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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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A textual analysis of pension funds' disclosures of sustainable investing.*

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Abstract:

In this paper, we analyze the disclosures of sustainable investing by Dutch pension funds in their annual reports from 2016 to 2021. We introduce a novel textual analysis approach using state-of-the-art natural language processing (NLP) techniques to measure the awareness and implementation of sustainable investing, where we define awareness as the amount of attention paid to sustainable investing in the annual report. We exploit a proprietary dataset to analyze the relation between pension fund characteristics and sustainable investing. We find that a pension fund's size increases both the awareness and the implementation of sustainable investing. Moreover, we analyze the role of signing the International Responsible Business Conduct (IRBC) initiative. Large pension funds, pension funds with more female trustees, or pension funds with a positive belief about the risk-return relation of sustainable investing are more likely to sign the IRBC initiative. Although signing this initiative increases the specificity of pension fund statements about sustainable investing, we do not find an effect on the implementation of sustainable investing.

Keywords: ESG, sustainability, SI initiatives, pension funds, textual analysis, natural language processing.
JEL classification: C8, G11, J32, M14, Q54

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1 Introduction

There is a global trend towards investment policies that take environmental, social, and governance (ESG) information into account. Sustainable investing reached 35.3 trillion dollars in assets under management in 2020 (GSIA (2021)).[1] Pension funds, as long-term investors, in particular may put their capital at work in a way that positively influences the environment and society. There is societal and political pressure on pension funds to do so; several recent examples exist of protesters pushing pension funds to divest from fossil fuels.[2] Moreover, there is growing recognition that climate-related risks are a source of financial risk, impacting the resilience of financial institutions, including pension funds.[3] Nevertheless, little is known about the design and development of SI policies by pension funds. Pension funds can implement sustainable investing using different strategies, for example, by excluding companies with a negative environmental impact from the investment portfolio (divestment), by voting on shareholder proposals (public engagement), or by directly communicating with companies (private engagement).

Over the years, governments and NGOs launched several initiatives to stimulate the development of a sustainable financial system and to promote the integration of ESG information into investment decisions. For example, the United Nations Environment Programme Finance Initiative (UNEP FI) established and co-created several international programs, including the well-known Principles for Responsible Investment (PRI). This program is a UN-supported initiative founded in 2006 by some of the world's largest institutional investors to stimulate the incorporation of ESG information into investment practices. There are also local SI initiatives, such as the International Responsible Business Conduct (IRBC) initiative (IRBC (2018)) in the Netherlands, which is a voluntary initiative of Dutch pension funds that aims to bring their investment policy into line with the OECD Guidelines for Multinational Enterprises (OECD Guidelines) and the United Nations Guiding Principles on Business and Human Rights (UNGPs).[4,5,6] This raises the question of whether pension funds that sign such an initiative enhance their SI policy more than non-signatories. This paper is the first paper investigating the impact of signing the IRBC initiative on a pension fund's SI policy.

This paper contributes to the literature by creating an overview of the disclosures of sustainable investing by a specific group of large institutional investors, Dutch occupational

[1] In this paper, we use the term sustainable investing (SI), which is also known as socially responsible investing (SRI), corporate social responsibility (CSR) or ESG investing.

[2] For example, there were protests at the Greater Manchester Pension Fund in July 2019, the Dutch civil service pension fund (ABP) in September 2021, and the Teachers Insurance & Annuity Association of America (TIAA) in October 2022.

[3] See, e.g., Vermeulen et al. (2018) and FSB (2020).

[4] The IRBC is the 'Convenant Internationaal Maatschappelijk Verantwoord Beleggen Pensioenfondsen' (IMVB) in Dutch.

[5] OECD (2011), *OECD Guidelines for Multinational Enterprises.*

[6] United Nations (2011), *Guiding Principles on business and human rights.*

pension funds, by exploiting a unique dataset with a novel tool. Dutch pension funds had more than 1.8 trillion euros worth of assets under management at the end of 2021 (DNB (2022)) and as such the Netherlands have the highest ratio of pension assets to GDP worldwide (ThinkingAheadInstitute (2022)). We introduce a novel textual analysis approach using state-of-the-art natural language processing (NLP) techniques to measure a pension fund's SI policy using qualitative data from annual reports. The textual analysis approach consists of two steps. To begin, we extract all SI-related sentences from the annual reports by applying a combined rule-based and classification approach using a pre-trained state-of-the-art language model called BERT. Subsequently, we exploit various NLP techniques (rule-based approach, topic modeling, and classification approach) to measure the SI policy of pension funds along two dimensions. First, we measure the awareness of sustainable investing, where we define awareness as the amount of attention paid to sustainable investing in the annual report. We use three measures to quantify awareness: intensity (fraction of SI-related sentences), spectrum (number of SI topics), and specificity (number of specific SI-related paragraphs). Second, we track the implementation of sustainable investing by constructing two measures: variety (number of implemented SI strategies) and scope (fraction of the portfolio included in the SI policy). We combine these SI measures with detailed financial and non-financial information about Dutch occupational pension funds, using a proprietary dataset from the prudential supervisor of pension funds, De Nederlandsche Bank (DNB).

We formulate three hypotheses to analyze the relation between pension fund characteristics and sustainable investing and the role of signing the IRBC initiative. First, we hypothesize that pension fund characteristics impact pension funds' awareness and implementation of sustainable investing. In particular, we expect large pension funds to have higher scores on all five SI measures, because large pension funds have more capacity to implement sustainable investing and might experience more societal pressure. We also expect that beliefs regarding the risk-return relation of sustainable investing impact the SI measures. We expect that board characteristics, such as the average board's age, gender, or stakeholder representation, do not impact the SI measures. Second, we hypothesize that pension fund characteristics also have an impact on the probability of signing the IRBC initiative in line with the first hypothesis. Third, we hypothesize that pension funds that signed the IRBC initiative enhance their SI policy more than pension funds that did not sign this initiative. We expect that the commitment of signatories to bring the investment policy into line with the OECD Guidelines and UNGPs will increase the awareness and implementation of sustainable investing.

The empirical results show that the pension fund's size increases the pension fund's awareness and implementation of sustainable investing. A positive belief about the risk-return relation of sustainable investing increases the awareness of sustainable investing. In line with our hypothesis, the board of trustees characteristics do not impact the SI measures. Further, we find that large pension funds, pension funds with more female trustees, and pension funds with a positive belief about the risk-return relation of sustainable investing are more likely to sign the IRBC initiative. Signing this SI initiative increases the specificity of statements about sustainable investing, but we do not find a significant effect on the implementation of sustainable investing.

This paper fits into the literature on institutional investors setting up their SI policy. Some papers use survey data to investigate perceptions about and the implementation of sustainable investing by institutional investors (Krueger et al. (2020), Amel-Zadeh and Serafeim (2018), and Ilhan et al. (2021a)). For instance, Krueger et al. (2020) show that institutional investors increasingly account for climate risk in their investment decision-making. Wagemans et al. (2018) investigate engagement at large Dutch pension funds using survey data and interviews.

Another strand of the literature focuses on the impact of institutional ownership on ESG performance. Dyck et al. (2019) and Chen et al. (2020) find a positive relationship between institutional ownership and firms' environmental and social performance. Ceccarelli et al. (2021) find a positive association between responsible institutional investors and ESG scores. The impact of SI initiatives on ESG performance is investigated by Bauckloh et al. (2021), Brandon et al. (2022), and Kim and Yoon (2022), focusing on the PRI. These papers provide mixed evidence. Bauckloh et al. (2021) and Brandon et al. (2022) find that institutional investors who signed the PRI initiative have better ESG scores compared to matched non-signatories. However, this result does not hold for US signatories in the research of Brandon et al. (2022), and Kim and Yoon (2022) also do not observe improved ESG scores for US mutual funds after signing. Bingler et al. (2022) measure the impact of signing different climate initiatives on the quality of corporate climate action disclosures and show that engagement initiatives considerably increase the quality and decision-relevance of corporate disclosures of climate-related commitments and actions.[7]

Finally, this paper relates to literature using textual analysis to measure climate risks in corporate documents. Berkman et al. (2021) follow a rule-based approach to measure climate risk exposure based on 10-K filings. Hail et al. (2021) and Sautner et al. (2021) use a predefined dictionary to measure climate change exposure in earnings conference calls.

The remainder of this paper is structured as follows. In Section 2, we describe the institutional setting of Dutch occupational pension funds, relevant legislation, SI initiatives, motives, and strategies. Section 3 presents the method for measuring sustainable investing. In Section 4, we provide an overview of the data and explain how the different SI measures are constructed. Section 5 introduces the empirical design and discusses the results. We conclude in Section 6.

[7] Bingler et al. (2022) consider the following climate initiatives: Task Force on Climate-Related Financial Disclosure, the Science-Based Targets Initiative and the Climate Action 100+.

2 Institutional setting

This study takes place in the Dutch occupational pension sector. We describe the organization of Dutch pension funds in Section 2.1 and the legal requirements regarding sustainable investing in Section 2.2. Section 2.3 gives an overview of SI initiatives that aim to enable and reinforce the development of a financial system. Section 2.4 describes why pension funds want to implement sustainable investing and Section 2.5 discusses strategies to realize sustainable investing.

2.1 Dutch occupational pension sector

Due to the quasi-mandatory status, the participation rate in the Netherlands is high: around 90% of the workforce participates in one or more occupational pension schemes (StvdA (2020)). For some industries, mandatory participation exists, which implies that all companies - and therefore all employees - in such an industry are required to join an industry-wide pension fund. Besides industry-wide pension funds, there are also pension funds for the employees of a specific company (corporate pension funds) or a particular profession (professional group pension funds).

In the Netherlands, pension funds are legally independent, non-profit organizations whose task is to execute the pension scheme that representatives of employers and employees have negotiated as part of labor compensation. The board of trustees is responsible for managing the assets and administering the benefits and consists of employee representatives (labor unions), employer representatives, and external experts. This board formally sets the investment policy and strategic asset allocation, with the help of several advisory councils, consultants, and investment advisors. Most pension funds outsource the implementation of the investment policy to one or more asset management firms. Besides implementing the investment policy, asset management firms can also act as an advisor to the pension fund when developing the SI policy because they often possess more expertise on this topic. Specifically for engagement, pension funds sometimes use ESG service providers who conduct the engagement conversations regarding sustainable investing independently from the asset manager.

2.2 Legislation

A number of features in the legislation on Dutch occupational pension funds are relevant to sustainable investing. An important article of the Dutch Pension Act states that pension funds should invest their assets in the sole interest of their beneficiaries. This is the so-called prudent person rule.[8] The prudent person rule is an open norm and does not contain

[8] Dutch Pension Act, Article 135.

quantitative investment restrictions.[9] To invest the assets in the best interest of beneficiaries, pension funds should take into account the beneficiaries' sustainability preferences. Moreover, Article 135 of the Dutch Pension Act states that pension funds should specify in their annual report how they incorporate ESG criteria in their investment policy.

In addition to Dutch legislation, European legislation is also relevant. IORP II states that pension funds can include ESG criteria in the prudent person rule as long as the application of ESG criteria does not harm the financial interests of the beneficiaries.[10] Another IORP II requirement is the incorporation of ESG risks in risk management.[11] The only hard requirement regarding sustainable investing for Dutch pension funds is the prohibition of cluster munition investments, which has been in place since 2013.[12]

Additional requirements are applicable as of March 2021, resulting from the European Sustainable Finance Disclosure Regulation (SFDR) regarding the provision of information on the sustainability of investments. Pension funds should explain to what extent they integrate ESG risks in their investment process. Moreover, they should indicate whether they take the adverse impacts of investment decisions on ESG factors into account.

2.3 SI initiatives

Besides the legal requirements, there has also been a rapid increase in voluntary initiatives to stimulate sustainable investing. Such initiatives aim to enable and reinforce the development of a sustainable financial system by promoting ESG integration into investment decisions or transparent disclosures. For example, the United Nations Environment Programme Finance Initiative (UNEP FI) comprised several international programs, including the well-known Principles for Responsible Investment (PRI). This program is a UN-supported initiative founded in 2006 by some of the largest institutional investors to stimulate the incorporation of ESG factors into investment practices. Other programs of the UNEP FI are the Principles for Responsible Banking (PRB), the Collective Commitment to Climate Action (CCCA), the Principles for Sustainable Insurance (PSI), and the Net-Zero Asset Owner Alliance (NZAOA). The best-known initiative in the Dutch pension fund sector is the IRBC initiative (IRBC (2018)) to identify, prioritize, and address ESG-related risks. A group of pension funds signed it at the end of 2018. The initiative aims to bring the investment policy into line with the OECD Guidelines and UNGPs. Another national example is the commitment of a group of financial institutions to the climate goals of the Dutch government in 2019. They agreed to measure the CO_2 emissions of their investments and to publish their CO_2 reduction goals as of 2022.

In this paper, we focus on one particular SI initiative that many Dutch pension funds

[9] The only restrictions are the prohibition on providing direct loans with a duration of one year or longer and the prohibition on investing more than 5 percent in the sponsoring corporation.

[10] IORP II, Article 19; implemented in Pension Act, Article 135.

[11] IORP II, Article 25; implemented in 'Besluit FTK', Article 18.

[12] 'Besluit marktmisbruik Wft', Article 21a.

embraced: the IRBC initiative. The pension funds participating in this initiative made joint arrangements with NGOs, labor unions, and the government regarding integration into the investment policy, outsourcing, monitoring, and reporting. For example, they agreed that the SI policy should include an explanation of how sustainability is integrated into the various asset classes in which the pension fund invests. Moreover, the pension fund should disclose its approach towards voting and engagement and provide its stakeholders with information on which companies are excluded (IRBC (2018)). This raises the question of whether pension funds that sign such an SI initiative enhance their SI policy more than non-signatories. We hypothesize that signatories enhance their SI policy more than non-signatories. The SI measures include the integration of sustainable investing into various asset classes and the implementation of different SI strategies. The measures will be described in more detail in Section 4.2.

2.4 Sustainable investment motives

In this section, we discuss the motivation of pension funds to invest sustainably. Pension funds can have financial and moral objectives. Other possible motives are reputational risk and legislation.

The first motive for sustainable investing can be driven by financial objectives. As discussed briefly in the introduction, there is growing recognition that climate-related risks are a source of financial risk. Companies with a positive impact on society may be more likely to attract customers and employees and avoid potential environmental fines or regulatory intervention. These companies generate higher risk-adjusted returns if these benefits are not fully priced (Edmans and Kacperczyk (2022)). As a result, pension funds can decide to invest sustainably based on financial objectives.

Moral objectives can drive the second motive for sustainable investing. It can be a result of the perceived moral obligation of a pension fund to contribute to a sustainable world or a reflection of the preferences of the beneficiaries of the pension fund. Research shows that most pension participants have strong preferences for sustainability even at the expense of lower financial performance (Delsen and Lehr (2019) and Bauer et al. (2021)). Especially in the context of the Dutch pension sector, in which beneficiaries are not able to switch their pension provider, pension funds have a strong responsibility to ensure that they act in the best interest of their beneficiaries.

A third motive is a concern about reputational risk. As mentioned in the introduction, there is societal and political pressure on pension funds, and several examples exist of protesters pushing pension funds to divest. Pension funds are aware that the material consequences of their investments cause lasting reputational damage. Peer pressure and benchmarking can also accelerate the activities of a pension fund in the SI domain. An example is the VBDO Benchmark for Responsible Investment by Pension Funds (VBDO (2021)), which compares sustainable investing by the 50 largest pension funds in the Netherlands.

Finally, there are legal requirements regarding sustainable investing, as discussed in Section 2.2, which can stimulate (or in the future possibly force) sustainable investing by pension funds.

2.5 Sustainable investment strategies

In this section, we discuss different SI strategies. There are several strategies to realize sustainable investing. We distinguish the following strategies in this paper: divestment, ESG integration, screening, public engagement, and private engagement. It is noteworthy, however, that it is not always possible to distinguish clearly between these five investment strategies. For instance, there is some overlap between the different strategies and it is also possible to distinguish more strategies.

We consider these five SI strategies in this paper. The first strategy is divestment (or exclusion) in which a pension fund excludes companies or projects with a negative (environmental) impact from the investment portfolio. This strategy can have several objectives, for example to shift capital to positive investments or meet the beneficiaries' demand. Many examples exist of pension funds that publicly declare their divestment from particular industries, such as the tobacco or nuclear weapons industry. In the Netherlands, pension funds have faced considerable pressure from stakeholders recently to divest from fossil fuel producers. Possibly in response to this pressure, some Dutch pension funds recently announced that they would stop investing in fossil fuel producers (IPE (2021a) and IPE (2021b)). There is disagreement in the literature on the effectiveness of a divestment strategy. For instance, Choi et al. (2021) posit that divestment pushes companies to adopt climate-friendly policies and decrease carbon footprints. In contrast to this finding, Berk and van Binsbergen (2021) evaluate the quantitative impact of ESG divestitures and conclude that ESG divestiture strategies had little impact on the cost of capital and will likely have little impact in the future. A disadvantage of exclusion is that it takes away the opportunity to directly influence corporate decision-making via engagement (see below).

A second strategy is integrating ESG criteria into the investment process. The key objective of this strategy is to improve the risk-adjusted return of investments. When determining the strategic asset allocation, for instance, financial information is complemented by sustainability information. Since this strategy is quite broad, the exact implementation of this strategy may differ between pension funds. There is no single view in the literature on the impact of, for instance, climate risks on the risk-adjusted return of investments. Some papers provide evidence that carbon risk is starting to be priced in the market (e.g., Boermans and Galema (2020), Bolton and Kacperczyk (2021), and Ilhan et al. (2021b)). Bolton and Kacperczyk (2021) find higher returns for stocks with higher total CO_2 emissions. This evidence indicates that investors demand compensation for carbon emission risk. However, Sautner et al. (2021) do not find a positive risk premium for climate change exposure and Faccini et al. (2021) find that transition and physical risks that take longer to materialize are not yet priced. Integrating sustainability can be done by, for example, tilting portfolios toward certain Sustainable Development Goals or mandates with a small, selected number of highly sustainable companies.

A third strategy is screening. The key objective of screening is to improve the portfolio performance based on specific ESG criteria. Screening is the process of selecting investments based on these criteria. There are several screening approaches in practice. For example, under negative (or exclusionary) screening, certain sectors or companies that fail to meet specific ESG criteria are excluded.[13] In the case of positive screening, certain sectors or companies are selected based on their positive (or best-in-class) ESG performance relative to industry peers. With norm-based screening, companies that do not adhere to widely accepted norms of business conduct are excluded. Heinkel et al. (2001) and Gollier and Pouget (2014) predict with an equilibrium model that companies will be incentivized to implement reforms when a significant fraction of investors apply the same screening approach. Opposing conclusions exist in the empirical literature on the impact of screening approaches on asset prices. For example, Hong and Kacperczyk (2009) show that sin stocks have depressed prices relative to otherwise comparable stocks.

The fourth and fifth strategies are two types of engagement. Engagement is the process of shareholders influencing corporate decision-making. The objective of engagement is to encourage companies to adopt more sustainable practices. In this paper, we distinguish two types of engagement: public and private engagement. Investors can engage in active ownership strategies by voting on and sponsoring shareholder proposals (public engagement) or by directly communicating with companies (private engagement) via meetings, calls, or letters. Engagement on ESG topics has become increasingly prevalent in financial markets worldwide. Besides engagement on an individual basis, shareholders regularly join forces and engage in a dialogue with companies as a group of institutional investors (collaborative engagement). By speaking with a unified voice, investors can more effectively communicate their concerns to companies and trigger action. SI initiatives can coordinate these collaborative engagements. Examples are the PRI collaboration platform and the IRBC deep track. Dimson et al. (2015) show that collaboration significantly increases the success rate of environmental and social engagements. Bauer et al. (2022) show that firms targeted by successful material private ESG engagements significantly outperform their peers. Hoepner et al. (2022) provide evidence that investor shareholder engagement can reduce downside ESG risks, especially those from climate change.

One of the five SI measures, the variety measure, counts the number of SI strategies each pension fund implements. Section 4.2 describes this measure in more detail. Before describing the measures in more detail in Section 4, Section 3 first explains how sustainable investing can be measured.

[13] There is some overlap between divestment and screening, i.e., negative screening can be classified as both a screening strategy and an exclusion strategy.

3 Measuring sustainable investing using NLP and self-reported information

To measure sustainable investing, many papers use ESG ratings of companies to calculate a portfolio's average ESG rating, which acts as a measure of the ESG performance (e.g., Dyck et al. (2019), Gibson et al. (2020), Chen et al. (2020), and Ceccarelli et al. (2021)). A drawback of this approach is that several studies document that ESG ratings can be very different across different ESG rating providers (Chatterji et al. (2016), Gibson Brandon et al. (2021), and Berg et al. (2022)). Berg et al. (2022) investigate the ratings of six prominent ESG rating providers and find correlations between ESG ratings from 0.38 to 0.71. Besides this low correlation, there are other drawbacks to using ESG ratings to measure the SI efforts of institutional investors. First, engagement activities are not directly visible in the ESG ratings compared to other SI strategies (e.g., divestment). It can take some time before successful engagement activities induce ESG rating adjustments. Second, ESG ratings are not available for all asset classes. While the coverage of ESG ratings for equity and corporate bonds is high, ESG ratings are often not available for alternative asset classes such as private equity or infrastructure.

In this study, we do not rely on ESG ratings and measure sustainable investing in an alternative way by using qualitative data from annual reports. We exploit three different NLP techniques (classification approach, topic modeling, and rule-based approach) to measure the awareness and implementation of sustainable investing by pension funds using five different measures that will be explained in Section 4.2. In this section, we discuss these three NLP techniques and discuss how the textual analysis pipeline is built.

First, text classification is a supervised machine learning technique that allocates categories to input text. For the classification approach, we use a recent NLP innovation exploiting deep neural network models for text classification called BERT. BERT is a trained transformer-based language model which learns contextual word embeddings (Devlin et al. (2019)).[14] One of the key advantages of using a BERT model for text classification is that it is trained on large amounts of unannotated data. This allows the model to learn more general text patterns and complex non-linear patterns, which significantly improves the model's performance. We use the RobBERT model: a trained Dutch RoBERTa-based language model.[15] This model is trained on large amounts of unlabeled Dutch text, generating powerful semantic representations of words and patterns. To perform text classification, we finetune this model on a supervised task using a labeled dataset. Finetuning is done by adding an output layer to the original model architecture (Devlin et al. (2019)). Finetuning a trained model instead of

[14] Besides the basic BERT model, various model configurations exist, such as RoBERTa, DistilBERT, and ALBERT.

[15] The RoBERTa model is the robustly optimized English BERT model. The RobBERT model uses the RoBERTa architecture and trains it with Dutch data.

training a model from scratch is preferred because it is less computationally intensive, faster, and improves generalized performance (Hendrycks et al. (2020)), even for smaller datasets. We finetune the RobBERT model twice for two different classification tasks using labeled datasets. These labeled datasets are created with an annotation approach. Appendix A contains more details on this annotation approach, and Appendix B contains more details on the finetuning and performance of the model.

Some recent studies have used BERT models to measure climate risk in corporate documents. Our classification approach is similar to Kölbel et al. (2022), who use BERT to quantify regulatory disclosure of climate risks in 10-K reports in order to analyze the impact on the spread in the credit default swap market. Friederich et al. (2021) use both BERT and RoBERTa to analyze the development of climate risk disclosures in annual corporate documents over the last 20 years. Webersinke et al. (2021) developed ClimateBERT by pretraining the DistilRoBERTa model with climate-related news articles, research abstracts, and corporate climate reports. Bingler et al. (2022) use this ClimateBERT model to measure cheap talk in corporate climate commitments.[16]

Second, topic modeling is an unsupervised machine learning technique that identifies topics in text by detecting patterns and recurring words. We use a topic modelling tool that exploits the same class of language models as BERT, namely BERTopic (Grootendorst (2022)). BERTopic extracts latent topics from a collection of documents by producing topic representations. BERTopic is well suited to the analysis of sentences or paragraphs acting as documents, so coherent and consistent themes can be derived from the text. We use this tool to identify different SI topics and determine which are discussed in each annual report. We discuss this application in more detail in Section 4.2.

Third, in a rule-based approach, texts are analyzed using carefully prepared keyword lists. For simple, straightforward tasks, rule-based approaches are suitable because of their transparency and flexibility. In this paper, we use a rule-based approach, for example, to extract sentences with SI-related words. We use a dictionary with SI-related keywords and combinations of keywords to extract all SI-related sentences using a lemmatized keyword search.[17] A well-known example of a rule-based application is the word list of Loughran and McDonald (2011) to measure sentiment in financial texts, which is used in several studies in the finance and accounting literature (for example, Das et al. (2014), Kearney and Liu (2014), and Gandhi et al. (2019)). In the literature on climate-related disclosures, Berkman et al. (2021) use a rule-based approach to measure climate risk exposure in 10-K filings, and Hail et al. (2021) investigate potential greenwashing using a keyword approach by analyzing earning calls. A drawback of a rule-based approach is that such a method falls short of incorporating the language's richness, context dependence, and high dimensionality. Moreover, these ap-

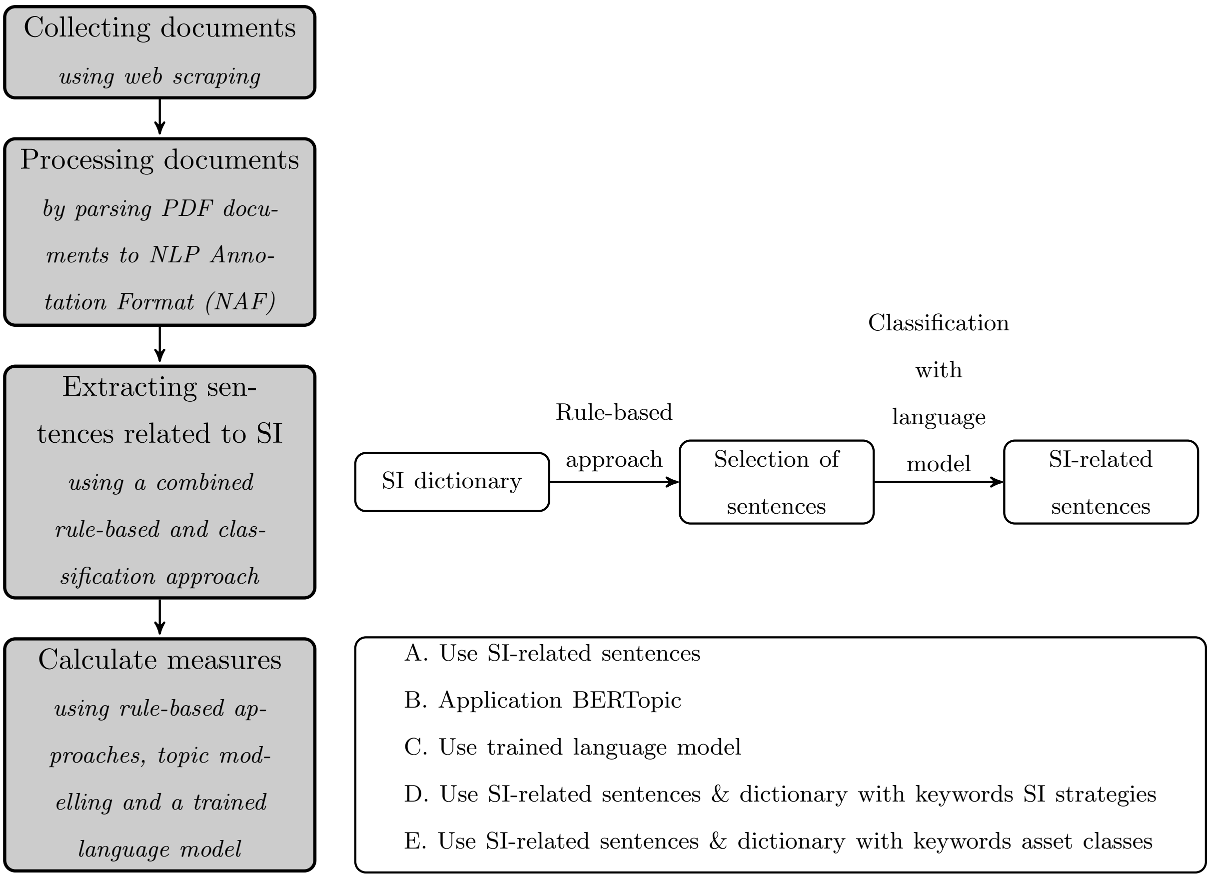
[16] Since the reports of Dutch pension funds are in Dutch, we cannot use a trained climate-related model such as the ClimateBert model.

[17] Negations are excluded from the keyword search.

proaches are subjective because they weigh prior information heavily (Gentzkow et al. (2019)). Using a state-of-the-art NLP model such as BERT can overcome these limitations.

Figure 1: Textual analysis pipeline

This figure visualizes the textual analysis pipeline built to collect the documents, process the qualitative data, and calculate the SI measures (left side of figure). The different NLP techniques used to calculate the five SI measures are presented in the box at the bottom right of the figure.



In order to measure sustainable investing by pension funds using qualitative data, we first build a textual analysis pipeline which is visualized in Figure 1.[18] The objective of a textual analysis pipeline is to facilitate the collection and processing of text data. We start by collecting the annual reports of Dutch pension funds from 2016 to 2021 in an efficient way using web scraping. Subsequently, we process the documents by parsing them to NLP Annotation Format (NAF) files containing all relevant NLP information, such as sentences, headers, parts of speech, and lemmatized words.[19] We extract all SI-related sentences from

[18] The source code of the textual analysis pipeline is published in a Github repository: `https://github.com/Annickv0ol/si-measures`.

[19] The NLP Annotation Format (NAF) is designed to represent linguistic annotations in complex NLP architectures (Fokkens et al. (2014)). We use the Python package nafigator to convert the PDF documents to

the documents using a combined rule-based and classification approach. In the rule-based approach, we use an SI dictionary to extract all SI-related paragraphs. Subsequently, the classification approach consists of a language model that is finetuned with a labeled dataset. This model determines whether a sentence is related to sustainable investing or not. Table 1 presents some examples of labeled sentences and the upper part of Table 2 presents the performance of the trained language model: the accuracy of the model equals 92 percent in the test set. We use a combined approach because some keywords in the dictionary can have another interpretation unrelated to sustainable investing (see Table 1). Moreover, the rule-based approach functions as a preselection method, lowering the number of sentences that have to be labeled and classified. After generating a dataset with all sentences related to sustainable investing, we measure the awareness and implementation of sustainable investing with five different measures using various NLP techniques. Figure 1 presents an overview of the techniques used for each measure. In the next section, we discuss the construction of the measures in more detail.

Table 1: Labeled sentences with regard to sustainable investing

This table presents some examples (translated from Dutch to English) of sentences related to sustainable investing (label 1) and sentences that are not related to sustainable investing (label 0).

Sentence	Label
The fund also strives to contribute to investments needed to protect people against the impact of *climate change*.	1
This growth held up in April and May 2016, but was not stable despite a fairly favourable economic *climate*.	0
With impact investments the pension fund wants to contribute to solutions to world-wide problems, such as poverty and *inequality*.	1
In this way possible *inequality* within the board is prevented if the role is assigned to trustees.	0
Portfolio risks resulting from climate risks can be mitigated by implementing an effective and reliable ESG policy, especially regarding *transition risks*.	1
In 2017 the board paid extra attention to the *transition risk* of the participant and benefit payment administration.	0

NAF files (https://github.com/DeNederlandscheBank/nafigator).

Table 2: Performance language models

This table shows the performance results of the language models. The upper part shows the results for the classification based on whether sentences are SI-related or not. This classification is used to create a dataset with all SI-related sentences. The lower part shows the results for the classification based on whether paragraphs are specific or not. This classification is used to create the specificity measure. The language models (RobBERT model) are finetuned with labeled datasets. Accuracy equals the overall number of correctly classified sentences (or paragraphs), divided by the total number of sentences in the test set. Precision equals the number of sentences that are correctly classified, divided by the total number of sentences classified as SI-related (or as specific) by the model. Recall equals the number of sentences that are correctly classified as SI-related by the model, divided by the total number of SI-related sentences in the test set. The F1 score is the harmonic mean of precision and recall.

	Accuracy	Precision	Recall	F1 score
SI-related (dataset SI-related sentences)				
Training set	99.9%	99.9%	99.9%	99.9%
Test set	91.9%	91.9%	91.9%	91.8%
Specificity (measure C)				
Training set	99.7%	99.7%	99.7%	99.7%
Test set	87.1%	86.8%	87.1%	86.9%

4 Variable construction and data

In this section we discuss the construction of the SI measures and describe the data. Section 4.1 describes the documents we use and Section 4.2 describes the construction of the SI measures. The data on the SI initiative are described in Section 4.3 and the proprietary dataset containing pension fund and board characteristics is described in Section 4.4.

4.1 Documents

In the analysis, we use qualitative data from annual reports and statements of investment principles of 160 Dutch pension funds from 2016 to 2021. We employ web scraping to collect these documents efficiently (see Figure 1). However, some annual reports are unavailable online, in which case we collect them via DNB archives. In total, we process more than 1,000 documents. We calculate the five SI measures using the annual reports and by exploiting various NLP techniques. We use the statements of investment principles to extract a pension fund's beliefs regarding the risk-return relation of sustainable investments using a rule-based approach.

We consider the period from 2016 to 2021 because this period allows us to investigate the impact of the IRBC initiative that was initiated and signed by most pension funds at the end of 2018. Moreover, we expect that sustainable investing became a greater priority for pension funds after the Paris Agreement in 2015. Boermans and Galema (2019) find that before 2016 most pension funds did not start measuring or externally disclosing the carbon emissions of their investments, whereas they increasingly started to do so as of 2016.

This paper focuses on annual reports for several reasons. First, all pension funds publish an annual report each year, so we have a balanced panel of pension funds. Second, pension funds are legally required to specify in their annual report how they incorporate ESG criteria in their investment policy and ESG risks in their risk management (see Section 2.2). However, since there are no requirements governing how and with how much detail this should be done, there is no guarantee that the relevant statements in the annual report are a complete representation of the SI policy.

Because we focus on disclosures of sustainable investing by pension funds in annual reports, there is concern about potential greenwashing or window-dressing. In the corporate finance literature, there is evidence that companies report mainly positive or general information about sustainable investing and that disclosures therefore suffer from greenwashing (Kim and Lyon (2015), Marquis et al. (2016), Fabrizio and Kim (2019), and Bingler et al. (2022)). Greenwashing or window-dressing incentives could potentially occur in pension funds' annual reports, although the institutional setting of pension funds differs from companies. Dutch pension funds are non-profit organizations but can have other incentives to focus on sustainable investing, e.g., because of beneficiaries' preferences for sustainability (Bauer et al. (2021)).

4.2 SI measures

As discussed in the previous section, the SI measures are calculated using annual reports. We construct five measures to measure a pension fund's SI policy along two dimensions. First, we measure the awareness of sustainable investing. We use three measures to quantify awareness: intensity, spectrum, and specificity. Second, we track the implementation of sustainable investing by constructing two additional measures: variety and specificity. In this section, we describe the construction of these five measures one by one.

A. Intensity

Intensity quantifies the attention a pension fund pays to sustainable investing by calculating the proportion of the annual report devoted to sustainable investing. As discussed in Section 3, we create a dataset with all SI-related sentences using a combined rule-based and classification approach. Using this dataset, the intensity measure for each pension fund i in year t is calculated as follows

$$\text{Intensity}_{i,t} = \frac{\#\text{ SI-related sentences}_{i,t}}{\#\text{ sentences annual report}_{i,t}}.$$

B. Spectrum

Spectrum determines how many SI topics are discussed in the annual report in a year. We construct a spectrum of SI topics by applying the BERTopic tool to the dataset of all SI-related sentences. Our dataset of SI-related sentences consists of more than 40,000 sentences. The BERTopic tool generates 27 relevant topics. Table 3 presents these topics. The topics consist of, amongst others, different SI initiatives (e.g., PRI, IRBC), SI strategies (e.g., exclusions, engagement), and excluded firms (e.g., coal mines, weapons manufacturers). Figure 2 shows for a selection of topics five related words in order of their c-TF-IDF score.[20] This score represents the importance of a word in the sentence. For example, a sentence on energy transition frequently contains the words energy, renewable, and solar. Figure 3 shows for a selection of topics how many pension funds discuss this topic over time. It shows that attention paid to the green bond topic has increased significantly over time: in 2016, only four pension funds discussed this topic, whereas forty pension funds discussed it in 2021. Moreover, the graph shows that pension funds discussed the IRBC initiative the most in 2018, which makes sense since the IRBC initiative started in 2018. The spectrum measure is equal to the number of topics pension fund i discusses in the annual report of year t

$$\text{Spectrum}_{i,t} = \#\ \text{SI topics}_{i,t}.$$

Table 3: SI topics

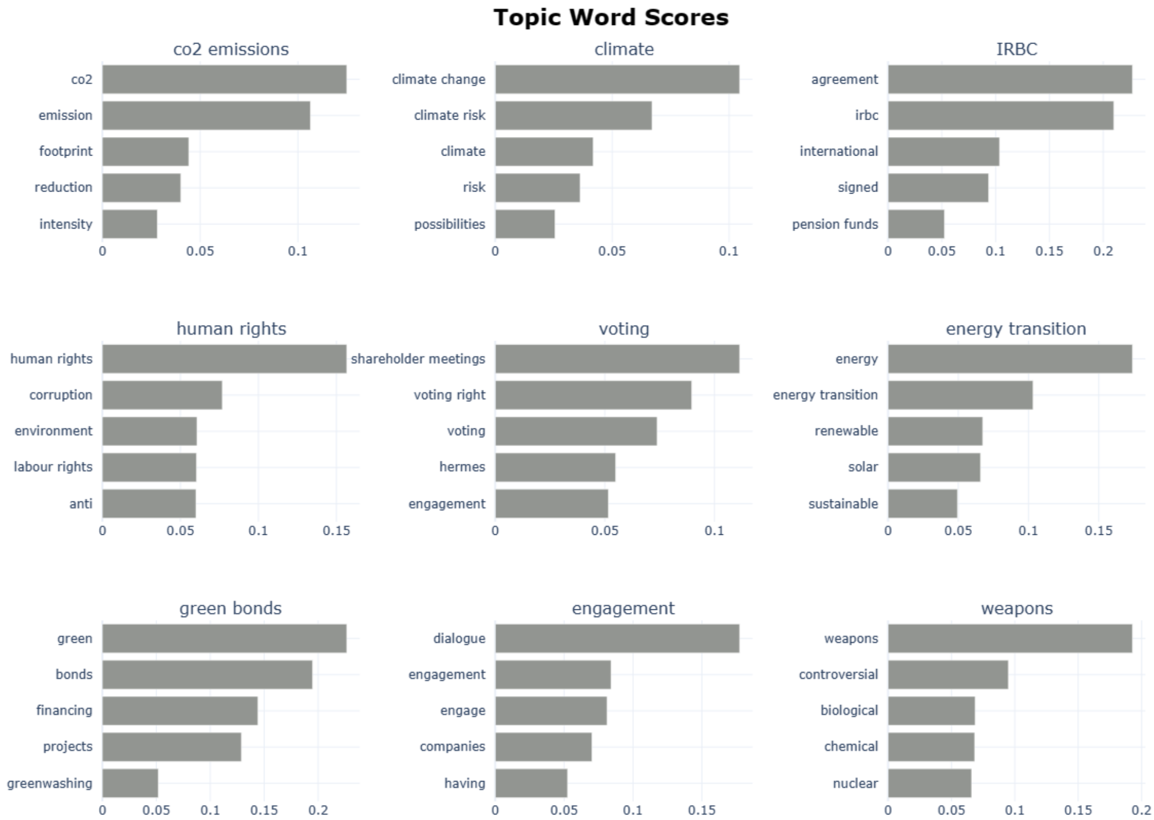
Overview of the SI topics generated with the BERTopic tool applied to the dataset with all SI-related sentences.

Climate	Exclusions	SFDR
Cluster munitions	Green bonds	Socially responsible investing
CO_2 emissions	GRESB	SRD
Coals	Human rights	Sustainable property
Energy transition	IRBC	Sustainability report
Engagement	OECD guidelines	UN principles
ESG integration	PRI	VBDO
ESG policy	Sanctions	Voting
ESG risk management	SDGs	Weapons

[20] c-TF-IDF represents Class-based Term Frequency - Inverse Document Frequency, a procedure that can be used to generate features from textual documents based on their class.

Figure 2: Topic word scores

This figure presents the word scores of the five most relevant words for a selection of topics in the BERTopic model.



C. Specificity

Specificity quantifies the number of statements regarding sustainable investing that contain details of actions specific to the pension fund, detailed performance information, or tangible and verifiable targets set by the pension fund. A pension fund's statement is non-specific if it only contains generalized descriptions that can apply to each pension fund or general and non-verifiable goals without explaining how to achieve them. A pension fund's statement is also non-specific if it contains a description of SI legislation without explaining how the pension fund is implementing it. Our approach is similar to Subramanian et al. (2019), who consider political speeches, and Bingler et al. (2022), who analyze climate-related disclosures of companies. We use a classification approach to determine which SI-related paragraphs are specific and which are not. Table 4 presents some examples of labeled paragraphs, and Table 2 shows the performance of the trained language model. The specificity measure is then calculated as follows for each pension fund i in year t

$$\text{Specificity}_{i,t} = \#\ \text{specific SI-related paragraphs}_{i,t}.$$

Figure 3: Development of topics over time

This graph shows the number of pension funds which discuss a certain topic in a certain year based on the BERTopic output.

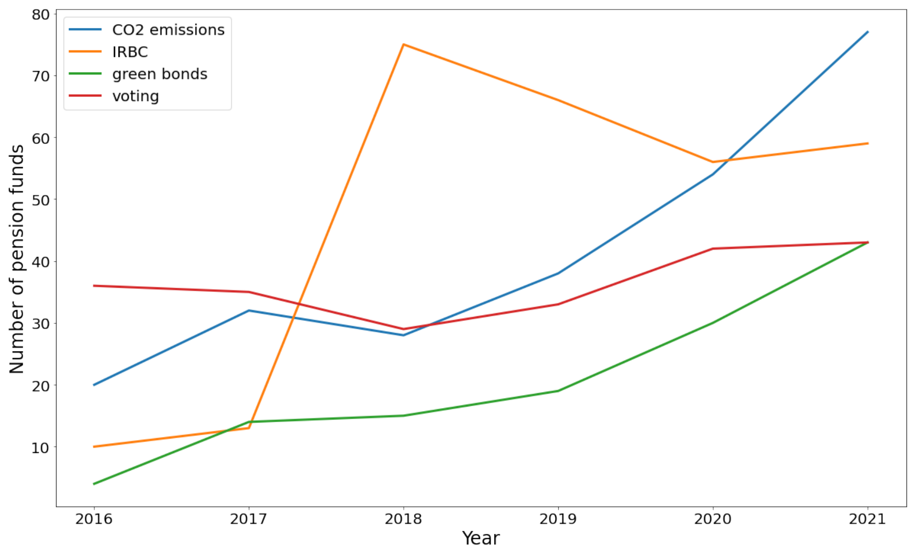


Table 4: Labeled sentences with regard to specificity

This table presents some examples (translated from Dutch to English) of specific paragraphs (label 1) and non-specific paragraphs (label 0).

Paragraph	Label
We continued making the investment portfolio more sustainable, without sacrificing return and risks. The ultimate goal is to have €20 billion in investments that contribute to solving social issues. Moreover, we want to combat climate change by a 50% reduction of CO_2-emissions in our investment portfolio compared to the baseline measurement in 2014. The recovery contributes to the possibility of achieving our ambition.	1
Besides voting at shareholder meetings, we believe it is important to enter into a dialogue with companies (engagement). In this way the pension fund as an investor makes sure its opinion is heard irrespective of the shareholder meetings. In this continuous dialogue there is a strong focus on ESG issues. In 2021, 1,620 engagements were carried out with 564 companies, of which 122 were closed successfully.	1
It has been decided to implement a best-in-class strategy for the separate allocation to European equity. We invest in companies in the top quartile in terms of ESG scores within the sector. This allocation was implemented at the beginning of 2019.	1
In 2020 we looked at the investment policy for the coming years, the aim of which is that the own portfolio will contribute to a more liveable world. The starting point is a most profitable portfolio which has more positive impact on the living environment and has more relevance for participants.	0
The economy and society face challenges which affect us as an investor. Climate change, the growing demand for renewable energy, and scarcity of natural resources are examples of topics which demand adaptation and innovation.	0
The SFDR contains two key elements for implementation, namely (1) transparency with regard to the inclusion of negative sustainability impact in investment decisions and (2) publication of pre-contractual sustainability information. Each pension provider must also have a description in its pre-contractual information of (1) the way in which sustainability risks are part of the investment decision-making process, or the investment advice or insurance advice, (2) the probable effect of the sustainability impact on the return of the pension fund.	0

D. Variety

The variety measure quantifies the SI implementation by counting the number of SI strategies implemented by each pension fund. As discussed in Section 2.5, we distinguish the following five SI strategies: divestment, ESG integration, screening, public engagement, and private engagement. We apply a rule-based approach to the dataset with SI-related sentences using a dictionary with keywords and combinations of keywords for each strategy. In this way, we determine which strategies are implemented by pension fund i in year t. The variety measure equals

$$\text{Variety}_{i,t} = \#\text{ implemented SI strategies}_{i,t}.$$

E. Scope

Finally, scope quantifies the fraction of the asset portfolio that is covered by the pension fund's SI policy. Pension funds invest in various asset classes, but may apply the SI policy only in specific asset classes. We consider the asset classes specified in the OECD guidance for institutional investors (OECD (2017)): equity, corporate bonds, government bonds, real estate, infrastructure, and private equity. We add mortgages as an additional asset class because Dutch pension funds invest a significant fraction of their assets in mortgages.[21] We apply a rule-based approach to the dataset with SI-related sentences using a dictionary with keywords and combinations of keywords for each asset category. In this way, we determine which asset classes are covered by the SI policy of pension fund i in year t. We combine this information with asset allocation data of pension funds (see Section 4.4). This yields the scope measure

$$\text{Scope}_{i,t} = \frac{\sum_k c_{i,k,t} W_{i,k,t}}{\sum_k W_{i,k,t}}$$

where $c_{i,k,t}$ takes value one if asset category k is covered by the SI policy of pension fund i in year t and zero otherwise. $W_{i,k,t}$ is the amount pension fund i invests in asset category k in year t.

We exploit a novel textual analysis approach to construct these five SI measures that quantify the awareness and implementation of sustainable investing. By measuring the sustainable investment policy along two dimensions and considering five SI measures, we robustly measure sustainable investing by pension funds, and we reduce the risk of subjectivity. We track the implementation of sustainable investing by constructing two measures that quantify the implementation of sustainable investing at a meta level: the variety measure counts the number of SI strategies implemented and the scope measure is the fraction of the portfolio included in the SI policy. However, these two measures do not quantify the actual quality of the implementation of sustainable investing. While some measures are concrete and objective (e.g., the intensity measure), others are more abstract and somewhat subjective (e.g., the specificity

[21] Dutch pension funds invest, on average, 5% of their assets in mortgages.

measure). Sometimes, the term ‘measure’ refers to concrete or objective attributes, and the term ‘metric’ refers to abstract or somewhat subjective attributes. For consistency purposes, we use the term ‘measure’ only.

4.3 Data on the SI initiative

The SI measures, described in the previous section, are used to investigate the impact of signing an SI initiative on the awareness and implementation of sustainable investing. This paper focuses on the IRBC initiative because it is the best-known SI initiative in the Dutch pension sector.[22] The initiative started with a declaration of intent signed by 40 pension funds in March 2017. Subsequently, 73 pension funds signed the initiative at the end of 2018, and several others signed later. The number of pension funds in our sample that signed the initiative in 2018 is 60 instead of 73, because some pension funds left the initiative and some ceased to exist.[23] In our sample, six pension funds signed the initiative in 2019, two in 2020 and two in 2021.[24]

4.4 Pension fund characteristics

In addition to the public annual reports and SI initiative data, the analysis is based on a proprietary dataset from the prudential supervisor of pension funds, De Nederlandsche Bank (DNB), containing information on occupational pension funds in the Netherlands. All pension funds are obliged to report this information to DNB. This dataset has been used before, by e.g., Bikker et al. (2012), De Haan (2018), Boermans and Galema (2019), and Broeders et al. (2021). We use a balanced panel of 160 occupational pension funds that reflects almost the entire population of Defined Benefit (DB) pension funds in the Netherlands from 2016 to 2021.[25,26] Pension funds must report general statistics, such as funding ratio, assets under management, liability duration, and the type of pension fund (corporate, industry-wide, or professional group pension fund). Moreover, pension funds report information on their stakeholders. They report information on the board of trustees, including the gender, age, and tenure of each trustee. Finally, pension funds report information on their actual asset allocation, i.e., how much a pension fund invests in each asset category. This information is used to calculate the scope measure.

[22] The IRBC is the ‘Convenant Internationaal Maatschappelijk Verantwoord Beleggen Pensioenfondsen’ (IMVB) in Dutch.

[23] If a pension fund ceases to exist, it transfers its benefits to a different pension fund or insurer.

[24] The pension funds that signed the IRBC initiative owned 92 percent of total pension assets at the end of 2021.

[25] The pension funds in our panel owned 98 percent of total pension assets at the end of 2021.

[26] We exclude pension funds that did not exist throughout the whole sample period and general pension funds (pension funds that can execute several pension schemes) from the panel.

5 Empirical design and results

In this section, we present the empirical design and results. Section 5.1 starts with a description of the data. Subsequently, we present the hypotheses in Section 5.2 and the models used to test the hypotheses in Section 5.3. Finally, the results are presented in Section 5.4.

5.1 Pension fund sample overview

Table 5 shows the statistics of pension fund and board of trustees characteristics for the balanced panel of 160 pension funds. This table shows that the average funding ratio equals 112 percent and the average liability duration is 20.3 years.[27] The average size of total assets under management is about 9 billion euros. The sample contains a small number of very large pension funds, hence the skewness in the distribution. Some 66 percent of the pension funds in our panel are corporate pension funds, 28 percent are industry-wide pension funds, and 6 percent are professional group pension funds. Further, 64 percent of the pension funds invest (part of their assets) actively. Only 18 percent of the pension funds have a positive belief regarding the risk-return relation of sustainable investments, i.e., sustainable investing pays off after correcting for risk. The other pension funds either have a more neutral position or do not report their beliefs about the risk-return relation of sustainable investing in their statement of investment principles. The board of trustees' size varies between three and 16 trustees, and the average age of an individual trustee is almost 56. The average fraction of female trustees is 21%, but there are also pension fund boards with no female trustees. There is a wide dispersion in the average tenure of trustees, which varies between one and 20 years.

Table 6 shows some statistics on annual reports. We analyzed 938 annual reports from 160 pension funds from 2016 to 2021.[28] The average report consists of about 2,000 sentences and 840 paragraphs, but there is substantial variation between pension funds.[29] There is also a wide dispersion in the amount of SI-related sentences. In some annual reports, sustainable investing is not discussed at all, whereas one report contains more than 750 sentences related to sustainable investing.

[27] All pension funds in the sample are Defined Benefit (DB) pension funds.

[28] Unfortunately, 22 annual reports could not be collected via either the pension fund website or DNB archives. As a result, the dataset is not completely balanced.

[29] Note that this ratio of sentences and paragraphs may seem odd. Since, e.g., titles, subheaders, and footnotes count as separate paragraphs, the average number of sentences per paragraph is small.

Table 5: Statistics on pension fund and board of trustees characteristics

Panel A presents information on pension funds' characteristics and Panel B on the boards of trustees for the 160 pension funds in our sample. The mean and standard deviation are measured across pension funds and over time for each variable.

	Obs	Mean	Std dev	Min	25th	75th	Max
A. Pension fund characteristics							
Funding ratio (%)	960	111.7%	13.3%	83.2%	103.3%	117.3%	212.0%
Liability duration	960	20.3	3.9	0.0	17.8	22.5	32.3
Total assets (billion)	960	9.2	41.1	0.0	0.5	4.1	554.4
Log total assets	960	21.1	1.8	12.3	20.0	22.1	27.0
% professional group pension funds	960	5.6%	23.1%	0.0%	0.0%	0.0%	100.0%
% corporate pension funds	960	66.3%	47.3%	0.0%	0.0%	100.0%	100.0%
% industry-wide pension funds	960	28.1%	45.0%	0.0%	0.0%	100.0%	100.0%
% active investing	960	63.6%	48.1%	0.0%	0.0%	100.0%	100.0%
% positive belief risk-return relation SI	960	18.1%	38.5%	0.0%	0.0%	0.0%	100.0%
B. Board of trustees characteristics							
Number of trustees	960	7.6	2.4	3.0	6.0	9.0	16.0
Average age trustees	960	55.9	4.0	43.8	53.5	58.4	67.5
Average tenure trustees	960	5.8	2.9	1.0	3.9	7.2	20.0
% female trustees	960	0.21	0.16	0.00	0.11	0.33	0.83

Table 6: Statistics on annual reports

This table presents information on pension funds' annual reports. The mean and standard deviation are measured across pension funds and over time for each variable.

	Obs	Mean	Std dev	Min	25th	75th	Max
#sentences	938	2014.9	613.4	2.0	1591.5	2376.0	5125.0
#paragraphs	938	842.3	350.9	1.0	627	968.3	5444.0
#SI-related_sentences	938	45.5	52.6	0.0	18.0	57.0	763.0
#SI-related_paragraphs	938	18.0	20.8	0.0	7.0	22.0	267.0

For a first inspection of the SI measures data, we plot the distribution of the SI measures in Figure 4. In this figure, each plot visualizes the distribution of a particular measure in a specific year. Two stylized facts stand out. First, the figure shows that for each measure the median, visualized by the dotted vertical black line, increases over time. Second, the value of the scope measure equals zero for a significant number of pension funds. Although this number decreases over time, 40 pension funds still do not report which asset classes are covered by their SI policy in 2021.

Figure 4: Distribution of SI measures

This figure presents the distribution of the different SI measures for all years. Each plot visualizes the distribution of a particular measure in a specific year. The dotted black vertical line in each plot represents the median.

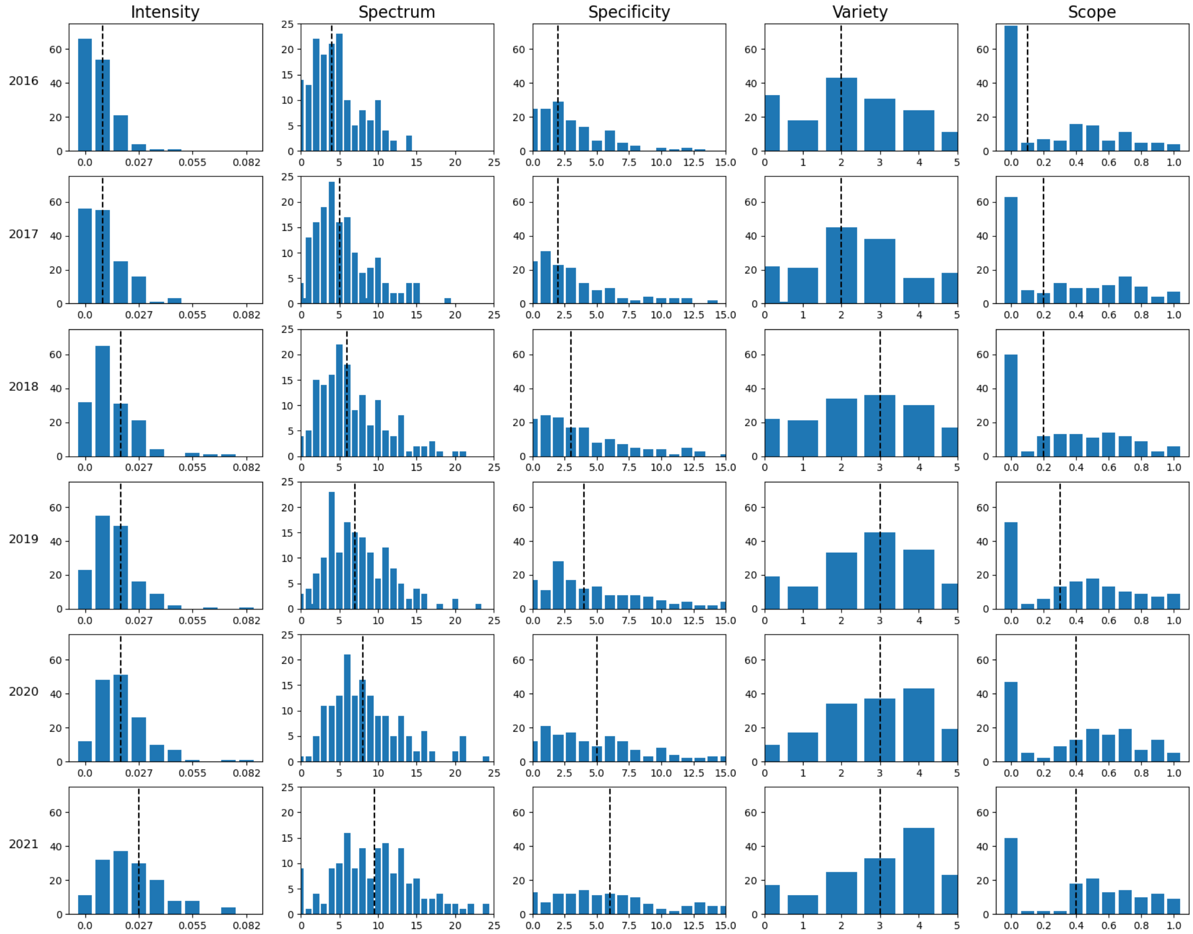


Table 7 contains statistics on the SI measures (see Figure 1). The table shows that the average value for all measures increases over time. The intensity and specificity measures show the most significant increase: the average score for these measures increased by 150 percent between 2016 and 2021. Moreover, the standard deviation of these two measures has increased, i.e., there is more dispersion between pension funds in recent years. As in the case of the intensity measure, Brié et al. (2022) calculate the importance of climate-related information relative to other information in the annual reports of publicly listed European firms. In their sample, the relative importance almost doubled from less than 5.5 percent in 2010 to nearly 10 percent in 2020. In our sample, the average intensity measure increased from 1.2 percent in 2016 to 3.0 percent in 2021.

Table 7: Statistics on SI measures

This table presents information on the five SI measures over time. The first three measures quantify awareness of sustainable investing and the last two measures track the implementation of sustainable investing. The mean and standard deviation are measured across pension funds for each variable.

Awareness of sustainable investing							
	Obs	Mean	Std dev	Min	25th	75th	Max
A. Intensity							
2016	151	1.2%	0.8%	0.0%	0.6%	1.7%	4.6%
2017	155	1.5%	1.2%	0.0%	0.6%	2.0%	9.5%
2018	160	1.8%	1.3%	0.0%	1.0%	2.3%	7.6%
2019	159	2.1%	1.7%	0.0%	1.1%	2.5%	16.3%
2020	160	2.6%	2.2%	0.2%	1.5%	3.0%	21.2%
2021	153	3.0%	1.8%	0.0%	1.7%	3.7%	11.4%
B. Spectrum							
2016	151	5.2	3.0	0.0	3.0	7.0	15.0
2017	155	5.9	3.5	0.0	3.0	8.0	21.0
2018	160	7.5	4.0	0.0	5.0	10.0	22.0
2019	159	8.3	3.7	0.0	6.0	10.0	18.0
2020	160	9.6	4.0	0.0	7.0	11.0	22.0
2021	153	11.0	4.4	0.0	8.0	14.0	22.0
C. Specificity							
2016	151	3.2	3.2	0.0	1.0	4.0	18.0
2017	155	4.1	5.9	0.0	1.0	5.0	56.0
2018	160	4.6	5.4	0.0	1.0	6.0	40.0
2019	159	5.9	7.8	0.0	2.0	8.0	76.0
2020	160	7.1	10.7	0.0	2.0	8.0	107.0
2021	153	8.3	9.2	0.0	3.0	12.0	74.0

Continued on next page

Implementation of sustainable investing							
	Obs	Mean	Std dev	Min	25th	75th	Max
D. Variety							
2016	151	2.3	1.5	0.0	1.0	3.0	5.0
2017	155	2.4	1.5	0.0	1.0	3.0	5.0
2018	160	2.5	1.5	0.0	1.0	4.0	5.0
2019	159	2.7	1.4	0.0	2.0	4.0	5.0
2020	160	2.9	1.4	0.0	2.0	4.0	5.0
2021	153	3.1	1.4	0.0	2.0	4.0	5.0
E. Scope							
2016	151	25.6%	29.3%	0.0%	0.0%	45.7%	98.7%
2017	155	30.2%	31.5%	0.0%	0.0%	60.0%	97.5%
2018	160	29.0%	29.7%	0.0%	0.0%	55.2%	97.6%
2019	159	34.9%	31.6%	0.0%	0.0%	59.4%	100.0%
2020	160	37.9%	31.6%	0.0%	0.0%	61.2%	100.0%
2021	153	41.1%	32.5%	0.0%	0.0%	65.8%	100.0%

To better understand the implementation of sustainable investing, Figure 5 and 6 provide more information on the data underlying the variety and the scope measure. Figure 5 shows the fraction of pension funds that implemented an SI strategy over time. Divestment is the most popular strategy. This can be explained by the legal requirement introduced in 2013 that pension funds are not allowed to invest in cluster munitions. As a result, most pension funds are forced to implement a divestment strategy for these specific investments. ESG integration shows the biggest relative increase over time, while screening, public engagement, and private engagement have also grown steadily over time.

Similarly, Figure 6 shows the fraction of pension funds that covered a specific asset class with their SI policy. All asset classes show a significant increase over time. The most popular asset category covered by the SI policy is equity. This observation can be explained by the fact that the SI policy can cover this asset category in various ways. A pension fund can implement exclusion, screening, and ESG integration based on ESG ratings of listed equity. While the coverage of ESG ratings for listed equity is high, ESG ratings are often not available for alternative asset classes. Moreover, the SI policy can cover equity by influencing the decisions of companies in the equity portfolio (engagement). As the green bond market has increased five times in size between 2016 and 2021, it has become easier for pension funds to include fixed income (government bonds and corporate bonds) in their SI strategy.[30]

[30] Source: Bloomberg Finance.

Figure 5: Variety measure over time

The percentages in this figure represent the fraction of pension funds that implemented a certain SI strategy over time.

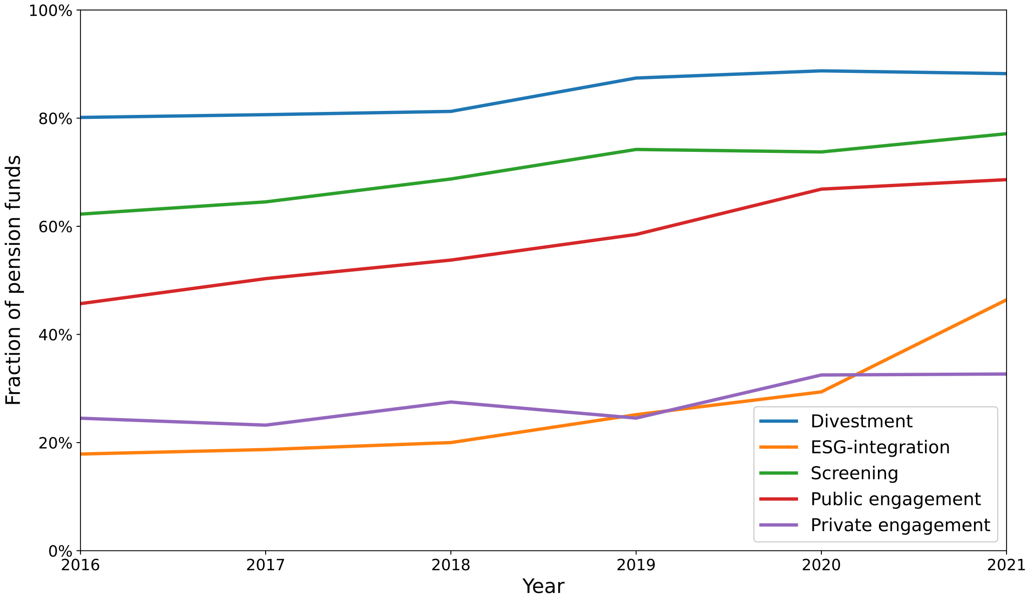
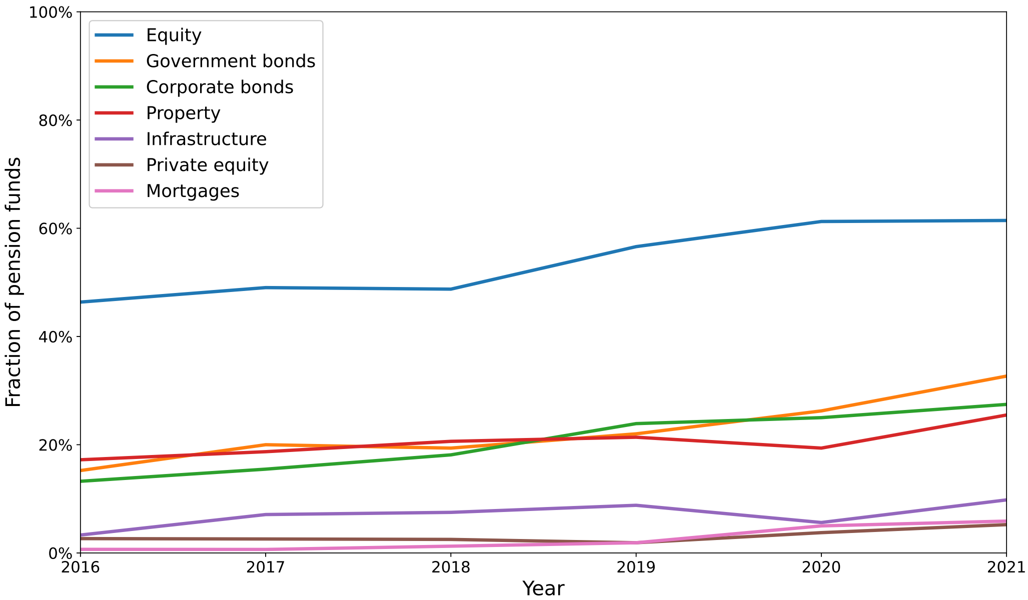


Figure 6: Scope measure over time

The percentages in this figure represent the fraction of pension funds that covered a certain asset category with their SI policy over time.



5.2 Hypotheses

In this section, we summarize three hypotheses to explain the impact of pension fund characteristics on the awareness and implementation of sustainable investing and the impact of signing an SI initiative.

First, we hypothesize that a pension fund's characteristics impact its SI policy. In particular, we expect that large pension funds will have higher scores for all five SI measures. This hypothesis is in line with the general notion that larger pension funds are more concerned about corporate responsibility (Scholtens (2006)), and are more capable of screening stocks on environmental criteria due to the monitoring cost involved with active management (Kempf and Osthoff (2008), Sievänen et al. (2013), and Egli et al. (2022)). We also expect that pension funds with relatively young beneficiaries, reflected in a higher liability duration, will have higher scores on the SI measures. This hypothesis is in line with empirical findings of Bauer and Smeets (2015) and Bauer et al. (2021), who find that young people have stronger preferences for sustainable investing, and Riedl and Smeets (2017), who find that young people are more likely to hold socially responsible mutual funds. Moreover, we hypothesize that board characteristics do not impact the SI measures. Because the board of trustees makes decisions on behalf of the beneficiaries, we do not expect board characteristics to impact the SI policy. In contrast to this hypothesis, Bauer et al. (2020a) find that the average board age and representation of stakeholders impact the asset allocation of corporate pension funds. Finally, we hypothesize that beliefs regarding the return on sustainable investments impact the SI measures. Although no systemic relation can be found between ESG performance and worldwide stock returns during the past two decades (Alves et al. (2022)), pension funds' boards of trustees increasingly express their beliefs regarding the risk-return relation of sustainable investing in the statement of investment principles. We expect that a positive belief about the risk-return relation, i.e., sustainable investing pays off after correcting for risk, has a positive impact on the SI measures.

Second, we hypothesize that pension fund characteristics also have an impact on the probability of signing an SI initiative in line with the first hypothesis. In particular, we expect that large pension funds are more likely to sign the IRBC initiative because they have more capacity to enhance their SI policy. In the same sense, we expect that the liability duration decreases and a positive belief about the risk-return relation of sustainable investments increases the probability of signing the IRBC initiative.

Third, we are interested in the impact of signing the IRBC initiative on the development of the SI policy over time. We hypothesize that signatories of the IRBC initiative enhance their SI policy more than non-signatories. We expect that this holds for both the awareness and implementation of sustainable investing. The goal of the IRBC initiative is to bring the investment policy into line with the OECD Guidelines and UNGPs, and the signatories of the initiative made joint arrangements on how to realize this. We expect that this commitment will increase the awareness and implementation of sustainable investing. This hypothesis is in line with Bauckloh et al. (2021) and Brandon et al. (2022). They find that institutional investors who signed the PRI initiative have better ESG scores than matched non-signatories.

5.3 Empirical model

In this section, we present empirical models for the three hypotheses of the previous section. To test the first hypothesis, we use the following pooled OLS model

$$ESG_{i,t} = \alpha + \beta' \cdot \mathbf{X}_{i,t} + \theta_t + \epsilon_{i,t}, \tag{1}$$

where $ESG_{i,t}$ is one of the five SI measures of pension fund i in year t and $\mathbf{X}_{i,t}$ contains several explanatory variables. θ_t is a set of year dummies to control for year-specific conditions and $\epsilon_{i,t}$ is the error term. $\mathbf{X}_{i,t}$ contains both pension fund characteristics and board of trustees characteristics that might impact the SI measures. The pension fund characteristics include the size of the pension fund, represented by the natural logarithm of the total assets under management, the funding ratio, and the liability duration, which is the average time to maturity of the pension liabilities. Further, two dummies for professional group pension funds and corporate pension funds represent the type of pension fund. Industry-wide pension funds are the omitted category. Finally, we include a dummy for active investing. This dummy variable equals one if the pension fund invests (part of its assets) actively and zero otherwise. The board characteristics include the average age of the board of trustees, the fraction of female trustees, and the average tenure of the board of trustees. Moreover, we include a dummy variable that represents the belief regarding the risk-return relation of sustainable investing. This dummy variable equals one if the pension fund expects a positive impact of sustainable investing on the risk-return relation and zero otherwise.

For the second hypothesis, we use a probit model to analyze the effect of pension fund and board characteristics on the probability of signing an SI initiative

$$P[SIGN_i = 1] = \Phi[\alpha + \beta \cdot \mathbf{X}_{i,t} + \epsilon_{i,t}], \tag{2}$$

where $SIGN_i$ takes value zero for non-signatories and value one for signatories and $\mathbf{X}_{i,t}$ contains several explanatory variables (pension fund and board of trustees characteristics) that explain whether or not a pension fund signs the IRBC initiative. $\epsilon_{i,t}$ is the error term.

To test the third hypothesis concerning the impact of signing the IRBC initiative on the development of SI measures over time, we use a difference-in-differences (diff-in-diff) specification to estimate the differential effect of signing the IRBC (treatment) on the SI policy measures. We apply the diff-in-diff specification with staggered treatments on the panel of IRBC signatories and non-signatories to evaluate the between-group differences of the change in SI measures over time.[31] The diff-in-diff model is specified as follows:

$$ESG_{i,t} = \alpha + \gamma \cdot SIGN_i + \delta \cdot IRBC_{i,t} + \beta' \cdot \mathbf{X}_{i,t} + \theta_t + \epsilon_{i,t}, \tag{3}$$

where $ESG_{i,t}$ is one of the five SI measures of pension fund i in year t and $SIGN_i$ takes value zero for non-signatories and value one for signatories. $IRBC_{i,t}$ takes value zero for non-signatories and signatories before signing and value one for signatories after signing, and $\mathbf{X}_{i,t}$ contains several explanatory variables. Finally, θ_t is a set of year dummies to control for year-specific conditions and $\epsilon_{i,t}$ is the error term of pension fund i in year t. We are interested in the coefficient δ, which measures the effect of signing the IRBC initiative on the SI measure. A positive coefficient δ indicates that, on average, the difference between the SI measure of IRBC signatories and non-signatories has increased after the signatory year.

Because signing the IRBC is voluntary, self-selection bias arises in our sample. Pension funds that have already been enhancing their SI policy in the past or are planning to do so are more likely to sign the IRBC initiative. Therefore, pension funds that signed the IRBC may not be representative and could differ systematically in their main characteristics compared to pension funds that did not sign the IRBC. A simple comparison of IRBC signatories and non-signatories is thus not feasible. Since we cannot analyze pension funds in two conditions (signatory and non-signatory) simultaneously, we use a matching methodology. Matching aims to equate the distribution of covariates in the treated (signatories) and control (non-signatories) groups (Stuart (2010)). While several matching methods exist, one of the most common methods is r:1 nearest neighbor matching (Rubin (1973)). Nearest neighbor matching matches control units to the treated group. For each treated unit i nearest neighbor matching selects the r control units with the smallest distance from i.

We conduct a 3:1 nearest neighbor matching with probit regression-based propensity scores using the pension fund and board characteristics as matching variables.[32] The method matches pension funds in the control group (non-signatories) to the treated group (signatories) with the smallest distance, discarding non-matched pension funds. We use nearest neighbor matching with replacement allowing the same control fund to be matched multiple times. The propensity score is used as the similarity measure between pension funds and is defined as the probability of signing the IRBC initiative given the observed pension fund and board characteristics. Subsequently, we weight the regression in Equation (3) with these propensity scores.

Another point of concern is omitted variable bias. Potentially, some variables not included in the model impact the pension fund's SI policy and correlate with the explanatory variables in $\mathbf{X}_{i,t}$. As a result, the estimates of the model are potentially biased. By including fixed effects as additional explanatory variables in the model, one can control for omitted

[31] Because pension funds can sign the IRBC initiative at different moments in time, the treatment is staggered over time.

[32] It is also possible to conduct a 1:1 matching or 2:1 matching, but 3:1 matching yields a better balance between both groups without further reducing the size of the sample.

variable bias based on the assumption that the omitted variables are constant over time. Therefore, we add pension fund fixed effects κ_i to the model in Equation (3) and analyze this model as a robustness check

$$ESG_{i,t} = \alpha + \delta \cdot IRBC_{i,t} + \beta' \cdot \mathbf{X}_{i,t} + \theta_t + \kappa_i + \epsilon_{i,t}. \tag{4}$$

In this model, $\mathbf{X}_{i,t}$ contains fewer explanatory variables compared to Equation (3) because the time-invariant variables are excluded from $\mathbf{X}_{i,t}$. The pension fund fixed effects capture the effect of these variables.

5.4 Results

In this section, we present the key results of the empirical models discussed in the previous section. For our first hypothesis, we run the pooled OLS model of Equation (1) for each SI measure. Table 8 presents the regression results. In line with our hypothesis, we find a statistically significant positive effect for the pension fund's size on the SI measures. This effect is highly significant for each SI measure (i.e., for both awareness and implementation of sustainable investing). However, in contrast to our hypothesis, we do not find an effect for the liability duration. So pension funds with young participants do not have a stronger focus on sustainable investing. In line with our hypothesis, the board of trustees characteristics do not impact the SI policy. The only exception is a statistically significant negative effect of the average tenure of the board of trustees on the spectrum measure and variety measure. However, the size of this effect is rather limited. In line with our hypothesis regarding beliefs about the risk-return relation of sustainable investing, we observe that a positive belief regarding the risk-return relation of sustainable investing increases awareness of sustainable investing. For example, the positive coefficient 0.008 for the intensity measure indicates that pension funds with the belief that sustainable investing pays off devote, on average, 0.8 percent extra of the annual report to sustainable investing. This effect seems small at first glance, but with average attention to sustainable investing of 2 percent of the annual report, this effect is quite substantial. A positive belief regarding the risk-return relation of sustainable investing does not have a significant effect on the implementation of sustainable investing. This result could indicate that pension funds with a positive belief about sustainable investing want to enhance their SI policy and also talk about it (reflected by the higher awareness), but are still trying to find out how to integrate sustainable investing in their investment strategy.

For our second hypothesis, we run the probit model of Equation (2). Table 9 presents the results. In line with our hypothesis, large pension funds are more likely to sign the IRBC initiative. A positive belief about the risk-return relation also increases the probability of signing the IRBC initiative. This effect is highly significant. The results in Table 9 show that some additional variables impact the probability of signing. First, corporate pension funds are less likely to sign the IRBC initiative. A possible explanation for this effect is that other types of pension funds, i.e., professional group pension funds and industry-wide pension funds,

Table 8: The effect of pension fund characteristics on SI measures

This table presents the results of the pooled OLS model in Equation (1) for all five SI measures as dependent variable. Pension fund characteristics and board of trustees characteristics are used as explanatory variables. The model includes year fixed effects and the standard errors are clustered at the pension fund level to correct for serial correlation. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Awareness of sustainable investing			*Implementation of sustainable investing*	
	Intensity	Spectrum	Specificity	Variety	Scope
	(A)	(B)	(C)	(D)	(E)
Log(assets)	0.004***	1.352***	2.119***	0.309***	0.0506***
	(0.001)	(0.158)	(0.394)	(0.055)	(0.011)
Funding ratio	0.000	-1.778	-4.432	-0.287	-0.313
	(0.008)	(1.747)	(3.821)	(0.617)	(0.194)
Liability duration	0.000	0.014	-0.020	0.017	0.004
	(0.000)	(0.063)	(0.086)	(0.022)	(0.006)
Professional group pension funds	0.001	1.196	-0.231	0.515	-0.032
	(0.003)	(1.187)	(1.613)	(0.383)	(0.083)
Corporate pension funds	0.002	0.561	0.466	-0.002	0.017
	(0.002)	(0.590)	(0.940)	(0.215)	(0.047)
Positive belief risk-return relation SI	0.008**	1.275**	3.201*	0.151	0.069
	(0.003)	(0.633)	(1.784)	(0.241)	(0.042)
Active investing	0.001	0.769*	0.957	0.216	-0.007
	(0.002)	(0.395)	(0.623)	(0.159)	(0.036)
Fraction female trustees	-0.002	0.278	0.671	0.495	0.096
	(0.004)	(1.225)	(1.772)	(0.603)	(0.118)
Average age trustees	0.000	0.044	-0.006	-0.007	-0.003
	(0.000)	(0.048)	(0.069)	(0.023)	(0.005)
Average tenure trustees	-0.000	-0.135**	0.008	-0.057**	0.001
	(0.000)	(0.063)	(0.092)	(0.028)	(0.006)
Constant	-0.086***	-25.000***	-37.730***	-3.883*	-0.421
	(0.024)	(5.430)	(9.426)	(2.124)	(0.514)
N	938	938	938	938	938
adj. R^2	0.337	0.440	0.301	0.227	0.127

Table 9: The effect of pension fund characteristics on the probability of signing the IRBC initiative

This table presents the results of the probit model in Equation (2) with robust standard errors. The probability of signing the IRBC initiative is the dependent variable and pension fund characteristics and board of trustees characteristics are used as explanatory variables. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	$P[SIGN = 1]$
Active investing	0.042
	(0.111)
Average age trustees	0.009
	(0.016)
Average tenure trustees	-0.032*
	(0.0181)
Corporate pension funds	-0.409***
	(0.128)
Fraction female trustees	1.259***
	(0.374)
Funding ratio	-1.491***
	(0.529)
Liability duration	-0.012
	(0.015)
Log(assets)	0.613***
	(0.050)
Positive belief risk-return SI	0.666***
	(0.135)
Professional group pension funds	-0.170
	(0.234)
Constant	-11.640***
	(1.638)
N	960

might experience more societal and political pressure to commit to SI initiatives. Moreover, this result is in line with Hoepner et al. (2021), who find that public pension funds are more likely to sign the PRI than corporate pension funds. Juravle and Lewis (2008) point out that this relationship can be explained by (i) the focus of public opinion on public pension funds rather than corporate pension funds and (ii) the absence of conflicts of interest in public pension funds due to non-reliance on corporate sponsorship. Second, the funding ratio decreases the probability of signing. This surprising result indicates that pension funds with a lower funding ratio are more likely to sign the IRBC initiative. This result suggests at least that pension funds with lower funding ratios are not reluctant to join the IRBC initiative because of their weaker financial position. This result could also be explained by strategic reasons: pension funds with a poor reputation due to their weak financial position focus more on sustainable investing to improve their reputation. Finally, the fraction of female trustees increases the probability of signing the IRBC initiative. This effect is in line with Harjoto et al. (2015) and Velte (2016), who find that female members on the management board positively impact ESG performance.

For the third hypothesis we conduct a 3:1 nearest neighbor matching with probit regression-based propensity scores using the pension fund and board characteristics. The results are presented in Table 10. The table shows that for all matching variables the difference in mean value between the treated group (signatories) and control group (non-signatories) is much smaller after matching compared to the original sample. For example, the mean funding ratio of non-signatories is higher than signatories, but after matching the mean funding ratio is approximately equal. A good balance requires statistically insignificant differences between the matched signatories (treated group) and matched non-signatories (control group). For all matching variables the difference between the signatories and matched non-signatories is statistically insignificant.

We run the diff-in-diff model in Equation (3) weighted with the propensity scores to investigate the impact of signing the IRBC initiative on the development of the SI measures over time.[33] The results presented in Table 11 provide evidence that signing the IRBC initiative increases the specificity of pension fund statements about sustainable investing because the estimate of the IRBC dummy is positive and highly significant for the specificity measure. The positive coefficient 2.083 indicates that IRBC signatories show an average differential increase of almost three specific SI-related paragraphs compared to non-signatories after signing. Since the average value of the specificity measure equals 5.53, this is an increase of more than 50 percent. Surprisingly, we do not find an effect of signing on the other SI measures. As a robustness check, we run the diff-in-diff model in Equation (4), which includes pension fund fixed effects. Table 12 presents these results. Although the values of the estimates are lower, the conclusions stay the same.

[33] When running the diff-in-diff model without weighting with propensity scores, the values of the estimates of the IRBC dummy are significantly higher due to the self-selection bias for all SI measures.

Table 10: Evaluation of nearest neighbor matching

This table presents the mean values of pension fund and board characteristics for signatories and non-signatories before and after matching using a 3:1 nearest neighbor matching procedure.

	Signatories	Non-signatories	Matched signatories	Matched non-signatories
Active investing	0.72	0.57	0.71	0.75
Average age trustees	56.06	55.80	55.76	55.12
Average tenure trustees	5.03	6.47	5.43	5.3
Corporate pension funds	0.44	0.83	0.54	0.62
Fraction female trustees	0.25	0.17	0.20	0.22
Funding ratio	1.10	1.13	1.09	1.09
Liability duration	20.52	20.06	20.61	20.58
Log(assets)	22.27	20.18	21.17	21.20
Positive belief risk-return SI	0.29	0.10	0.18	0.16
Professional group pension funds	0.07	0.04	0.10	0.10
N	420	540	220	508

The results of the diff-in-diff models in Equation (3) and (4) imply that the IRBC initiative improves the specificity of pension fund statements about sustainable investing. However, signing the IRBC initiative does not accelerate the implementation of sustainable investing. This conclusion does not necessarily imply that IRBC signatories do not seriously commit to the IRBC initiative or did not improve the implementation of sustainable investing. First, it could be the case that IRBC signatories want to enhance their SI policy and also talk about it more specifically (reflected by the increased specificity measure), but are still trying to find out how to integrate sustainable investing into their investment strategy. Second, the measures are not a perfect representation of the SI policy of a pension fund. For example, the variety measure counts the number of implemented SI strategies but does not consider to what extent a pension fund uses a specific strategy. A pension fund can, for example, exclude cluster munition investments only, which are prohibited by law. However, a pension fund can also have an extensive exclusion strategy banning all sin and brown stocks. The variety measure does not capture this difference. Third, it could be the case that the IRBC signatories took the lead with the implementation of sustainable investment already before signing the IRBC initiative, and non-signatories are possibly following the forerunners subsequently.

Table 11: The effect of signing the IRBC initiative on SI measures

*This table shows the results of the pooled OLS model in Equation (3) weighted with propensity scores for all five SI measures as dependent variable. $SIGN_i$ takes value zero for non-signatories and value one for signatories. $IRBC_{i,t}$ takes value zero for non-signatories and signatories before signing and value one for signatories after signing. Pension fund characteristics and board of trustees characteristics are used as control variables. The model includes year fixed effects and the standard errors are clustered at the pension fund level to correct for serial correlation. t statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

	Awareness of sustainable investing			*Implementation of sustainable investing*	
	Intensity	Spectrum	Specificity	Variety	Scope
	(A)	(B)	(C)	(D)	(E)
IRBC	0.002	0.518	2.803***	0.0350	-0.001
	(0.002)	(0.950)	(0.736)	(0.323)	(0.066)
SIGN	0.001	1.287*	-1.139	0.248	0.098*
	(0.002)	(0.686)	(0.996)	(0.253)	(0.045)
Active investing	0.002	0.603	-0.010	0.144	0.001
	(0.001)	(0.549)	(0.574)	(0.204)	(0.047)
Average age trustees	0.000	0.044	-0.072	0.016	0.002
	(0.000)	(0.076)	(0.077)	(0.032)	(0.005)
Average tenure trustees	0.000	-0.054	-0.070	-0.036	0.003
	(0.000)	(0.077)	(0.081)	(0.030)	(0.007)
Corporate pension funds	0.004**	1.810*	1.421	-0.134	0.106*
	(0.002)	(0.943)	(1.233)	(0.261)	(0.058)
Fraction female trustees	-0.003	-0.207	0.273	0.769	0.021
	(0.005)	(1.829)	(2.118)	(0.793)	(0.139)
Funding ratio	-0.016*	-6.031*	-4.749	-2.144*	-0.668**
	(0.009)	(3.276)	(4.624)	(1.110)	(0.284)
Liability duration	0.000	-0.027	-0.029	-0.027	0.007
	(0.000)	(0.077)	(0.104)	(0.028)	(0.007)
Log(assets)	0.004***	1.744***	2.499***	0.275**	0.061**
	(0.001)	(0.545)	(0.769)	(0.107)	(0.024)
Positive belief risk-return SI	0.003	0.631	0.584	-0.031	0.094
	(0.002)	(0.754)	(0.771)	(0.345)	(0.061)
Professional group pension funds	0.001	0.554	-0.909	-0.063	-0.082
	(0.004)	(1.618)	(1.773)	(0.356)	(0.098)
Constant	-0.071***	-30.280***	-39.620***	-1.929	-0.777
	(0.021)	(10.010)	(14.730)	(3.487)	(0.681)
N	472	472	472	472	472
R^2	0.369	0.391	0.360	0.143	0.134

Table 12: The effect of signing the IRBC initiative on SI measures - robustness check

This table shows the results of the fixed effects model in Equation (4) with pension fund fixed effects and weighted with propensity scores for all five SI measures as dependent variable. $SIGN_i$ *takes value zero for non-signatories and value one for signatories.* $IRBC_{i,t}$ *takes value zero for non-signatories and signatories before signing and value one for signatories after signing. Pension fund characteristics and board of trustees characteristics are used as control variables. The model includes year fixed effects and the standard errors are clustered at the pension fund level to correct for serial correlation. t statistics are in parentheses. ** $p < 0.10$, **** $p < 0.05$, ***** $p < 0.01$.

	Awareness of sustainable investing			*Implementation of sustainable investing*	
	Intensity	Spectrum	Specificity	Variety	Scope
	(A)	(B)	(C)	(D)	(E)
IRBC	0.002	0.027	2.391***	-0.186	-0.023
	(0.003)	(1.028)	(0.697)	(0.353)	(0.078)
Active investing	-0.001	0.148	1.018	-0.324	-0.0710
	(0.002)	(1.131)	(0.692)	(0.280)	(0.055)
Average age trustees	0.000	-0.216	0.072	-0.082**	-0.005
	(0.000)	(0.157)	(0.124)	(0.034)	(0.011)
Average tenure trustees	0.000	0.042	0.047	0.012	0.009
	(0.000)	(0.176)	(0.088)	(0.082)	(0.011)
Fraction female trustees	-0.004	-0.293	2.575	-0.362	-0.380
	(0.015)	(3.364)	(4.592)	(1.278)	(0.255)
Funding ratio	0.022	5.886	6.839	0.041	-0.085
	(0.021)	(9.014)	(6.583)	(2.605)	(0.752)
Liability duration	-0.001	-0.340	-0.217	-0.097	-0.013
	(0.002)	(0.573)	(0.443)	(0.195)	(0.034)
Log(assets)	-0.010	-3.781	-1.666	-1.060	-0.423**
	(0.008)	(3.038)	(3.313)	(0.918)	(0.202)
Constant	0.24	102.80	33.44	33.60	10.40**
	(0.18)	(64.98)	(75.92)	(21.37)	(4.60)
N	472	472	472	472	472
R^2	0.576	0.643	0.738	0.480	0.428

6 Conclusion

Pension funds, as long-term institutional investors, play a key role in driving sustainable investing. Nevertheless, little is known about how pension funds implement sustainable investing. This paper creates an overview of the disclosures of sustainable investing by Dutch pension funds in annual reports from 2016 to 2021 by introducing a novel textual analysis approach using state-of-the-art NLP techniques. We measure the awareness and implementation of sustainable investing using five different measures. Further, we analyze the relation between pension fund characteristics and sustainable investing and investigate the impact of signing an SI initiative focusing on the best-known Dutch SI initiative for pension funds: the IRBC initiative.

The empirical results show that the average fraction of SI-related sentences in annual reports and the average specificity of pension fund statements regarding sustainable investing have increased by 150 percent during the past five years, with substantial variation between pension funds. Also, the implementation of sustainable investing has increased significantly over time. We find that the pension fund's size increases both awareness and implementation of sustainable investing. This finding is in line with the general notion that larger pension funds are more concerned about corporate responsibility and are more capable of screening stocks on environmental criteria due to the monitoring cost involved with active management. A positive belief about the risk-return relation of sustainable investing has a positive effect on awareness of sustainable investing but not on the implementation of sustainable investing.

Focusing on the IRBC initiative, we find that large pension funds, pension funds with more female trustees, and pension funds with a positive belief about the risk-return relation of sustainable investing are more likely to sign the IRBC initiative. To analyze the effect of signing the IRBC initiative on sustainable investing, we adopt a diff-in-diff model with propensity score matching to control for possible self-selection bias. Signing the IRBC initiative has a positive and economically significant impact on the specificity of pension fund statements about sustainable investing. However, we do not find an effect on the other SI measures.

Our findings are subject to some limitations. First, we do not aim to make any causal claims about the effect of signing the IRBC initiative on the SI policy. Moreover, we cannot exclude that an underlying trend towards more sustainable investing drives both the IRBC initiative and the development of SI policies. Second, we are aware that the pension fund statements in the annual report regarding sustainable investing can be an incomplete representation of the SI policy. Although pension funds are legally required to specify in their annual report how they incorporate ESG criteria in their investment policy, there are no requirements about how and with how much detail they should do this.

The results provide important insights for pension funds and the regulatory authority. First, the state-of-the-art textual analysis approach introduced in this paper generates an interesting dataset, including five SI measures exploiting unstructured, qualitative data from annual reports. For example, this approach quantifies the specificity of pension fund statements about sustainable investing, which makes it possible to identify possible vague talk. Second, the results give insights into which pension funds are forerunners in sustainable investing and which pension funds are followers. We show that some pension fund and board characteristics impact the SI policy and the probability of signing an SI initiative. Third, signing an SI initiative improves the specificity of pension fund statements about sustainable investing. However, signing does not accelerate the implementation of sustainable investing. The IRBC initiative does not require that pension funds implement specific SI strategies or cover specific asset classes. However, the initiative requires pension funds to explain their SI strategies and how they integrate sustainable investing in various asset classes. In line with our result, the monitoring committee of the IRBC initiative concluded in 2021 that signatories of the initiative needed to catch up in implementing the agreements of the initiative. Only 13 percent of the pension funds were implementing the agreements thoroughly (IRBC (2021)). This paper does not check whether signatories of the initiative live up to their duties regarding the initiative, but does give insight into the development of the SI policy of signatories compared to non-signatories.

Given that pension fund and board characteristics impact the SI policy and the probability of signing an SI initiative, an interesting area for future research is the possible impact of additional stakeholders on the SI policy. For example, it would be interesting to investigate whether advisors (i.e., the asset manager or actuary firm) impact the SI policy. Bauer et al. (2020b) show that asset managers and actuaries impact strategic investment decisions by Dutch pension funds. Moreover, it would be interesting to investigate whether trustees with a seat on multiple boards can explain similarities in the SI policy.

Another interesting research question is whether pension funds 'walk their talk' by comparing the SI measures with the ESG performance of the pension fund's asset portfolio. This question can be answered as better ESG scores become available due to more standardized ESG disclosure frameworks. Including the ESG performance of the pension fund's asset portfolio makes it possible to investigate the effectiveness of SI policies and to identify potential window-dressing or greenwashing by pension funds. This question is especially relevant since our finding that the pension fund's size increases both awareness and implementation of sustainable investing is in contrast to the finding of Boermans and Galema (2019) that large pension funds tend to have higher carbon footprints. Therefore, it is interesting to integrate asset portfolio data in the analysis and compare the ESG performance or carbon footprint of the pension fund's asset portfolio with the pension fund's SI measures in this paper.

References

Alves, R., Krueger, P., and van Dijk, M. (2022). Drawing up the bill: Does sustainable investing affect stock returns around the world? *Netspar Design Paper*, 209.

Amel-Zadeh, A. and Serafeim, G. (2018). Why and how investors use esg information: Evidence from a global survey. *Financial Analysts Journal*, 74(3):87–103.

Bauckloh, T., Schaltegger, S., Utz, S., Zeile, S., and Zwergel, B. (2021). Active first movers vs. late free-riders? an empirical analysis of un pri signatories' commitment. *Journal of business ethics*, pages 1–35.

Bauer, R., Bogman, R., Bonetti, M., and Broeders, D. (2020a). The impact of trustees' age and representation on strategic asset allocations. *Available at SSRN 3743962*.

Bauer, R., Bonetti, M., and Broeders, D. (2020b). Common advisor effect in strategic asset allocations. *Available at SSRN 3279390*.

Bauer, R., Derwall, J., and Tissen, C. (2022). Private shareholder engagements on material esg issues. *Available at SSRN 4171496*.

Bauer, R., Ruof, T., and Smeets, P. (2021). Get real! individuals prefer more sustainable investments. *The Review of Financial Studies*, 34(8):3976–4043.

Bauer, R. and Smeets, P. (2015). Social identification and investment decisions. *Journal of Economic Behavior & Organization*, 117:121–134.

Berg, F., Koelbel, J. F., and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings. *Forthcoming Review of Finance*.

Berk, J. and van Binsbergen, J. H. (2021). The impact of impact investing. *Available at SSRN 3909166*.

Berkman, H., Jona, J., and Soderstrom, N. S. (2021). Firm-specific climate risk and market valuation. *Available at SSRN 2775552*.

Bikker, J. A., Broeders, D. W., Hollanders, D. A., and Ponds, E. H. (2012). Pension funds' asset allocation and participant age: a test of the life-cycle model. *Journal of Risk and Insurance*, 79(3):595–618.

Bingler, J. A., Kraus, M., Leippold, M., and Webersinke, N. (2022). Cheap talk and cherry-picking: What climatebert has to say on corporate climate risk disclosures. *Finance Research Letters*, page 102776.

Boermans, M. and Galema, R. (2020). Carbon home bias of european investors. *Available at SSRN 3632723*.

Boermans, M. A. and Galema, R. (2019). Are pension funds actively decarbonizing their portfolios? *Ecological Economics*, 161:50–60.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Brandon, R. G., Glossner, S., Krueger, P., Matos, P., and Steffen, T. (2022). Do responsible investors invest responsibly? *Forthcoming Review of Finance*.

Brié, B., Stouthuysen, K., and Verdonck, T. (2022). Mandatory csr reporting in europe: A textual analysis of firms' climate disclosure practices. *Available at SSRN 4231567*.

Broeders, D. W., Jansen, K. A., and Werker, B. J. (2021). Pension fund's illiquid assets allocation under liquidity and capital requirements. *Journal of Pension Economics & Finance*, 20(1):102–124.

Ceccarelli, M., Glossner, S., Homanen, M., and Schmidt, D. (2021). Which institutional investors drive corporate sustainability? *Available at SSRN 3988058*.

Chatterji, A. K., Durand, R., Levine, D. I., and Touboul, S. (2016). Do ratings of firms converge? implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37(8):1597–1614.

Chen, T., Dong, H., and Lin, C. (2020). Institutional shareholders and corporate social responsibility. *Journal of Financial Economics*, 135(2):483–504.

Choi, D., Gao, Z., Jiang, W., and Zhang, H. (2021). Global carbon divestment and firms' actions. *Available at SSRN 3589952*.

Das, S. R. et al. (2014). Text and context: Language analytics in finance. *Foundations and Trends in Finance*, 8(3):145–261.

De Haan, L. (2018). Recovery measures of underfunded pension funds: higher contributions, no indexation or pension cuts? *Journal of Pension Economics & Finance*, 17(4):437–468.

Delsen, L. and Lehr, A. (2019). Value matters or values matter? an analysis of heterogeneity in preferences for sustainable investments. *Journal of Sustainable Finance & Investment*, 9(3):240–261.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT*.

Dimson, E., Karakaş, O., and Li, X. (2015). Active ownership. *The Review of Financial Studies*, 28(12):3225–3268.

DNB (2022). Financiele positie pensioenfondsen. *https://www.dnb.nl/algemeen-nieuws/nieuwsbericht-2022/financiele-positie-pensioenfondsen-in-het-vierde-kwartaal-verbeterd/.*

Dyck, A., Lins, K. V., Roth, L., and Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, 131(3):693–714.

Edmans, A. and Kacperczyk, M. (2022). Sustainable finance. *Review of Finance*, 26(6):1309–1313.

Egli, F., Schärer, D., and Steffen, B. (2022). Determinants of fossil fuel divestment in european pension funds. *Ecological Economics*, 191:107237.

Fabrizio, K. R. and Kim, E.-H. (2019). Reluctant disclosure and transparency: Evidence from environmental disclosures. *Organization Science*, 30(6):1207–1231.

Faccini, R., Matin, R., and Skiadopoulos, G. S. (2021). Dissecting climate risks: Are they reflected in stock prices? *Available at SSRN 3795964.*

Fokkens, A., Soroa, A., Beloki, Z., Rigau, G., van Hage, W. R., Vossen, P., and Donostia, B. C. (2014). Naf: the nlp annotation format. *Technical Report.*

Friederich, D., Kaack, L. H., Luccioni, A., and Steffen, B. (2021). Automated identification of climate risk disclosures in annual corporate reports. *arXiv preprint arXiv:2108.01415.*

FSB (2020). The implications of climate change for financial stability. *Basel: FSB.*

Gandhi, P., Loughran, T., and McDonald, B. (2019). Using annual report sentiment as a proxy for financial distress in us banks. *Journal of Behavioral Finance*, 20(4):424–436.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as data. *Journal of Economic Literature*, 57(3):535–74.

Gibson, R., Krueger, P., and Mitali, S. F. (2020). The sustainability footprint of institutional investors: Esg driven price pressure and performance. *Swiss Finance Institute Research Paper*, (17-05).

Gibson Brandon, R., Krueger, P., and Schmidt, P. S. (2021). Esg rating disagreement and stock returns. *Financial Analysts Journal*, 77(4):104–127.

Gollier, C. and Pouget, S. (2014). The "washing machine": Investment strategies and corporate behavior with socially responsible investors. *TSE Working Paper.*

Grootendorst, M. (2022). Bertopic: Neural topic modeling with a class-based tf-idf procedure. *arXiv preprint arXiv:2203.05794.*

GSIA (2021). Global sustainable investment review 2020. *gsi-alliance.org*.

Hail, L., Kim, S., and Zhang, R. X. (2021). How do managers greenwash? evidence from earnings conference calls. Technical report.

Harjoto, M., Laksmana, I., and Lee, R. (2015). Board diversity and corporate social responsibility. *Journal of business ethics*, 132(4):641–660.

Heinkel, R., Kraus, A., and Zechner, J. (2001). The effect of green investment on corporate behavior. *Journal of financial and quantitative analysis*, 36(4):431–449.

Hendrycks, D., Liu, X., Wallace, E., Dziedzic, A., Krishnan, R., and Song, D. (2020). Pretrained transformers improve out-of-distribution robustness. *arXiv preprint arXiv:2004.06100*.

Hoepner, A. G., Majoch, A. A., and Zhou, X. Y. (2021). Does an asset owner's institutional setting influence its decision to sign the principles for responsible investment? *Journal of Business Ethics*, 168(2):389–414.

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., and Zhou, X. (2022). Esg shareholder engagement and downside risk. *Available at SSRN 2874252*.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of financial economics*, 93(1):15–36.

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2021a). Climate risk disclosure and institutional investors. *Swiss Finance Institute Research Paper*, (19-66).

Ilhan, E., Sautner, Z., and Vilkov, G. (2021b). Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571.

IPE (2021a). Dutch civil service scheme abp to exit fossil fuel firms. *https://www.ipe.com/news/dutch-civil-service-scheme-abp-to-exit-fossil-fuel-firms/10055857.article*.

IPE (2021b). Dutch hospitality sector fund ditches fossil fuels. *https://www.ipe.com/news/dutch-hospitality-sector-fund-ditches-fossil-fuels/10054789.article*.

IRBC (2018). Dutch pension funds agreement on responsible investment. *https://www.imvoconvenanten.nl/en/pension-funds*.

IRBC (2021). Tweede voortgangsmeting monitoringcommissie imvb convenant pensioenfondsen. *https://www.imvoconvenanten.nl/nl/pensioenfondsen/convenant/publicaties*.

Juravle, C. and Lewis, A. (2008). Identifying impediments to sri in europe: A review of the practitioner and academic literature. *Business Ethics: A European Review*, 17(3):285–310.

Kearney, C. and Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33:171–185.

Kempf, A. and Osthoff, P. (2008). Sri funds: Nomen est omen. *Journal of Business Finance & Accounting*, 35(9-10):1276–1294.

Kim, E.-H. and Lyon, T. P. (2015). Greenwash vs. brownwash: Exaggeration and undue modesty in corporate sustainability disclosure. *Organization Science*, 26(3):705–723.

Kim, S. and Yoon, A. (2022). Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment. *Management Science*.

Kölbel, J. F., Leippold, M., Rillaerts, J., and Wang, Q. (2022). Ask bert: How regulatory disclosure of transition and physical climate risks affects the cds term structure. *Forthcoming Journal of Financial Econometrics*.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of finance*, 66(1):35–65.

Marquis, C., Toffel, M. W., and Zhou, Y. (2016). Scrutiny, norms, and selective disclosure: A global study of greenwashing. *Organization Science*, 27(2):483–504.

OECD (2017). Responsible business conduct for institutional investors: Key considerations for due diligence under the oecd guidelines for multinational enterprises. *OECD*.

Riedl, A. and Smeets, P. (2017). Why do investors hold socially responsible mutual funds? *The Journal of Finance*, 72(6):2505–2550.

Rubin, D. B. (1973). Matching to remove bias in observational studies. *Biometrics*, pages 159–183.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2021). Pricing climate change exposure. *Available at SSRN 3792366*.

Scholtens, B. (2006). Finance as a driver of corporate social responsibility. *Journal of business ethics*, 68(1):19–33.

Sievänen, R., Rita, H., and Scholtens, B. (2013). The drivers of responsible investment: The case of european pension funds. *Journal of business ethics*, 117(1):137–151.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, 25(1):1.

StvdA (2020). Aanvalsplan witte vlek. *Stichting van de Arbeid*.

Subramanian, S., Cohn, T., and Baldwin, T. (2019). Deep ordinal regression for pledge specificity prediction. *arXiv preprint arXiv:1909.00187*.

ThinkingAheadInstitute (2022). Global pension assets study 2022. *thinkingaheadinstitute.org*.

VBDO (2021). Benchmark on responsible investment by pension funds in the netherlands 2021. *vbdo.nl*.

Velte, P. (2016). Women on management board and esg performance. *Journal of Global Responsibility*.

Vermeulen, R., Schets, E., Lohuis, M., Kolbl, B., Jansen, D.-J., Heeringa, W., et al. (2018). An energy transition risk stress test for the financial system of the netherlands. *dnb.nl*, 16-7.

Wagemans, F. A., Van Koppen, C., and Mol, A. P. (2018). Engagement on esg issues by dutch pension funds: is it reaching its full potential? *Journal of Sustainable Finance & Investment*, 8(4):301–322.

Webersinke, N., Kraus, M., Bingler, J. A., and Leippold, M. (2021). Climatebert: A pretrained language model for climate-related text. *arXiv preprint arXiv:2110.12010*.

Appendix

A Annotation approach

As discussed in 3, we finetune the RobBERT model for the following two classification tasks:

- Determining whether a sentence is SI-related or not.
- Determining whether a paragraph is specific or not.

For both tasks, we create a labeled dataset. In the first dataset, a sentence gets label 1 if it is a full sentence and is in any way related to sustainable investing. A sentence gets label 0 if it is not a full sentence (e.g., header) or not related to sustainable investing. Sentences are preselected using a dictionary with SI keywords as discussed in Section 3. Table 1 shows a few examples of labeled sentences. The sentences with label 0 contain a dictionary keyword, but the keyword's interpretation is unrelated to sustainable investing. The labeled dataset consists of 2000 sentences. Table 13 in Appendix C shows a few examples of the original labeled sentences in Dutch.

Second, we label a dataset with paragraphs in which a paragraph gets label 1 if it is specific and gets label 0 if it is non-specific. A paragraph is specific if it satisfies one of the following conditions:

1. The paragraph contains details of actions that are specific to the pension fund.
2. The paragraph contains detailed performance information.
3. The paragraph contains a description of tangible and verifiable targets set by the pension fund.

A paragraph is non-specific if it satisfies one of the following conditions:

1. The paragraph contains a general description regarding sustainable investing (e.g., strategies, risks) that can apply to any pension fund.
2. The paragraph contains a description of general and non-verifiable goal(s) regarding sustainable investing without an explanation of how to achieve it.
3. The paragraph contains a description of SI legislation without an explanation of how the pension fund is implementing it or going to implement it.

Table 4 shows a few examples of labeled paragraphs. The labeled dataset consists of 1,000 paragraphs. Table 14 in Appendix C shows a few examples of the original labeled sentences in Dutch.

B Finetuning of the language model

As discussed in Section 3, we finetune a trained Dutch RoBERTa-based language model with labeled datasets two times (see Appendix A): we finetune the model to classify whether a sentence is SI-related and whether a paragraph is specific. Both labeled datasets are split up into a training set (80 percent) and a test set (20 percent). The model's tokenizer truncates inputs longer than 256 tokens.[34] The model is finetuned for five epochs and we use AdamW as an optimizer with a learning rate of 3e-5.

Table 2 contains the performance results after finetuning both models. Both models show good performance results with an accuracy in the test set of 92 percent for the SI-related classification and 87 percent for the specificity classification. The lower performance of the specificity classification can be the result of a smaller labeled dataset or because the specificity classification is more complex. Subsequently, both finetuned language models are applied to the complete datasets. The preselected sentences dataset consists of 82,744 sentences, in which 39,725 sentences get label 0 and 43,019 sentences get label 1. The paragraphs dataset consists of 17,022 paragraphs, in which 11,807 get label 0 and 5,215 get label 1.

[34] This implies that long paragraphs are truncated. However, increasing the maximum number of tokens to 512 does not improve the performance of the model.

C Examples of labeled text in original Dutch language

Table 13: Labeled Dutch sentences with regard to sustainable investing

This table presents some original examples (Dutch language) of sentences related to sustainable investing (label 1) and sentences that are not related to sustainable investing (label 0).

Sentence	Label
Het fonds streeft ernaar ook een bijdrage te leveren aan investeringen die nodig zijn om de mens te beschermen tegen de impact van *klimaatverandering*.	1
Die groei hield stand in april en mei 2016, maar was niet stabiel ondanks een vrij gunstig economisch *klimaat*.	0
Met impactinvesteringen wil het pensioenfonds een bijdrage leveren aan de oplossing van wereldwijde problemen, zoals armoede en *ongelijkheid*.	1
Hiermee wordt mogelijke *ongelijkheid* binnen het bestuur indien het houderschap bij bestuurders wordt belegd voorkomen.	0
Portfoliorisico's inzake klimaatrisico's kunnen gemitigeerd worden door effectief en betrouwbaar ESG-beleid te implementeren, met name als het gaat om *transitierisico's*.	1
Gedurende het jaar 2017 heeft het bestuur extra aandacht besteed aan het *transitierisico* van de deelnemers- en uitkeringenadministratie.	0

Table 14: Labeled Dutch sentences with regard to specificity

This table presents some original examples (Dutch language) of specific paragraphs (label 1) and non-specific paragraphs (label 0).

Paragraph	Label
In 2017 zijn we verder gegaan met het verduurzamen van onze beleggingsportefeuille, zonder concessies te doen aan rendement en risico's. Met als uiteindelijk doel om in 2020 €20 miljard aan beleggingen te hebben die bijdragen aan het oplossen van maatschappelijke vraagstukken. Daarnaast willen we de klimaatverandering tegengaan door een reductie van de CO_2-uitstoot met 50% in onze beleggingen vergeleken met de nulmeting in 2014. Het ingezette herstel draagt bij aan de mogelijkheid om onze ambitie te realiseren.	1
Naast het stemmen op aandeelhoudersvergaderingen vinden wij het belangrijk om met bedrijven in dialoog te gaan (engagement). Zo zorgt het fonds er als investeerder voor dat zijn mening ook los van de aandeelhoudersvergaderingen gehoord wordt. In deze voortdurende dialoog ligt sterk de nadruk op ESG-kwesties. In 2021 zijn 1.620 engagements gevoerd met 564 ondernemingen waarvan er 122 succesvol zijn afgesloten.	1
Er is besloten om de afzonderlijke allocatie naar Europese aandelen via een Best-in-class strategie in te vullen. Hiermee wordt belegd in ondernemingen die in het top kwartiel presteren op het gebied van ESG-scores binnen hun sector. Deze allocatie is begin 2019 geïmplementeerd.	1
In 2020 hebben we gekeken naar het beleggingsbeleid voor de komende jaren, dat beoogt dat de eigen portefeuille bijdraagt aan een meer leefbare wereld. Daarbij is het uitgangspunt een zo goed mogelijk renderende portefeuille die meer positieve impact heeft op de leefomgeving en die leidt tot meer relevantie voor de deelnemers.	0
De economie en maatschappij staan voor uitdagingen die ons als belegger raken. Klimaatverandering, de groeiende vraag naar hernieuwbare energie en grondstoffenschaarste zijn voorbeelden van onderwerpen die vragen om aanpassing en innovatie.	0
De SFDR kent twee kernelementen voor de implementatie, namelijk (1) transparantie in het meewegen van negatieve duurzaamheidsimpact bij investeringsbeslissingen en (2) publicatie van precontractuele duurzaamheidsinformatie. Elke pensioenuitvoerder zal daarnaast in de precontractuele informatie een beschrijving moeten hebben van (1) de wijze waarop duurzaamheidsrisico's onderdeel uitmaken van het besluitvormingsproces rondom investeringsbeslissingen, respectievelijk investeringsadvies of verzekeringsadvies, (2) het waarschijnlijke effect van de duurzaamheidsimpact op het rendement van het pensioenfonds.	0

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