, such as the risk of stranded assets and long-term tail risks associated with catastrophic events related to climate change (Andersson et al., 2016; Griffin et al., 2015; Hong et al., 2016).

In addition, institutional investors face pressure from stakeholders to reduce their investments in carbon-intensive stocks. Pension funds in particular are likely to face a high degree of public scrutiny regarding the social responsibility of their investments. This resulted in strong engagement by pension funds in socially responsible investment as they have been a powerful force in shaping company behavior (Dyck et al., 2016; McCahery et al., forthcoming; Sievanen et al., 2013). More generally, the market for sustainable investment has grown significantly in the past decade (Bohl et al., 2015).

It is *a priori* unclear whether investors like pension funds necessarily face a trade-off

[1] In recent years, numerous investors have joined a wide range of initiatives that aim to reduce investors' CFP including the Carbon Tracker Initiative, the Climate Disclosure Standard Board (CDSB), the Montréal Carbon Pledge, the Portfolio Decarbonization Coalition (PDC) and the United Nations Principles for Responsible Investment (PRI).

between low-carbon investments and returns. In general, literature on socially responsible investment (SRI) has yielded mixed results regarding the trade-offs between returns and social responsibility (e.g. Galema et al., 2008; Renneboog et al., 2008) as the sign and significance of the relationship depends strongly on the specific dimension of social responsibility (Ziegler et al., 2007). The same holds for the environmental dimension. Restricting the investment universe to stocks of firms with low CO_2 emissions hampers diversification and decreases expected risk-adjusted returns (Bauer et al., 2005; Kreander et al., 2005; Scholtens, 2006). This effect is abated if CO_2 emissions are highly concentrated in very few firms (Koch and Bassen, 2013). Indeed, investors can construct stock portfolios with lower CFP while following a market benchmark with negligible tracking error (Andersson et al., 2016).[2]

In this paper we focus on the environmental dimension of SRI—specifically the CO_2 exposures related to pension funds' stock investments. To investigate why some pension funds have a higher CFP than others we study Dutch pension funds, which have about 1.3 trillion euro under management. Proprietary security-by-security data from the Dutch central bank (DNB) on equity investment are used for the period 2009Q1-2015Q4. These data are matched with CO_2 emissions from the Thomson ASSET4 database and supervisory data on pension fund characteristics. We take a granular approach to determine the CFP of pension funds' equity investment. That is, like Andersson et al. (2016) we aggregate firm-level CO_2 emissions from security-by-security (stock) holdings data to the pension funds' portfolio level.

Our main results highlight the significant investment trade-offs faced by pension funds when reducing portfolio CO_2 exposures. First, there is a trade-off between the portfolio's carbon dioxide emissions and the expected dividend returns. This raises a concern because pension funds typically have a strong preference for high-dividend stocks (Allen et al., 2000; Short et al., 2002; Dahlquist et al., 2014; Bams et al., 2016). We

[2] De Jong and Nguyen (2016) show that something similar holds for bond indexes.

find that the trade-off is to some extent driven by investments in firms from energy and utilities industries, which is in line with Andersson et al. (2016). Moreover, we only observe this trade-off for well-funded pension funds, suggesting they reduce CFP when they deem it affordable, which is consistent with other studies on pension funds' investment behavior (An et al., 2013) and the role of regulatory requirements (Andonov et al., 2015). One interpretation of this result is that reducing CFP is considered a luxury. Second, our main results show that there is a negative relationship between pension funds' active share (Cremers and Petajisto, 2009)—a measure that indicates the extent to which pension funds actively managing their portfolio by deviating from the benchmark—and their CFP. This suggests that pension funds reduce CFP by deviating from the market portfolio, i.e. lowering CFP is associated with higher market risk. Third, public pressure could be a possible motivation for reporting and subsequently reducing CFP. Indeed, we find that pension funds that reported CO_2 portfolio exposures had much lower CFPs.

This paper makes three contributions. First, we contribute to a small but growing literature on institutional investors and corporate social responsibility (CSR). This literature has focused mainly on how firms' CSR is affected by institutional holdings (e.g. Dyck et al., 2016; Dimson et al., 2015), whereas we investigate how institutional investors' CSR is affected by the portfolio of firms they invest in. Second, a related literature analyzes the consequences of reducing CFP for a hypothetical portfolio (e.g. Andersson et al., 2016; De Jong and Nguyen, 2016). By contrast, we use actual pension fund holdings to calculate portfolio level CFP. Third, we contribute to the literature on green investments, which mainly analyzes the performance of green compared to conventional mutual funds.[3] Instead of classifying funds dichotomously, our approach allows us to directly measure and explain carbon-related environmental performance.

[3] See e.g. Cortez et al. (2009, 2012); Climent and Soriano (2011); Nofsinger and Varma (2014); Ibikunle and Steffen (forthcoming); Rezec and Scholtens (2016); Silva and Cortez (2016); Shin et al. (forthcoming) and (e.g. Derwall et al., 2005; Ziegler et al., 2007; De Haan et al., 2012) who use replicating portfolios techniques that vary along the environmental dimension.

This paper is organized as follows: Section 2 presents the security-by-security holdings data, the firm-level data and the pension fund data. Section 3 explains how carbon exposures are measured and introduces our estimation model. Section 4 provides the main results. Section 5 presents some robustness tests for our carbon exposure measure. Section 6 concludes.

2 Data

We combine several data sources to analyze the carbon footprints (CFP) of pension funds. First, the Thomson Reuters ASSET4 database is used to obtain quarterly CO_2 emission levels, CE_{jt} for 5,260 firms for 2009-2015. The CO_2 emissions data are taken from company reports in line with the Greenhouse Gas Protocol, Kyoto Protocol or EU Trading Scheme where the reported Greenhouse Gas Protocol score is the preferred measure.[4] If a firm does not report carbon emissions, Thomson Reuters estimates them using their Carbon Data & Estimate Model (Thomson Reuters, 2016). These data are linked to firm-level characteristics from Datastream. Finally, at the firm-level, industry NACE classifications are obtained from the ECB Centralised Securities Database (CSDB).

Second, information on pension fund investments is obtained from a confidential dataset from the Dutch Central Bank (DNB). Data from the balance of payments and securities statistics department contain quarterly security-by-security portfolio investment positions in stocks of pension funds. In addition to pension fund holdings, we incorporate mutual funds data because a small number of pension funds hold substantial amounts of fiduciary investment through mutual funds. We use security-by-security stock holdings of 16 mutual funds so that we can 'look through' the pension fund shareholdings in these mutual funds and increase the coverage of the stock positions. Based

[4]The CO_2 emissions include direct and indirect equivalents of emissions, i.e. Scope 1 and Scope 2.

on the participation shares, we proportionally attribute the mutual fund positions for each stock to the pension fund's portfolio.[5] After merging the firm-level data with the pension fund holdings we observe the stock holdings of 41 pension funds for 4,657 unique stocks over the period 2009Q1-2015Q4. These security-by-security stock holdings consist of 1,476,385 observations for each pension fund's stock position over time.

The granular data is collapsed to the pension fund portfolio level. Pension fund characteristics are taken from aggregate supervisory reports to DNB.[6] Overall, the coverage of the security-by-security data on portfolio investments is high compared to the aggregated reported stock positions in the pension funds balance sheet items from the supervisory reports (on average 82.4 percent, see A.1). The coverage generally improves over time but is very constant across smaller and larger pension funds.[7] Finally, manually collected information from pension funds' websites and annual reports are used to observe which pension funds report their carbon emissions.

3 Method

3.1 Measuring carbon footprint of investments

To measure the carbon footprints of the stock investments for each pension fund a relative carbon efficiency measure of the portfolio is obtained, CFP_{it}. This variable is based on the CO_2 emissions of a firm j adjusted for the firm's output and the relative importance of the stock position in firm j in the overall portfolio of pension fund i at time t. Firm j's carbon (in)efficiency CI_j is derived as a ratio of CO_2 exposure in tonnes to sales in million euros in line with the literature and practice (Andersson et al., 2016; PGGM,

[5] See also Broeders et al. (2016) who use similar data to study pension fund herding behavior or more generally Ferson and Khang (2002) who construct performance measures of pension funds using portfolio holdings data and Bradley et al. (2016) how study firm-level characteristics of pension funds' portfolios to study political influences.

[6] See also de Dreu and Bikker (2012), Duijm and Steins Bisschop (2015) and De Haan (forthcoming) who use similarly aggregated data to study pension fund investments in general.

[7] By the end of 2015, total stock holdings of the pension funds in our final sample were 386 billion euro.

2016). CFP_{it} is calculated as the portfolio weighted average of the firms' CO_2 efficiency ratios.

Specifically, consider a pension fund i that holds stocks in firm j with an investment position I_{ij} where the firm's carbon inefficiency is CI_j. The CFP_i of each pension fund i is measured as the portfolio weighted average of CI_j in equity investments.

$$CFP_i = \sum_j w_{ij} \times CI_j \tag{1}$$

where $w_{ij} = I_{ij}/(\sum_{j=1}^{n} I_{ij})$ indicates the portfolio weight: the ratio of the market value of each stock investment (I_{ij}) to the total market value of the pension fund's equity investments $(\sum_{j=1}^{n} I_{ij})$. To compute CFP_{it} we take CI_{jt} with quarterly adjusted investment weights w_{ijt}. Thus, CFP_{it} captures the weighted average of how many units of CO_2 are emitted per unit of sales for each euro invested by pension fund i at time t.

Using this method, we can consistently create CFP_{it} across investors' stock portfolios over time.[8] A key advantage of this measure is that it is a relative carbon efficiency measure and is thus neither affected by the size of the stock holdings of the investor $(\sum_{j=1}^{n} I_{ijt})$ nor by the coverage of stocks in our dataset.[9]

[*Insert Table 1—"Summary statistics of carbon efficiency by industry"*]

Before applying this method to pension fund portfolios, let us elucidate how CFP varies across industries by inspecting the security-level data from Thomson Reuters. Table 1 presents summary statistics of security-level CI_{ijt} for a panel dataset of all stocks in our sample (2009Q1-2015Q4), which is weighted by the stock's market value

[8]The CFP_{it} scores are very similar to scores of pension funds that reported their CFP in 2014, which validates our measure.

[9]In general the coverage is better for larger firms. A potential bias in CFP_{it} would be created if the (smaller) excluded firms' CO_2 emissions are significantly different from the observed CO_2 emissions in terms of relative output efficiency while at the same time there are strong differences in stock coverage in the cross-section of pension funds' portfolios; note that the coverage is high across all pension funds, see A.1. In addition, these two variations (carbon efficiency and stock coverage) must be correlated with pension fund characteristics to create a bias in our results.

against total industry market value to create a stock-level CFP measure. It shows that the highest CFP firms can be found in the industry 'Electricity, gas and steam', followed by 'Mining and quarrying'. These high CFPs are due to high average firm CO_2 emissions and relatively modest firm sales within these industries.[10] There is considerable within-industry variation in CFP, although also the extent of this variation differs considerably across the industries.

To better understand the general market context of our CFP measure for the Dutch pension funds, we apply Equation (1) to calculate the CFP of a benchmark portfolio, $CFP^{Benchmark}$. The benchmark consists of all stocks in the ASSET4 universe and captures the carbon (in)efficiency of a market portfolio with an average underlying stock market value of 31 trillion euro. Figure 1 compares the average market $CFP_t^{Benchmark}$ to the average CFP_{it} of the pension funds in our sample. Clearly the average pension fund's CFP is much lower than that of the general market. Dutch pension funds perform better than the benchmark across the whole sample period and this differential is constant over time.[11] In addition, the $CFP^{Benchmark}$ has become much less carbon-intensive over time. In 2009Q1 the average $CFP^{Benchmark}$ was 440 and this decreased to 250 in 2015Q4: a 43% reduction.[12]

[*Insert Figure 1—"Average pension fund footprint versus a market benchmark"*]

The shaded area in Figure 1 shows the 10^{th} to 90^{th} percentiles of the CFP distri-

[10] Appendix B provides summary statistics for the different dimensions of our security-level data. To illustrate, Table B.1 shows that on average the largest firms in our sample in terms of market values are in 'Manufacturing'. Table B.2 indicates that pension funds also have the highest stock investments in 'Manufacturing', whose firms also have highest average output in terms of sales (see B.3). By contrast, B.4 shows that the highest absolute CO_2 emissions (not scaled by sales) are due to 'Electricity, gas and steam'.

[11] Unreported t-tests shows that this difference is significant at 1%. In addition, a panel unit root test shows that CFP is (trend) stationary.

[12] Indeed over time firms on average improved their carbon efficiency, however, the large reduction also stems from a compositional shift in the global market portfolio: High-tech firms with relatively low CO_2 emissions rapidly increased their market values (and thus their weights in the benchmark), while firms with high CO_2 emissions have witnessed relatively poor stock performance (Ibikunle and Steffen, forthcoming).

bution, which indicates significant CFP variation across pension funds at each point in time. Our estimation—to which we will turn to next—attempts to capture this variation while controlling for the time trend by including year-quarter fixed effects.

3.2 Estimation method

We estimate the following equation to explain the carbon footprint (CFP) of pension fund's i stock portfolio at time t:

$$CFP_{it} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Year\text{-}quarter_t + \epsilon_{it} \quad (2)$$

where X_{it-1} indicates our explanatory variables. Because there is a clear time trend in the $CFP^{Benchmark}$ we include year-quarter fixed effects to control for unobserved heterogeneity of CFP_{it} over time. Standard errors are clustered at the pension fund level.

Table 2 provides the summary statistics of the variables used in this study. The average absolute CO_2 emission level footprint is 1.6 million tonnes as measured by the weights of the pension funds' investments in the firm. Our dependent variables CFP_{it} averages 288.3 tonnes CO_2 per million euro of sales (Std.=76.4).

Our main estimations include the following variables, which are all lagged by one quarter to prevent simultaneity by construction. To capture pension fund size, log $TotalAssets_{it}$, we obtain total assets from the aggregate supervisory balance sheet items. We include several stock characteristics: previous four quarter average stock's $Returns_{it}$, $DividendYield_{it}$ and β_{it}.[13] We split the total stock returns in percentage price changes over the previous year, $Return_{it}$, and $DividendYield_{it}$. We winsorize $Return_{it}$, $DividendYield_{it}$ and β_{it} at 1% and aggregate all stock characteristics to the portfolio level using the market value of the stocks to weight the total stock portfolio.

[13] Note that Thomson Datastream computes the β based on monthly price movements of the share over a five year period compared to the Datastream total market index for the country.

Of the pension funds' portfolios, the yearly average stock returns are 4.3% plus a dividend yield of 2.9%. With an average number of stocks of around a thousand, pension funds hold broad stock portfolios, which is also evident from the average market β of 1 ($Std. = 0.1$).

One concern is that pension funds simply follow a market benchmark, accepting whatever CFP is implied by the benchmark. Cremers and Petajisto (2009) introduce $ActiveShare$, which measures the extent to which investors deviate from the investment benchmark. It consist of summing the absolute values of differences of investment weights with the benchmark and dividing by two, where the benchmark is the same as defined above. An $ActiveShare$ of zero implies completely following the benchmark, while an Active share of 100% implies completely deviating from it. This measure is closely related to the tracking error (Andersson et al., 2016). We include $ActiveShare_{it}$ to test whether pension funds shift their portfolio to increase or reduce CFP. Table 2 shows that the mean of $ActiveShare_{it}$ is 35%, which implies that on average pension funds have a tendency to track the benchmark, but not very strongly.

Next, we obtain several pension fund level characteristics using aggregated quarterly supervisory data. First, we calculate the share of equity $ShareEquity_{it}$ by taking total stock holdings from the balance sheet as a percentage of total assets. One average, 25% of the assets are allocated to stock investments, with considerable variation across pension funds and over time. These stock level and pension fund level characteristics will be used in our main regressions.

Pension funds report their funding ratios, $FundRatio_{it}$, which is a measure of the assets the pension fund holds against its long-term liabilities.[14] In the Netherlands there are regulatory requirements that aim to safeguard the financial health of pension funds mainly through avoiding being underfunded, where the required minimum funding

[14]The funding ratio is defined as the market value of the assets over the market value of the liabilities, which is calculated as the present value of future pension benefits using the term structure of the risk-free market interest rate (like a swap rate) as discount factor De Haan (forthcoming).

ratio is 105% (de Dreu and Bikker, 2012; Andonov et al., 2015; De Haan, forthcoming). This limit is set by the supervisor and once it is breached, pension funds must ensure they take precautionary actions against underfunding as set out in their mandatory recovery scheme. With an average funding ratio of 110%, pension funds in the sample are sufficiently funded. The indicator variable $FundRatio_{it} > 1.05$ equals one if the funding ratio exceeds 105% and is zero otherwise, indicating that there is a funding deficit (which occurs in 40% of our observations). The indicator variable $\Delta_{+}FundRatio_{it} > 1.05$ equals one once an initially underfunded pension fund reaches a funding ratio that exceeds minimum regulatory funding ratio of 105%, and zero otherwise. On average over time 10% of the pension funds experience such a situation. Funding ratio data will be used in an extended specification model.

$CarbonReporting_{it}$ is defined as an indicator variable equal to one when pension funds report carbon emissions in their annual report or on their website and zero otherwise. Table 2 shows that 19% of the observations in our unbalanced panel data report CFP. Note that the reporting only started recently and will therefore be analyzed separately.[15]

Finally in a distinct analysis we control for contemporaneous industry investment weights (based on market values). Table 2 shows that pension funds hold on average about a third of their equity in industry C ('Manufacturing') and about a fifth in industry K ('Financial and insurance activities').

[*Insert Table 2—"Summary statistics"*]

[15]Appendix D presents a correlation matrix which shows that the correlation coefficients among the explanatory variables are relatively low (i.e. below 0.35) with the exception of — as expected — the association between size and reporting (r = 0.53) and returns and dividends (r = -0.60). Note also that multicollinearity appears no concern as all VIF scores for the regressions run in this paper are well below 10.

4 Results

4.1 Main determinants of pension funds' carbon footprints

Table 3 presents our main estimates. Somewhat surprisingly it shows that larger pension funds have a higher CFP. Interpreting the effect size in terms of a semi-elasticity, a doubling in size (i.e. a 100% increase) is associated with an increase in CFP ranging from 12.79 to 14.67, which is modest compared to an average CFP of 288.3. These results are in line with Hoepner and Schopohl (2016) who find a negative relationship between pension fund size and the probability of signing the Principles for Responsible Investment (PRI). It is inconsistent with the notion that larger pension funds are more concerned about corporate responsibility (Scholtens, 2006) and the finding that larger investors are better able to screen environmental friendly firms due to the monitoring cost involved with managing CFP (Sievanen et al., 2013; Kempf and Osthoff, 2008).

[*Insert Table 3—"Main results: Determinants of pension funds' carbon footprints"*]

We find no relationship between previous year's portfolio stock returns and CFPs. This finding is consistent with literature that shows that portfolios of firms with better social, governance and environmental scores have risk-adjusted returns similar to that of the market (Margolis and Walsh, 2003; Orlitzky et al., 2003; Bauer et al., 2005; Cortez et al., 2009), although our returns exclude dividend payments.

The average expected dividend yield of the portfolios is strongly related to CFP. The outcomes suggest that pension funds that hold stocks with higher dividend yields tend to have a higher CFP, ceteris paribus. The estimated coefficients imply that a dividend yield rise in the portfolio by one percentage point is associated with a CFP increase of about 30 to 40 tonnes per million euros of sales, which is sizable compared to an average CFP of 289. These results contribute to the debate on the relationship between returns and environmental performance of stock portfolios as some studies suggest a positive link between returns and social responsible investments (Derwall et al., 2005; Shin et al., forthcoming), while others, in line with our dividend effect, suggest the contrary (e.g. Cortez et al., 2012; Climent and Soriano, 2011; Nofsinger and Varma, 2014; Rezec and Scholtens, 2016; Silva and Cortez, 2016).

Table 3 shows that pension funds with higher portfolio β have a lower CFP, ceteris paribus. As a pension fund moves its portfolio β up one standard deviation (0.1), CFP is reduced by about 20 tonnes per million of sales. One possible explanation for this relationship is that carbon-intensive industries like energy and utilities are generally less cyclical (Griffin et al., 2015). Also, Ibikunle and Steffen (forthcoming) note that more environmentally friendly mutual funds tend to have greater exposure to smaller firms and growth stocks, which have higher β's and lower carbon emissions.

In addition to introducing more market risk, pension funds can decide to let their portfolio deviate from the market portfolio as captured by $ActiveShare_{it}$. Here we find a strongly negative relationship between $ActiveShare_{it}$ and CFPs. This suggests that pension funds that deviate from the market portfolio, shift their portfolio to firms that emit less carbon per unit of sales. The estimated effect size is rather strong as a one standard deviation increase in $ActiveShare$ is associated with a decrease in CFP of about 12. Finally, we find no relationship between the share of assets allocated to equity and CFP. This suggests that pension funds' strategic asset allocation does not influence CFP.

Taken together, the combined results suggest that pension funds face stark trade-offs. Those that have managed to lower their carbon footprint have had to accept lower expected dividend yields and higher expected systematic risk (β). If anything, it seems that larger pension funds are not better positioned to reduce CFPs. Since pension funds seem to lower their CFP by deviating from the market portfolio, larger pension funds might find it more difficult to reduce CFP. Their sheer size may make it more difficult to deviate substantially.

4.2 Carbon footprints, pension funds' funding ratios and dividends

Pension funds must pay very close attention to their funding ratios in order to determine whether they are able to meet future liabilities (Andonov et al., 2015; De Haan, forthcoming). In the Netherlands, the supervisor has regulatory powers to demand an investment recovery scheme of pension funds once they are underfunded, i.e. having a funding ratio of less than the minimum 105%. During the recovery phase pension funds have less leeway to increase their risk profile. Although this applies mostly to their strategic asset allocation, they might also be intrinsically motivated to pursue more conservative investment strategies. For instance, there could be a correlation between financially weaker pension funds and the degree to which pension funds tilt their portfolio towards investments with lower CFP. In the short run, underfunded pension funds might care more about financial returns than CFP reduction. In the main results we find a strong trade-off between pension funds' expected portfolio dividend yield and CFP. In this section we investigate to what extent this trade-off applies when a pension fund's financial situation changes in terms of its funding ratio.

Table 4 augments the main results from Table 3 by further inclusion of various measures of the funding ratio and interactions with the portfolio's overall dividend yields. Column (1) shows that there is no direct relationship between the level of the funding ratio and CFPs. Column (2) includes an interaction term with dividends and these results also do not present any associations with CFP. In Column (3) we include an indicator variable equal to one if a pension fund meets the regulatory minimum funding ratio of 105% and zero otherwise. Again there appears to be no direct relationship between the funding ratio and CFP. These findings seem to show that there is no relationship between funding ratio and CFP.

To study the relation between funding ratio, dividends and CFP further, Column (4) includes the interaction between the indicator for being well-funded with dividend yield. This association is weakly significant.[16] One interpretation of this finding is that pension funds consider lowering their CFP as a luxury. Once pension funds reach a sufficient level of funding, they could reduce CFP by reconsidering their preferences for dividends. To test explanation further, we include an indicator variable that equals one when a pension fund reaches a funding ratio higher than 105% and zero otherwise in Column (5), that is, as it move in or out being underfunded. In Column (6) we again interact this variable with dividends. The significant and positive interaction between the portfolio's dividend yield and the move towards being over-funded suggests that when pension funds are able to increase their funding ratios above the regulatory minimum, they have room to consider the trade-off between dividend yield and CFP. The marginal effect of $\Delta_{+}FundRatio_{it} > 1.05$ starts to become positive around the average dividend yield of 2.9%. If pension funds that have recently been able to increase their funding ratio want to decrease CFP, they are able to do so only if they are willing not to pick stocks associated with higher expected dividend yields.[17]

The finding that pension funds that are able to build up sufficient financial buffers and aim to reduce CFP face a trade-off between expected stable returns from dividends and reducing their portfolios' CO_2 emission levels is new in the literature. One interpretation of our results is that well-funded pension funds are willing to increase their systematic risk as captured by (β) to reduce CFP. This fits well with Rauh (2009) who shows that poorly-funded pension funds allocate a greater share of pension fund assets to safe assets (i.e. government bonds), while well-funded pension funds are more willing to take risk and invest more heavily in equity. In addition, underfunded pension funds may be unable to sacrifice dividend income (Mohan and Zhang, 2014), which explains the significant interaction effect between the funding ratio and dividend on CFP.

[16] Unreported results for a negative delta of the funding ratio do not yield any significant associations.

[17] Note that this interaction effect is absent for pension funds which funding ratio moves below 105 percent, which strengthens this explanation. These findings are complementary to our main results concerning the dividend ratios.

[*Insert Table 4—"Carbon footprints, pension funds' funding ratios and dividends"*]

4.3 The role of carbon footprint reporting by pension funds

In this section we analyze the effects of CO_2 reporting by pension funds. We use the fact that several pension funds have started reporting their CO_2 emissions recently, which enables us to test for recent periods whether the pension funds that report their CFP also perform better in terms of CFP or whether this is just window-dressing (Gupta and Mason, 2016). In addition, by considering a subsample over the period 2013Q1-2015Q4 we analyze if our main results from Table 3 are sensitive to the time period of our sample as several studies suggest that the sample period may drive the results (e.g. Van Beurden and Gössling, 2008).[18]

Table 5 shows that the effect of $CarbonReporting_i$ is negative and significant, as expected. Pension funds that report CO_2 emissions related to their stock investments on average have a CFP that is 23 tonnes per million of sales lower. The effect is sizeable in economic terms and refutes the notion of window-dressing with regard to investors, although future work in this area is warranted as this analysis is based on only seven pension funds that report against 29 that do not report over a relatively short time period.

[*Insert Table 5—"Role of carbon footprint reporting by pension funds(2013-2015)"*]

As a robustness test, Table 5 indicates that in the recent subsample the size of the pension funds is still positively related to CFP. The size of the estimated coefficients is very similar to that of coefficients reported in Table 3. We also confirm that there is no relationship between total stock returns and CFP in the recent subsample. These results are in contrast with Ibikunle and Steffen (forthcoming) who compare the performance of green, black and conventional mutual funds and only find higher returns of green

[18] As this exercise significantly reduces the number of observations, the power of our statistical tests is much lower so we may expect that some relationships are rendered insignificant.

funds in their most recent subsample of 2012-2014. They argue that green funds' risk adjusted returns have progressively improved over time (see also Climent and Soriano, 2011; Ziegler et al., 2007), while we find no relationship between pension funds' CFP and total stock returns.

The relationship between dividend yields and CFPs remains significant for the period 2013-2015, although only in two of the presented specifications. However, the estimated size of the dividend effect is highly stable over time. The results for the market β are also significant in the more recent time period and suggest that pension fund portfolios with a higher β are associated with lower CFP. The results on active share are robust and comparable in size to what we found in Table 3. We find that the share of pension funds total portfolio allocated to stocks is positively related to CFP, although it is only significant at 10%. By contrast, Thistlethwaite (2015) finds a negative relationship between the percentage of assets allocated to equity and CFPs.

4.4 Controlling for industry weights

The CFP industry exposures in Table 1 show that there are significant differences in terms of the average CFP across different industries. This raises the question whether the variation in pension funds' exposures to particular industries is driving our results. Therefore, we include the contemporaneous portfolio industry weights (NACE level 1) as explanatory variables in Table 6. We take contemporaneous weights instead of lagged weights to prevent industry weights capturing portfolio rebalancing effects.

In Column (1) to (15) of Table 6 we add industry weights one by one to test whether a single industry is driving our results. We find that the inclusion of industry weights one by one leaves most of our main results unaffected, except Column (3) and Column (6). Table 6 shows that once we add the portfolio weight in 'Electricity, gas and steam' (industry D)—the industry with the highest CFP—several of our effects reduce in size or disappear. The effect size of $DividendYield$ is much smaller and less significant for

'Electricity, gas and steam' and 'Wholesale and retail trade'. The portfolio weight in 'Electricity, gas and steam' appears to partially pick up the relationship between CFP and dividend yield, which is supported by the observation that industry D also has the highest dividend yield on average.[19] Also in Column (3), β is now insignificant. The low β observed for 'Electricity, gas and steam' appears to support this result.[20] The effect of $ActiveShare$ is much smaller and insignificant, which suggests that to some extent pension funds achieve a lower CFP by taking positions in 'Electricity, gas and steam' that are smaller than the ones in the benchmark.

[*Insert Table 6—"Determinants of carbon footprints and industry portfolio weights"*]

These results suggest that our main results on the trade-off between dividend yield and CFP and the trade-off between systematic risk and CFP are to some extent driven by the exposures to 'Electricity, gas and steam'. To further check this interpretation, we take a conservative specification that completely saturates the model with all industry weights, except the omitted category: 'Other' (Industry Z). Column (16) reports the results of this specification. The adjusted R-squared increases to 0.82, but with the exception of $Size$ we can no longer confirm the results from our baseline specification in Table 3. Again, this appears to be mostly driven by 'Electricity, gas and steam, because once we omit the weight of 'Electricity, gas and steam' in Column (17) all our effects are again comparable in size and significance to the main effects reported in Table 3. These results confirm our initial finding that the identified trade-offs are to some extent driven by the exposure to 'Electricity, gas and steam'.[21]

This highlights the intricate link between CFP reduction and industry effects (Monasterolo et al., 2016; Koch and Bassen, 2013). CFP is concentrated in a few highly polluting industries which only comprise a small share of the total stock market value as well

[19] See also Appendix Table C.1.

[20] See also Appendix Table C.2.

[21] Note that once we rerun the the whole analysis without the stocks from the 'Electricity, gas and steam' industry that the main results do not change.

as pension fund's stock investments (see Appendix B). In line with this, Andersson et al. (2016) show that it is therefore possible to significantly reduce CFP, while maintaining minimum tracking error with the general market benchmark portfolio. Our results are consistent with their findings to the extent that trade-offs are largely driven by very few polluting industries.

5 Robustness checks

We perform two robustness checks for our dependent variable CFP. First, we check whether CFP outliers could be driving the main results in Table 3. Instead of CFP, we take the natural logarithm of CFP as dependent variable. Appendix Table E.1 shows that our results remain qualitatively similar to those reported in Table 3. Second, CFP is a measure of pension funds' absolute carbon footprint, but what might matter more is pension funds' CFP performance compared to a benchmark. Therefore, we reestimate the main analyzes in Table 3 and take as dependent variable the ratio of CFP to $CFP^{Benchmark}$ (see also Figure 1). Appendix Table E.2 shows that the sign and significance of the parameters is very similar to those reported in Table 3. Apparently, those variables that explain the variation of pension funds' CFP performance also account for the variation of $CFP/CFP^{Benchmark}$, even though they explain less variation as witnessed by Adjusted R^2 values that are noticeably lower than in Table 3.

6 Conclusion

In this paper we study a possible explanation for the variation of carbon footprints (CFP) across pension funds' equity portfolios. We combine Dutch pension funds' security-by-security equity holdings—obtained from supervisory data—with securities' carbon levels, returns, dividend yield and beta. We analyze this data at the portfolio level, supplementing it with the portfolio's active share, the share pension funds invest in equity, their funding ratio, a variable indicating whether they report their CFP and industry weights.

Our main results indicate that pension funds face investment trade-offs when attempting to reduce their CFP. First, those that shift their portfolio towards high dividend yield stocks have lower CFP; a trade-off most pronounced for well-funded pension funds. Second, reduction in CFP is associated with pension funds deviating more from the benchmark and taking more systematic risk (β). These results suggest that lowering CFP could be contentious as it is associated with lower expected dividend returns, a higher active share and more systematic risk. To some extent these trade-offs seem to be driven by industry exposures to energy and utilities, which suggests that pension funds could significantly lower CFP without sacrificing risk-adjusted returns by divesting from a limited number of firms (Andersson et al., 2016).

This study is the first to calculate and analyze the CFP of pension funds' equity investment from disaggregated data. A critical element of this approach is the measurement and availability of CO_2 data. There is a wider call to increase the transparency (Liesen et al., 2015; Thistlethwaite, 2015) and quality (FSB, 2016; Gupta and Mason, 2016) of firm level CO_2 emissions. Firm information on CO_2 exposures allows investors to more accurately calculate their portfolio CFP. In this study, we find that those pension funds that calculate and disclose their CFP have a significantly lower CFP than those that refrain from doing so, suggesting measurement implies better management.

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Table 1: Summary statistics: security-level CFP by industry

Industry	**Mean**	**Std.**	**Min**	**Max**	**N**	**n**
B. Mining and quarrying	2,087.9	2,921.8	625.1	9,408.2	2,057	414
C. Manufacturing	275.3	63.3	197.1	407.5	8,031	1,389
D. Electricity, gas, steam	2,963.6	149.7	2,641.6	3,099.3	1,072	197
E. Water supply; sewerage, waste management	732.8	123.1	639.2	991.2	152	29
F. Construction	433.2	125.8	265.1	628.0	1,026	172
G. Wholesale and retail trade	62.0	9.5	47.5	80.0	1,613	294
H. Transportation and storage	615.5	64.8	498.1	713.0	971	169
I. Accommodation and food service activities	183.1	26.4	143.2	223.6	259	46
J. Information and communication	46.8	7.0	35.9	57.8	2,234	433
K. Financial and insurance activities	43.3	9.9	30.8	62.9	4,215	806
L. Real estate activities	467.5	484.4	137.7	1,607.5	564	195
M. Professional, scientific and technical activities	326.1	97.8	205.3	475.8	1,969	428
N. Administrative and support service activities	209.3	52.6	139.0	320.6	388	74
R. Arts, entertainment and recreation	68.5	17.8	55.1	108.1	243	44
Z. Other	329.2	242.4	97.7	774.2	1,218	247
Total	487.3	1,106.1	43.9	677.9	26,012	4,657

This table reports summary statistics of security-level CFP for a panel dataset of all stocks in our sample (2009Q1-2015Q4), weighted by market value to total industry market value. Portfolio weights are rebalanced each quarter for each industry. Industries are classified according to NACE level 1. Industry Z. 'Other' is created and consists of the following industries with limited stock market presence: A. 'Agriculture, forestry and fishing', O. 'Public administration and defence; compulsory social security', P. 'Education', Q. 'Human health and social work activities' and S. 'Other service activities'. N indicates the number of observations, n indicates the number of stocks.

Table 2: Summary statistics

Variable	**Mean**	**Std.**	**Min**	**Max**
CO_2 in million tonnes	1.63	4.88	0.07	1.99
CFP_{it}	288.29	76.22	201.61	390.62
Total number of stocks	1108.81	801.64	162.50	2197.50
Total assets in billions of euros	19.83	48.40	2.12	31.39
$\log Totalassets_{it}$	15.77	1.18	14.53	17.25
$Returns_{it} in\%$	15.60	16.96	-4.02	34.39
$DividendYield_{it}$ in %	2.94	0.53	2.38	3.58
β_{it}	0.99	0.08	0.91	1.07
$ActiveShare_{it}$	34.98	8.45	22.51	45.84
$ShareEquity_{it}$ in %	30.93	8.15	19.37	40.97
$FundRatio_{it}$	1.09	0.12	0.95	1.25
$FundRatio_{it} > 1.05$	0.62	0.49	0.00	1.00
$\Delta_{+}FundRatio_{it} > 1.05$	0.08	0.28	0.00	0.00
CarbonReporting	0.19	0.40	0.00	1.00
Industry weights				
B. Mining and quarrying	7.59	2.76	4.08	10.78
C. Manufacturing	33.58	5.24	28.16	38.72
D. Electricity, gas, steam	3.39	1.48	1.88	4.98
E. Water supply; sewerage, waste management	0.19	0.21	0.00	0.37
F. Construction	1.93	1.73	0.63	3.41
G. Wholesale and retail trade	5.31	2.14	3.25	7.82
H. Transportation and storage	2.20	1.09	1.28	3.50
I. Accommodation and food service activities	0.80	0.57	0.19	1.48
J. Information and communication	9.93	2.51	7.02	12.46
K. Financial and insurance activities	19.59	4.79	14.80	25.04
L. Real estate activities	2.98	4.87	0.18	7.22
M. Professional, scientific and technical activities	6.93	2.15	5.06	9.65
N. Administrative and support service activities	0.89	0.71	0.29	1.94
R. Arts, entertainment and recreation	0.64	0.39	0.25	1.07
Z. Other	4.05	5.48	1.52	6.48

This table reports summary statistics for the estimation sample: n=890; 41 pension funds over 2009Q1-2015Q4 (unbalanced). Except for the CFP variables and industry weights, all variables are lagged one quarter. CFP is measured in terms of tonnes of CO_2 per millions euros of sales.

Table 3: Main results: Determinants of carbon footprints

	(1)	(2)	(3)	(4)	(5)	(6)
$\log TotalAssets_{it}$	14.2608***	14.6706***	14.1575***	14.6311***	12.7900***	13.3307***
	[4.821]	[4.901]	[4.982]	[4.742]	[4.133]	[4.110]
$Returns_{it}$		−0.9571	0.8770	0.7945	0.5531	0.5299
		[1.227]	[1.056]	[0.991]	[0.968]	[0.951]
$DividendYield_{it}$			39.9173***	32.1008**	29.5052**	30.6811**
			[12.486]	[12.832]	[12.206]	[11.829]
β_{it}				−197.1518**	−226.7534**	−220.9720**
				[90.749]	[84.084]	[86.780]
$ActiveShare_{it}$					−1.5140***	−1.3766***
					[0.389]	[0.400]
$ShareEquity_{it}$						−0.6489
						[0.635]
Constant	176.0790**	145.3616*	31.3381	239.0102*	355.3267***	349.6864***
	[78.383]	[85.400]	[99.920]	[133.545]	[123.476]	[120.711]
Observations	890	890	890	890	890	890
Adjusted R^2	0.455	0.457	0.487	0.531	0.557	0.561
Number of pension funds	41	41	41	41	41	41

This table reports main effects of estimating equation 2. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Table 4: Carbon footprints, pension funds' funding ratios and dividends

	(1)	(2)	(3)	(4)	(5)	(6)
$\log TotalAssets_{it}$	13.5975^{***}	13.7339^{***}	13.8925^{***}	13.7100^{***}	13.3272^{***}	13.4796^{***}
	[4.093]	[4.059]	[4.166]	[4.047]	[4.116]	[4.056]
$Returns_{it}$	0.4372	0.4208	0.4733	0.4472	0.5450	0.6075
	[0.922]	[0.920]	[0.926]	[0.934]	[0.952]	[0.964]
$DividendYield_{it}$	31.8019^{**}	-49.7358	32.8839^{**}	18.0289	30.6683^{**}	26.6335^{**}
	[12.167]	[54.677]	[12.293]	[13.889]	[11.839]	[11.645]
β_{it}	-216.1469^{**}	-218.2207^{**}	-213.3187^{**}	-215.4248^{**}	-221.4931^{**}	-220.5942^{**}
	[88.015]	[88.227]	[87.760]	[87.513]	[86.778]	[86.766]
$ActiveShare_{it}$	-1.3317^{***}	-1.3412^{***}	-1.3388^{***}	-1.3062^{***}	-1.3756^{***}	-1.3787^{***}
	[0.389]	[0.394]	[0.388]	[0.387]	[0.400]	[0.396]
$ShareEquity_{it}$	-0.7452	-0.7002	-0.7037	-0.6655	-0.6525	-0.6614
	[0.659]	[0.632]	[0.625]	[0.596]	[0.636]	[0.635]
$FundRatio_{it}$	43.6957	-174.5525				
	[37.806]	[140.969]				
$FundRatio_{it} \times$ $DividendYield_{it}$		75.2839				
		[49.593]				
$FundRatio_{it} > 1.05$			15.1605	-55.0420		
			[10.078]	[33.552]		
$FundRatio_{it} > 1.05 \times$ $DividendYield_{it}$				23.6171^{**}		
				[11.126]		
$\Delta_{+}FundRatio_{it} > 1.05$					4.0882	-135.2408^{***}
					[4.679]	[47.080]
$\Delta_{+}FundRatio_{it} > 1.05 \times$ $DividendYield_{it}$						46.4594^{***}
						[16.166]
Constant	292.5806^{**}	538.5989^{**}	320.3421^{**}	379.0251^{***}	350.7378^{***}	366.5849^{***}
	[143.740]	[214.715]	[127.579]	[131.024]	[120.690]	[117.970]
Observations	890	890	890	890	890	890
Adjusted R^2	0.564	0.567	0.568	0.573	0.560	0.566
Number of pension funds	41	41	41	41	41	41

This table reports interactions of pension funds' funding ratio indicators with dividend yield. $FundRatio_{it}$ indicates the actual funding ratio. $FundRatio_{it} > 1.00$ and $\Delta_{+}FundRatio_{it} > 1.05$ are dummy variables indicating whether funding ratio is larger than 105 percent and whether a pension fund reaches a funding ratio larger than 105 percent, respectively. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Table 5: Role of carbon footprint reporting by pension funds (period 2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log TotalAssets_{it}$	14.3409***	14.3435***	14.8679***	12.1144***	10.0549***	8.2849***	13.1315***
	[4.040]	[4.059]	[4.253]	[3.301]	[2.621]	[2.665]	[3.375]
$Returns_{it}$		−0.9661	0.9346	0.9434	0.2554	0.3355	0.1825
		[1.381]	[1.245]	[1.111]	[1.092]	[0.995]	[1.019]
$DividendYield_{it}$			42.3110**	30.0382*	20.5472	16.4431	19.9430
			[16.062]	[16.730]	[17.153]	[16.784]	[16.293]
β_{it}				−244.1726*	−298.9879**	−318.2261***	−284.0480**
				[131.077]	[122.819]	[111.826]	[108.770]
$ActiveShare_{it}$					−1.5856***	−1.9205***	−1.9920***
					[0.421]	[0.490]	[0.511]
$ShareEquity_{it}$						1.2804*	1.1188*
						[0.661]	[0.642]
$CarbonReporting_{it}$							−23.0626**
							[9.666]
Observations	397	397	397	397	397	397	397
Adjusted R^2	0.319	0.322	0.389	0.466	0.545	0.570	0.586
Number of pension funds	36	36	36	36	36	36	36

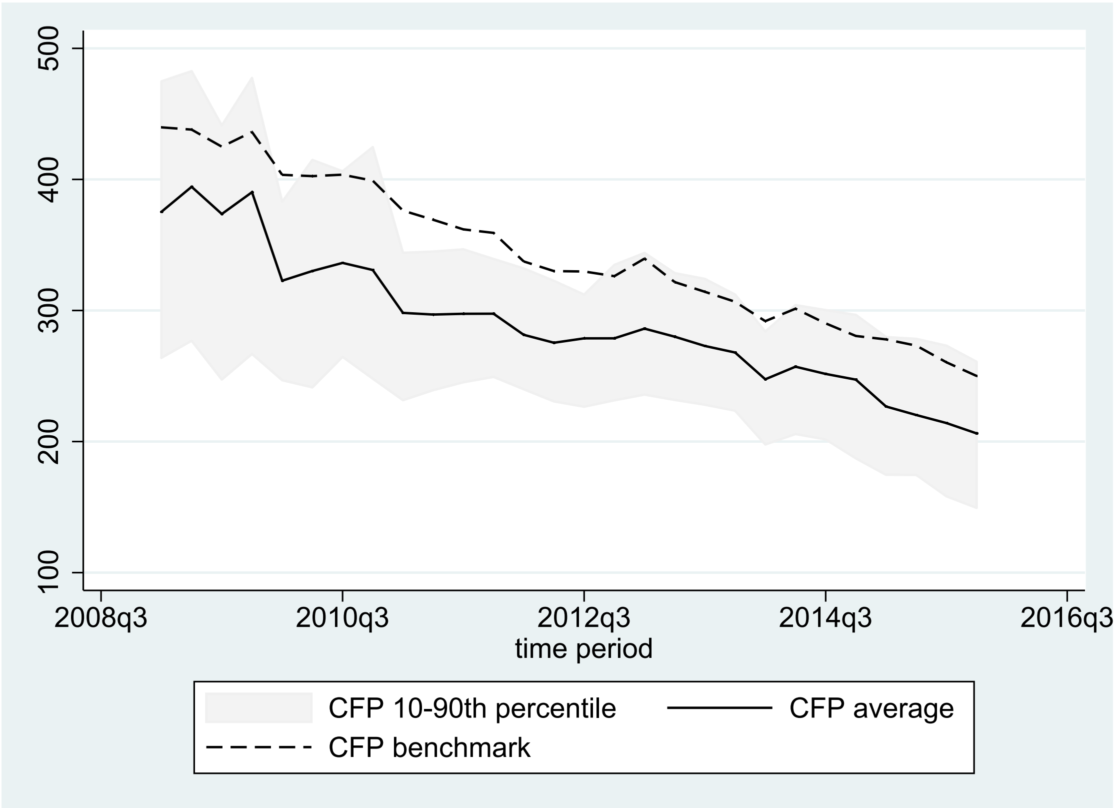
This table reports the main results of Table 4 for the subsample 2013-2015. In column (7) we add an additional explanatory variable $CarbonReporting$, which is an indicator variable equal to one if a pension fund reports its CFP and zero otherwise. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Table 6: Determinants of carbon footprints and industry portfolio weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\log TotalAssets_{it}$	13.18***	12.53***	10.49***	12.74***	15.15***	12.28***	12.66***	13.56***	14.63***	13.06***	14.22***	12.94***	13.14***	13.02***	13.30***	7.66***	10.54***
	[3.71]	[3.99]	[3.29]	[3.87]	[4.53]	[3.74]	[3.52]	[4.07]	[3.78]	[3.97]	[3.80]	[4.33]	[4.22]	[3.87]	[4.09]	[1.99]	[3.00]
$Returns_{it}$	0.94	0.24	0.70	0.38	1.00	0.20	0.97	0.50	0.88	0.49	1.54	0.67	0.45	0.73	0.52	0.35	0.80
	[0.99]	[0.97]	[0.68]	[0.91]	[1.01]	[0.85]	[0.88]	[0.93]	[0.86]	[0.98]	[0.94]	[0.88]	[1.01]	[0.96]	[0.93]	[0.60]	[0.79]
$DividendYield_{it}$	25.63**	27.77**	16.77*	32.71***	32.52***	18.23	51.44***	35.86**	33.34***	29.34**	46.35***	34.09**	23.93**	35.74***	30.78**	9.26	31.38**
	[11.94]	[11.81]	[9.01]	[11.81]	[11.87]	[16.35]	[13.81]	[13.68]	[11.18]	[12.87]	[11.74]	[12.86]	[11.75]	[12.55]	[11.83]	[11.30]	[13.52]
β_{it}	−237.63***	−228.40***	45.31	−216.98**	−190.19**	−263.12***	−197.38**	−195.02*	−201.37**	−230.82**	−211.55**	−223.03**	−230.58***	−213.73**	−221.32**	−29.26	−246.51***
	[85.75]	[84.29]	[63.98]	[85.36]	[91.44]	[88.08]	[77.35]	[98.43]	[82.03]	[92.66]	[86.83]	[84.37]	[83.74]	[91.11]	[86.64]	[42.92]	[69.76]
$ActiveShare_{it}$	−1.11***	−1.43***	−0.52	−1.35***	−1.21***	−1.22***	−1.92***	−1.35***	−1.17**	−1.36***	−1.15***	−1.27***	−1.15**	−1.37***	−1.38***	−0.33	−0.81*
	[0.39]	[0.43]	[0.33]	[0.39]	[0.44]	[0.39]	[0.52]	[0.41]	[0.44]	[0.38]	[0.41]	[0.42]	[0.44]	[0.41]	[0.40]	[0.36]	[0.47]
$ShareEquity_{it}$	−0.38	−0.63	−0.12	−0.61	−0.63	−0.64	−0.47	−0.64	−0.77	−0.62	−0.84	−0.60	−0.52	−0.64	−0.66	0.04	−0.32
	[0.58]	[0.63]	[0.47]	[0.63]	[0.61]	[0.60]	[0.62]	[0.64]	[0.59]	[0.64]	[0.59]	[0.67]	[0.70]	[0.63]	[0.65]	[0.30]	[0.48]
Industry B	6.75***															3.05**	3.35*
	[2.48]															[1.48]	[1.87]
Industry C		−0.74														−1.90**	−2.73***
		[1.20]														[0.73]	[0.91]
Industry D			27.74***													25.26***	
			[3.40]													[2.66]	
Industry E				31.59												41.58***	22.08
				[21.42]												[14.85]	[17.85]
Industry F					−5.40**											−0.77	−2.82
					[2.27]											[1.48]	[1.80]
Industry G						−4.66										−6.79**	−7.22**
						[4.35]										[2.55]	[3.00]
Industry H							15.54**									8.71**	13.69***
							[6.10]									[3.30]	[4.38]
Industry I								9.12								3.37	10.66
								[10.19]								[6.20]	[7.27]
Industry J									4.13							0.37	2.96*
									[2.86]							[1.21]	[1.68]
Industry K										0.38						−0.14	0.19
										[1.22]						[0.70]	[0.99]
Industry L											−3.39***					−2.86***	−3.70***
											[0.58]					[0.62]	[0.92]
Industry M												−2.33				2.54	0.96
												[3.06]				[2.06]	[2.55]
Industry N													−9.31			−7.53	−14.15*
													[7.42]			[5.16]	[7.46]
Industry R														16.36		−7.07	−0.62
														[14.75]		[6.18]	[9.75]
Industry Z															0.10		
															[0.47]		
Constant	323.62***	400.05***	59.36	334.66***	302.85**	464.21***	250.29**	293.05*	258.94**	359.34***	291.74**	356.35***	381.93***	323.89**	349.55***	235.16**	434.23
	[118.28]	[136.52]	[97.82]	[120.94]	[127.73]	[151.42]	[123.24]	[148.68]	[124.11]	[122.78]	[116.45]	[116.45]	[123.12]	[129.92]	[120.82]	[97.78]	[146.52]
Observations	890	890	890	890	890	890	890	890	890	890	890	890	890	890	890	890	890
Adjusted R^2	0.597	0.562	0.738	0.567	0.573	0.572	0.593	0.564	0.578	0.561	0.597	0.563	0.566	0.566	0.560	0.820	0.704
Number of pension funds	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41

This table reports our main estimates including contemporaneous industry weights as well. For an overview of the industry names, refer to Table 1. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Figure 1: Average pension fund footprint versus a market benchmark



Appendix A Sample coverage of CO_2 data

Table A.1: Percentage of equity investments covered by CO_2 data

Size quantiles	2009	2010	2011	2012	2013	2014	2015	Total
1	71.4	79.9	81.7	80.4	83.6	85.2	87.0	83.1
2	73.6	80.6	81.8	81.1	83.8	86.5	87.8	83.5
3	73.5	80.5	82.1	82.3	84.5	87.0	88.2	83.8
4	71.7	79.3	81.2	82.3	84.5	86.8	88.3	83.3
5	70.4	77.8	80.0	81.6	83.5	86.3	88.3	82.3
6	69.8	77.6	79.3	81.3	82.5	85.9	88.2	81.6
7	69.6	76.7	79.1	81.0	82.3	86.1	88.5	81.3
8	68.5	76.6	79.0	81.1	82.9	86.4	88.7	81.6
9	67.4	76.5	79.3	81.1	82.8	86.3	88.7	81.8
10	63.3	75.0	77.9	80.9	82.5	86.3	88.8	81.6
Total	69.8	77.8	80.1	81.3	83.3	86.3	88.2	82.4

This table reports the percentage of equity investment coverage by CO_2 data according to pension fund size quantiles and years. Size quantiles are based on pension funds' total assets.

Appendix B Summary statistics security-level data

Table B.1: Summary statistics security-level market values by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	2,548.0	313.3	1,989.5	2,957.9	2,057
C. Manufacturing	10,793.5	2,470.9	7,229.6	14,622.5	8,031
D. Electricity, gas, steam	1,275.1	54.1	1,193.4	1,352.9	1,072
E. Water supply; sewerage, waste management	75.6	18.8	50.3	107.9	152
F. Construction	580.9	134.8	413.9	794.3	1,026
G. Wholesale and retail trade	1,757.4	567.8	954.1	2,649.2	1,613
H. Transportation and storage	820.8	218.0	539.2	1,122.3	971
I. Accommodation and food service activities	267.9	77.4	137.4	368.9	259
J. Information and communication	3,403.4	966.3	2,281.6	5,077.0	2,234
K. Financial and insurance activities	5,772.7	1,326.3	4,062.1	7,509.0	4,215
L. Real estate activities	470.8	379.2	164.7	1,024.4	564
M. Professional, scientific and technical activities	2,185.7	928.9	1,202.1	3,890.5	1,969
N. Administrative and support service activities	257.3	86.3	124.9	349.0	388
R. Arts, entertainment and recreation	244.5	74.2	139.9	387.5	243
Z. Other (A, O, P, Q, S)	737.9	212.4	419.3	1,077.7	1,218

This table reports summary statistics for stocks' market values in billions of euros, summarized over 2009Q1-2015Q4. Industries are classified according to NACE level 1. Industry Z. 'Other' is created and consists of the following industries with limited coverage: A. 'Agriculture, forestry and fishing', O. 'Public administration and defence; compulsory social security', P. 'Education', Q. 'Human health and social work activities' and S. 'Other service activities'.

Table B.2: Summary statistics security-level pension fund stock holdings by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	14.4	1.5	11.7	16.3	2,057
C. Manufacturing	67.2	20.2	39.2	94.0	8,031
D. Electricity, gas, steam	6.9	1.8	5.0	9.8	1,072
E. Water supply; sewerage, waste management	0.4	0.2	0.2	0.7	152
F. Construction	5.4	1.0	3.9	6.5	1,026
G. Wholesale and retail trade	9.5	3.6	4.3	14.9	1,613
H. Transportation and storage	4.3	1.7	2.2	6.9	971
I. Accommodation and food service activities	1.3	0.6	0.5	2.1	259
J. Information and communication	19.2	7.2	11.1	30.8	2,234
K. Financial and insurance activities	44.3	11.3	28.7	63.4	4,215
L. Real estate activities	15.1	12.5	5.4	33.4	564
M. Professional, scientific and technical activities	14.8	6.5	7.6	26.0	1,969
N. Administrative and support service activities	1.7	0.5	1.0	2.2	388
R. Arts, entertainment and recreation	1.3	0.5	0.6	2.1	243
Z. Other (A, O, P, Q, S)	4.7	1.8	2.3	7.8	1,218

This table reports security-level summary statistics for pension funds' total stock holdings in billions of euros, summarized over 2009Q1-2015Q4. Industries are classified according to NACE level 1. Industry Z. Other includes: A. Agriculture, forestry and fishing, O. Public administration and defence; compulsory social security, P. Education, Q. Human health and social work activities and S. Other service activities.

Table B.3: Summary statistics security level sales by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	2,835.4	430.8	1,944.0	3,286.6	2,057
C. Manufacturing	9,213.1	1,043.8	7,027.6	10,490.2	8,031
D. Electricity, gas, steam	1,243.1	107.1	1,056.7	1,401.5	1,072
E. Water supply; sewerage, waste management	58.0	9.4	43.9	67.1	152
F. Construction	674.2	106.1	520.7	850.8	1,026
G. Wholesale and retail trade	2,939.6	544.3	2,078.7	3,817.0	1,613
H. Transportation and storage	857.2	113.7	649.9	1,025.2	971
I. Accommodation and food service activities	120.8	22.9	85.9	156.4	259
J. Information and communication	1,993.5	246.0	1,625.3	2,475.7	2,234
K. Financial and insurance activities	4,642.4	568.6	3,563.2	5,338.0	4,215
L. Real estate activities	102.4	62.9	46.4	191.4	564
M. Professional, scientific and technical activities	2,172.0	504.8	1,432.5	3,015.9	1,969
N. Administrative and support service activities	192.3	19.6	150.8	215.1	388
R. Arts, entertainment and recreation	111.2	17.0	90.9	145.3	243
Z. Other (A, O, P, Q, S)	783.4	140.5	532.0	997.8	1,218

This table reports summary statistics for stocks' sales in millions of euros, summarized over 2009Q1-2015Q4. Industries are classified according to NACE level 1. Industry Z. 'Other' is created and consists of the following industries with limited coverage: A. 'Agriculture, forestry and fishing', O. 'Public administration and defence; compulsory social security', P. 'Education', Q. 'Human health and social work activities' and S. 'Other service activities'.

Table B.4: Summary statistics security-level CO_2 by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	1,418.0	101.0	1,285.9	1,607.5	2,057
C. Manufacturing	2,750.1	275.1	2,147.3	3,056.1	8,031
D. Electricity, gas, steam	3,277.9	262.5	2,814.3	3,547.7	1,072
E. Water supply; sewerage, waste management	36.6	1.7	33.6	39.1	152
F. Construction	228.0	53.7	116.3	285.4	1,026
G. Wholesale and retail trade	177.3	40.6	121.2	229.5	1,613
H. Transportation and storage	574.8	51.7	470.4	634.8	971
I. Accommodation and food service activities	18.6	2.3	14.0	21.3	259
J. Information and communication	95.8	5.8	88.7	106.4	2,234
K. Financial and insurance activities	158.4	32.5	129.7	222.3	4,215
L. Real estate activities	35.7	32.9	6.3	75.7	564
M. Professional, scientific and technical activities	764.4	95.4	584.6	896.3	1,969
N. Administrative and support service activities	40.0	8.1	31.7	51.6	388
R. Arts, entertainment and recreation	7.4	0.7	6.5	8.6	243
Z. Other (A, O, P, Q, S)	106.0	62.1	43.7	206.5	1,218

This table reports summary statistics for stocks' absolute CO_2 emissions in millions of tonnes, summarized over 2009Q1-2015Q4. Industries are classified according to NACE level 1. Industry Z. Other includes: A. Agriculture, forestry and fishing, O. Public administration and defence; compulsory social security, P. Education, Q. Human health and social work activities and S. Other service activities.

Appendix C Dividend yield and β by industry

Table C.1: Summary statistics security-level dividend yield by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	3.0	0.7	1.9	4.4	2,057
C. Manufacturing	2.3	0.2	2.1	2.6	8,031
D. Electricity, gas, steam	3.7	0.3	3.2	4.3	1,072
E. Water supply; sewerage, waste management	3.5	0.4	2.8	3.9	152
F. Construction	2.3	0.3	2.0	2.8	1,026
G. Wholesale and retail trade	1.8	0.1	1.7	2.1	1,613
H. Transportation and storage	2.1	0.3	1.8	2.8	971
I. Accommodation and food service activities	2.2	0.2	1.8	2.5	259
J. Information and communication	2.9	0.4	2.4	3.5	2,234
K. Financial and insurance activities	2.9	0.3	2.4	3.6	4,215
L. Real estate activities	3.7	0.3	3.4	4.2	564
M. Professional, scientific and technical activities	2.3	0.3	2.1	2.8	1,969
N. Administrative and support service activities	1.3	0.2	1.0	1.6	388
R. Arts, entertainment and recreation	2.1	0.5	1.5	2.8	243
Z. Other (A, O, P, Q, S)	1.9	0.2	1.5	2.3	1,218

This table reports summary statistics of security-level $DividendYield$ for a panel dataset of all stocks in our sample (2009Q1-2015Q4), weighted by market value to total industry market value. Portfolio weights are rebalanced each quarter, for each industry. Industries are classified according to NACE level 1. Industry Z. 'Other' is created and consists of the following industries with limited coverage: A. 'Agriculture, forestry and fishing', O. 'Public administration and defence; compulsory social security', P. 'Education', Q. 'Human health and social work activities' and S. 'Other service activities'.

Table C.2: Summary statistics security-level β by industry

Industry	Mean	Std.	p10	p90	N
B. Mining and quarrying	1.2	0.0	1.1	1.2	2,057
C. Manufacturing	1.0	0.0	0.9	1.0	8,031
D. Electricity, gas, steam	0.7	0.0	0.7	0.8	1,072
E. Water supply; sewerage, waste management	0.6	0.0	0.5	0.6	152
F. Construction	1.3	0.1	1.1	1.3	1,026
G. Wholesale and retail trade	0.9	0.0	0.8	0.9	1,613
H. Transportation and storage	0.9	0.0	0.8	1.0	971
I. Accommodation and food service activities	0.9	0.1	0.8	1.0	259
J. Information and communication	0.8	0.0	0.8	0.9	2,234
K. Financial and insurance activities	1.3	0.1	1.2	1.4	4,215
L. Real estate activities	1.0	0.1	0.8	1.2	564
M. Professional, scientific and technical activities	0.9	0.0	0.9	1.0	1,969
N. Administrative and support service activities	1.1	0.1	1.1	1.3	388
R. Arts, entertainment and recreation	1.2	0.1	1.0	1.4	243
Z. Other (A, O, P, Q, S)	1.0	0.1	0.9	1.1	1,218

This table reports summary statistics of security-level β for a panel dataset of all stocks in our sample (2009Q1-2015Q4), weighted by market value to total industry market value. Portfolio weights are rebalanced each quarter, for each industry. Industries are classified according to NACE level 1. Industry Z. 'Other' is created and consists of the following industries with limited coverage: A. 'Agriculture, forestry and fishing', O. 'Public administration and defence; compulsory social security', P. 'Education', Q. 'Human health and social work activities' and S. 'Other service activities'.

Appendix D Additional summary statistics main estimates

Table D.1: Correlations

	1	2	3	4	5	6
1. $\log TotalAssets_{it}$	1					
2. $Returns_{it}$	0.0923^{***}	1				
3. $DividendYield_{it}$	-0.1043	-0.5967^{*}	1			
4. β_{it}	0.0335	0.1225^{**}	-0.2286^{***}	1		
5. $ActiveShare_{it}$	-0.2051^{***}	-0.0571	0.048	-0.1736^{***}	1	
6. $ShareEquity_{it}$	0.0547	0.0686^{**}	0.0049	0.0685^{**}	0.1954^{***}	1

This table reports pairwise correlations between our main independent variables: ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively (n=890).

Appendix E Robustness checks

Table E.1: Robustness check: log CFP instead of CFP as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
$\log TotalAssets_{it}$	0.0557^{***}	0.0567^{***}	0.0551^{***}	0.0564^{***}	0.0477^{***}	0.0489^{***}
	[0.018]	[0.018]	[0.018]	[0.017]	[0.014]	[0.015]
$Returns_{it}$		-0.0023	0.0034	0.0032	0.0020	0.0020
		[0.005]	[0.004]	[0.004]	[0.004]	[0.004]
$DividendYield_{it}$			0.1231^{**}	0.1016^{**}	0.0894^{*}	0.0920^{**}
			[0.049]	[0.049]	[0.047]	[0.046]
β_{it}				-0.5421^{*}	-0.6816^{**}	-0.6689^{**}
				[0.310]	[0.273]	[0.279]
$ActiveShare_{it}$					-0.0071^{***}	-0.0068^{***}
					[0.002]	[0.002]
$ShareEquity_{it}$						-0.0014
						[0.002]
Constant	5.1041^{***}	5.0312^{***}	4.6796^{***}	5.2507^{***}	5.7986^{***}	5.7862^{***}
	[0.284]	[0.302]	[0.348]	[0.471]	[0.414]	[0.406]
Observations	890	890	890	890	890	890
Adjusted R^2	0.438	0.438	0.461	0.487	0.532	0.534
Number of pension funds	41	41	41	41	41	41

This table reports main effects of a robustness check in which we replace the dependent variable in equation 2, CFP_{it} with the natural logarithm of this variable, $\log CFP_{it}$. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

Table E.2: Robustness check: $CFP_{it}/CFP_{it}^{Benchmark}$ as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
$\log TotalAssets_{it}$	0.0429^{***}	0.0439^{***}	0.0424^{***}	0.0439^{***}	0.0380^{***}	0.0391^{***}
	[0.014]	[0.014]	[0.014]	[0.014]	[0.012]	[0.012]
$Returns_{it}$		-0.0024	0.0029	0.0026	0.0019	0.0018
		[0.004]	[0.003]	[0.003]	[0.003]	[0.003]
$DividendYield_{it}$			0.1159^{***}	0.0915^{**}	0.0832^{**}	0.0855^{**}
			[0.039]	[0.040]	[0.038]	[0.037]
β_{it}				-0.6142^{**}	-0.7088^{***}	-0.6977^{***}
				[0.256]	[0.235]	[0.242]
$ActiveShare_{it}$					-0.0048^{***}	-0.0046^{***}
					[0.001]	[0.001]
$ShareEquity_{it}$						-0.0013
						[0.002]
Constant	0.2439	0.1657	-0.1653	0.4817	0.8534^{**}	0.8425^{**}
	[0.221]	[0.248]	[0.289]	[0.361]	[0.335]	[0.329]
Observations	890	890	890	890	890	890
Adjusted R^2	0.087	0.090	0.143	0.229	0.283	0.286
Number of pension funds	41	41	41	41	41	41

This table reports main effects of a robustness check in which we replace the dependent variable in equation 2, CFP_{it} with a benchmark-adjusted dependent variable: $CFP_{it}/CFP_{it}^{Benchmark}$. All explanatory variables are lagged by one period. All estimations include year-quarter fixed effects. Standard errors are clustered at the pension fund level and are reported in parentheses and ***, **, * correspond to the 1%, 5%, and 10% level of significance, respectively.

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