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Let's talk about risk! : Stock market effects of risk disclosure for European energy utilities

Let's talk about risk! Stock market effects of risk disclosure for European energy utilities☆

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ABSTRACT

We analyze how risk reporting by European energy utilities is related to uncertainty about firms' future prospects. Using an unsupervised machine learning topic model, we classify the content of the risk reports presented in the notes to the financial statements into different risk topics over the period from 2007 to 2017. We find that more risk reporting is related to lower idiosyncratic volatility and that this relation is especially evident for reporting about credit risk, risk management processes, economic risk, and accounting-related risk. We also find that the uncertainty-decreasing effect of risk disclosure extends to a positive relation between risk disclosure and firm value. Our study contributes to the call for more transparency in risk reporting and disclosure. Interestingly, we are unable to identify a climate-related risk topic, and further tests show only a rudimentary disclosure of climate-related risks. Combining the usefulness of the current risk disclosure regulation with the current lack of climate-related risk disclosures, we see good reasons for increased mandatory climate-related risk disclosures.

1. Introduction

Recent literature emphasizes the impact of different risks on the business of energy utilities, e.g. volatile commodity prices (Lin et al., 2020), weather risks (Pérez-González and Yun, 2013), (climate change induced) policy uncertainty (Tulloch et al., 2017; Breitenstein et al., 2022), and geopolitical risk (Finon and Locatelli, 2008). Risk disclosure is an important tool for listed companies to transparently communicate their known risks and risk management procedures. It can help (potential) investors make more precise cash flow estimates and regulators identify systemic risks incurred by energy utilities. However, from a company's perspective, the disclosure of serious risks, which were previously unknown outside the company, can be connected to negative consequences such as decreasing share prices. Consequently, risk disclosure tends to be rather opaque (Dobler et al., 2011; Kravet and Muslu, 2013), which inhibits its usefulness for investors and could even increase stock price volatility due to implied uncertainty about future cash flows. Against the backdrop of high risk exposures of energy utilities and the ambiguous role of risk disclosure, we analyze whether increased risk disclosure is related to higher or lower stock volatility. In other words, we aim to better understand whether investors perceive risk disclosure as bad news or as a signal indicating the high quality of a utility's risk management.

Among the information disclosed in annual reports, risk disclosure plays a special role (Kravet and Muslu, 2013). Utility managers generally know much more about the firm's risk exposure. Companies' disclosure activities aim to lower the information asymmetry between the informed managers and the shareholders. Therefore, transparency, risk communication, and risk management appear to be the main goals

of risk disclosure.[1] This information is also important for regulators and rating agencies for their duty to supervise and monitor risk levels (Healy and Palepu, 2001).

Risk disclosure contains a forward-looking perspective and is more qualitative in nature. Forward-looking information contains expectations that are difficult to quantify, and quantified forward-looking information on company risks is often related to the high indirect costs of disclosure (Leuz and Wysocki, 2016) when competitors are likely to use this information against the disclosing company. In fact, the empirical literature finds that companies refrain from disclosing forward-looking and quantitative information (Linsley and Shrives, 2006), risk disclosures lack transparency and clarity (Dobler et al., 2011), or only provide boilerplate statements and cheap talk (Dobler, 2008; Kravet and Muslu, 2013). However, empirical studies confirm the usefulness of risk disclosure for capital market participants (Campbell et al., 2014; Elshandidy and Shrives, 2016). Therefore, interested readers of risk disclosures need to tackle the challenge of filtering relevant information about risks to interpret this information correctly and, finally, evaluate it.

In this context, the literature on risk disclosure increasingly profits from quantitative methods to measure the content of firm communication (Elshandidy et al., 2018). These methods are widely used in the literature on accounting, finance (Loughran and McDonald, 2020), and economics (Hansen et al., 2018; Gentzkow et al., 2019) to capture the sentiment or the topical content of statements.[2] We employ an unsupervised machine learning algorithm called Latent Dirichlet Allocation (LDA, Blei et al., 2003). The method assumes that a document (risk reports in our case) is composed of a mixture of different topics and that each topic is related to a set of specific words or word groups (n-grams). The topics are inferred from patterns of word occurrences throughout the document. It allows to discover unknown topics and their distribution over a collection of documents. Unlike supervised text analysis techniques, LDA does not need predefined labels or a list of words to define topics. The closest to our study is Wei et al. (2019b). The authors use LDA to extract 66 risk factors from firm disclosure (10-K) of energy companies in a hierarchical system. We deviate from their study in that we aim for a more concise set of topics in the risk disclosure rather than extracting risk measures and by analyzing stock market effects of these risk disclosures.

The literature that analyzes a firm's practice of disclosing risks has focused on particular countries or regions (e.g. Amran et al., 2009) or on specific branches (e.g. Dobler et al., 2011, on the manufacturing

sector). To our knowledge, the present study is the first to examine the risk disclosure practices of the energy utilities themselves. We consider the risk reports presented in the notes to the financial statements and apply a topic model that identifies six specific risk topics (namely market risk, credit risk, risk management, country risk, economic risk, and accounting risk) and one residual risk topic. We investigate the effects on the stock volatility of these risk disclosures.

There is a broad literature on firm risk and stock volatility (Xu and Malkiel, 2003; Wei and Zhang, 2006). In the context of energy companies, studies generally look at the risk exposure of the market (Mohanty and Nandha, 2011; Sadorsky, 2012). In addition to oil and gas risk exposure, Lyocsa and Todorova (2021) also investigate the spillover risk from financial markets in terms of global, country, and industry volatility. To the best of our knowledge, we provide a first assessment on the impact of risk disclosure on energy companies' volatility.

We contribute to the literature and to policy-making in at least three ways.

1. Our focus on the relationship between risk disclosure and stock volatility improves our understanding of company-focused regulation and its impact on volatility. Previous literature has found evidence of a negative association between extensive risk disclosure and firm risk (Kim and Yasuda, 2018; Benlemlih et al., 2018). We add to this literature by focusing on the specific role of risk disclosure and its topics. We also refer to the aforementioned literature on firm risk of energy companies in particular. In addition, we show the connection to the market value of a company, which contains market expectations about a firm's future performance. Thus, not only do we show that higher transparency (more risk disclosure) leads to less uncertainty (lower risk), but we also provide empirical evidence that the increased transparency also transfers to firm value and that markets perceive more extensive risk disclosure as a positive signal of a firm's subsequent performance.

2. We add to the literature on the measurement of risk disclosure (and, more generally, corporate governance-related disclosures) through the application of LDA. Machine learning approaches and automated content analysis are being increasingly applied in research to assess risk disclosure (e.g., Kravet and Muslu, 2013; Campbell et al., 2014; Yang et al., 2018) and to assess specific risks, for example, climate-related risks (Nguyen et al., 2021) or market risks (Sadorsky, 2001). In particular the method allows to analyze a large number of annual reports and can help to discover new topics.

3. We contribute to the literature and policy discussion by explicitly linking the results of the content analysis to the firm's risk and valuation. Despite a relatively large body of research on risk disclosures, most studies either have a broader focus across different sectors or focus on the financial sector. Our focus on energy utilities allows for a more specific interpretation of the content analysis and of our results.

The main practical implications of our study are to underpin the usefulness of risk disclosure regulation by establishing a positive relationship between risk disclosure and firm risk. From a regulatory perspective, the current level of risk disclosure regulation appears beneficial to companies.

A secondary implication is that the content analysis *does not* identify risk topics related to climate change. We carry out manual text analyzes to search for climate-related information and, indeed, find a very low level of climate-related risk disclosures. This is surprising given the huge impact of energy utilities on climate change and the increasing regulatory, market, and physical risks that these companies face from climate change. Since our first implication suggests that risk disclosure regulation is useful for capital market participants and can even be related to lower risk and increased firm value, we conclude that a more

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[1] Regulators and supervisors are aware of the challenges to informative risk disclosure. The International Accounting Standards Board (IASB) developed standards, such as IFRS 7, to build the foundation for transparent and comparable disclosures. Since 2007, IFRS 7 requires to cover disclosure of financial instruments and, consequently, reporting of financial risks. It is complemented, e.g., by IAS 32, 37, and IFRS 9, which include mandatory statements and describe how to measure and present financial instruments.

[2] With the inclusion of word lists (Frankel et al., 2022), topic modeling (Hannigan et al., 2019), or supervised machine learning (Wei et al., 2019a), scholars can generate quantitative evidence from textual narrative communication. For example, Bybee et al. (2023) uses LDA to measure the structure of newspaper topics over time and relate it to the business cycle. Sautner et al. (2023) use the number of bigram occurrences in conference earnings calls to measure climate change exposure, which the authors relate to risk premia in Sautner et al. (2023). Perhaps the most prominent example is Baker et al. (2016), who uses the joint appearance of words in newspaper articles from predefined bags of words to measure Economic Policy Uncertainty. Our method of choice, LDA, in that regard is not very different; only that the topics are not predefined, but labeled in a second step by the researcher. This particular method is also used in energy economics. Zhang et al. (2021) and Ye and Xue (2021) use LDA to define news topics, which are later used for sentiment analysis. Polyzos and Wang (2022) employ LDA to extract topics from energy market-related tweets to further test market efficiency.

specific climate-related risk disclosure regulation[3] could be beneficial for energy utilities.

2. Literature review and development of the hypotheses

2.1. Literature review

Over the past few years, a substantial body of literature has evolved focusing on risk disclosure. Table 1 provides an overview of this literature. It makes evident the heterogeneity of the research. Studies investigate different countries and branches, look at different time periods, use a wide range of sample sizes, and employ different methods. In the following, we provide a more structured overview.

Most studies conduct research on developed countries (the United States, European countries, Australia, Canada, Japan) (i.e. Amran et al., 2009; Hassan, 2009; Mokhtar and Mellett, 2013). Only very few studies aim at specific sectors: the majority focus on either non-financial or financial companies. The types of risk are very different for non-financial companies than they are for financial companies, and also the guidelines for risk management and risk disclosure differ. However, the role of risk reporting and the materiality of risk categories are sector-specific. Therefore, a focus on all non-financial (or all financial) companies is likely not suitable to acknowledge the sector-specific characteristics of risk disclosure. Some studies focus on a concrete sector: commercial banks (Oliveira et al., 2011b), high-polluting industries (Dobler et al., 2014), and manufacturing firms (Dobler et al., 2011; Lajili et al., 2012).

Methods applied by previous research can be classified into three categories: content analysis, disclosure index, and other methods. Most recent studies apply content analysis to risk disclosure and measure the amount of information related to risk disclosed (among others Dobler et al., 2014, 2011; Abraham and Cox, 2007; Linsley and Shrives, 2006). Content analyzes focuses on code words, phrases, sentences, or 'thought units' (Srnka and Koeszegi, 2007), and subsequently counts instances meeting certain criteria. For example, how often is forward-looking risk information mentioned in unique sentences in the annual report? The code output can be analyzed and hypotheses can be tested using regression models. Few studies concentrate solely on parts of reports, such as management reports or notes (Dobler et al., 2011). Usually, coding and analysis are performed manually. However, more recently, studies have relied on automated content analysis (software-based) (Elshandidy et al., 2013; Campbell et al., 2014; Yang et al., 2018).

Some studies develop disclosure indices. Based on a set of items, this method yields a score that represents the level of disclosure of a report, where higher scores indicate more and/or better disclosure. This score can be weighted or unweighted to control the importance of different elements of the index (Marston and Shrives, 1991; Cooke, 1989). Some studies also use this technique to measure the level of risk disclosure (among others Mokhtar and Mellett, 2013; Hassan, 2009). Other studies, for example, Filzen (2015) and Brown et al. (2018) rely on word counts, simply focusing on the number of occurrences of certain predefined words. Others, such as Hope et al. (2016) use Named Entity Recognition, which counts how often specific names (named entities) are mentioned in a report. With this approach, Hope et al. (2016) aim to capture the specificity of risk disclosure.

As mentioned above, most research articles are limited to companies from a specific region or country. A reason for this restriction can be seen in the regulatory differences between countries (e.g., different accounting standards might apply in different countries). For example, Kravet and Muslu (2013) explain the regulatory setting in the U.S., for which different accounting standards and reforms are concerned

with different aspects of risk disclosure. Dobler et al. (2011) explain the regulation on risk disclosure for their sample of countries (namely, the United States, Canada, the UK and Germany). The adoption of the International Financial Reporting Standards (IFRS) within the European Union (Regulation EC 1606/2002) has led to very similar regulatory settings within the EU member states. However, Dobler et al. (2011) argue that even outside of this setting, firms provide comparable risk disclosures in North America.

So far, no study has conducted an in-depth analysis of energy utilities. Dobler et al. (2014) examine energy companies and general utilities, but with the intent of identifying environmental performance. However, the authors state that energy and utility companies disclose more risks in their 10-K (SEC) fillings than other high-pollution industries in the sample. In our study, we focus on energy utilities, namely power utilities and companies providing or developing oil or gas. Additionally, we build on the question of how capital market participants perceive risk disclosures. On the one hand, more risk disclosure can indicate a higher risk exposure of the disclosing firm. On the other hand, more risk disclosure can indicate that the disclosing firm has a better risk management system.

Although previous studies are often concerned with the content and determinants of risk disclosure (e.g. Dobler et al., 2011; Lajili et al., 2012; Elshandidy et al., 2013), some studies focus on the consequences (e.g. Kravet and Muslu, 2013; Bao and Datta, 2014; Yang et al., 2018). Our study falls into the latter category and complements existing research, which typically focuses on measures of capital market risk and information asymmetry. Thus, on the side of the dependent variable, we differentiate between total, systematic, and idiosyncratic volatility, and on the side of independent variables, we not only analyze the extent of total risk disclosure, but also apply a statistical topic model to analyze the most common risk categories, which energy utilities report on, and the extent of risk disclosure on these specific risk categories.

2.2. Hypothesis development

Regarding risk disclosure and firm volatility, there are three possible relationships: (1) no, (2) positive, or (3) negative relationship (Bao and Datta, 2014). If the risk disclosure is not related to volatility, then the content of the risk disclosure may be irrelevant. This is the case if the risk disclosure contains mainly boilerplate statements (Campbell et al., 2014) or the information disclosed is not new to the market. Another reason for such an outcome could be that the positive and negative effects of risk disclosure counteract each other.

A positive relation between risk disclosure and volatility indicates that the risk-relevant information disclosed helps investors better estimate the firm's future cash flow, which also means that uncertainty about (the variance of) future cash flow expectations is reduced. For example, if a firm uses risk disclosure to explain the specific range of potential charges to be paid in an ongoing dispute, then this helps investors to more accurately estimate the financial impact of that risk. Therefore, investors might decrease their expectations about the variance of future cash flows (e.g., if the disclosed range of potential charges is narrower than previously expected). Consistent with this argument, Schiemann and Sakhel (2019) report that for companies in sectors dominated by carbon emissions, increased disclosure of physical risks related to climate change is correlated with lower information asymmetry. As risk disclosure is intended to reveal firm-specific risks, we expect that the relationship is especially strong for risk disclosure and idiosyncratic volatility. It is also possible that risk disclosure is related to systematic volatility if it reveals or, more likely, mirrors fundamental risk assessments that apply to the whole market (e.g., changing expectations about the general economic development).

From a theoretical perspective, the positive relation between risk disclosure and idiosyncratic volatility can be explained as the signaling effect. Through risk disclosure, firms signal the high quality of their risk management system and their expectations of relevant risks. For

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[3] For example, following suggestions of the Task Force on Climate-related Disclosures, TCFD, www.fsb-tcfd.org.

Table 1

Summary of recent literature regarding risk disclosure. The methods are Content Analysis (CA) or Disclosure Index (DI). Sub-method NER abbreviates Named Entity Recognition.

Authors	Sample	# Firms	Region	Branch	Method	Sub-method
Beretta and Bozzolan (2004)	2001	85	Italy	Non-financial	CA	Manual
Chalmers and Godfrey (2004)	1992–1996	199	Australia	Non-financial	DI	Unweighted
Lajili and Zéghal (2005)	1999	228	Canada		CA	Manual
Linsley and Shrives (2005)	2000	79	UK	Non-financial	CA	Manual
Linsley and Shrives (2006)	2000	79	UK	Non-financial	CA	Manual
Linsley et al. (2006)	2001	18	Canada, UK	Banks	CA	Manual
Abraham and Cox (2007)	2002	71	UK	Non-financial	CA	Manual
Lopes and Rodrigues (2007)	2005	55	Portugal		DI	Unweighted
Boussanni et al. (2011)	2004	21	Western Europe	Financial	CA	Manual
Deumes (2008)	Late 1990s	90	Netherlands		CA	manual
Amran et al. (2009)	2005	100	Malaysia		CA	Manual
Hassan (2009)	2005	41	UAE		DI	Unweighted
Dobler et al. (2011)	2005	160	Canada, Germany, UK, USA	Manufacturing	CA	Manual
Rajab and Schachler (2009)	1998, 2001, 2004	52	UK	Non-financial	CA	Manual
Oliveira et al. (2011a)	2006	190	Portugal	Banks	CA	Manual
Oliveira et al. (2011b)	2005	81	Portugal	Non-financial	CA	Manual
Oliveira et al. (2011c)	2006	111	Portugal	Commercial banks	CA	Manual
Miihkinen (2012)	2005–2006	99	Finland	Non-financial	CA	Manual
Lajili et al. (2012)	2006–2009	30	USA	Manufacturing	CA	Manual
Elzahar and Hussainey (2012)	2009	72	UK	Non-financial	CA	Manual
Elshandidy et al. (2013)	2005–2009	290	UK	Non-financial	CA	Automated
Mokhtar and Mellett (2013)	2007	105	Egypt	Non-financial	CA, DI	Manual, unweighted
Barakat and Hussainey (2013)	2008–2010	85	European Union	Banks	DI	Unweighted
Kravet and Muslu (2013)	1997–2007	4,315	USA		CA	Automated
Bao and Datta (2014)	2006–2010	1,924	USA		CA	Automated
Campbell et al. (2014)	2005–2008	ca. 2,400	USA		CA	Automated
Dobler et al. (2014)	2010	89	USA	Pollution	CA	Manual
Elshandidy et al. (2015)	2005–2010	878	Germany, UK, USA	Non-financial	CA	Automated
Filzen (2015)	2006–2010	2,179	USA		Other	Word count
Elshandidy and Shrives (2016)	2005–2009	143	Germany	Non-financial	CA	Automated
Hope et al. (2016)	2006–2011	ca. 2,400	USA		Other	NER
Brown et al. (2018)	2005–2010	ca. 2,000	USA		Other	Cosine-similarity, word count
Yang et al. (2018)	2003–2012	3,164	USA		CA	Automated
Nagel et al. (2021)	2010–2015	179	USA		CA	Automated

example, companies that report environmental risks show that they are aware of these risks. Firms also use such reporting to highlight their management's actions to reduce the impact of these risks. Therefore, investors value risk management because it signals the existence of a high-quality risk management system and adequate management actions, which subsequently will lead to less volatile cash flows. This theoretical notion is supported, at least indirectly, by empirical evidence. Pérez-González and Yun (2013) show that risk management can increase firm value, specifically for energy utilities. It should be noted that a prerequisite for finding a positive relationship is that the information about the disclosed risk is useful and new to the capital market. Empirical research provides some evidence that risk disclosure is indeed interpreted favorably by capital market participants. For example, Rajgopal (1999) find evidence that risk disclosure by oil and gas companies is related to price sensitivities to oil and gas prices. Hope et al. (2016) find more specific risk disclosure is related to positive capital market reactions. Based on this explanation, we formulate H1, which we refer to as the 'Signalling Hypothesis':

H1 (*Signaling Hypothesis*)**.** Increased risk disclosure within the annual report is related to lower volatility.

There are also theoretical arguments supporting a negative relationship between risk disclosure and volatility. Increased corporate risk disclosure can lead investors to become aware of risks to future cash flows that where previously unknown or the extent of the risk was previously underestimated. In other words, more risk disclosure can lead to increased investor uncertainty about future cash flow expectations. If this is the case, then it might be a good strategy for companies to refrain from risk disclosure. However, risk disclosure is mandatory, but management can exercise some discretion on what and how to disclose. For example, managers can decide to obfuscate risk disclosure by including unspecific boilerplate statements. A more

concrete and/or thorough disclosure of risks might reveal additional risks. In fact, previous research shows that capital market participants can become more uncertain about the future prospects of a firm when they receive new and negative information (Kothari et al., 2009; Ng et al., 2009). Risk disclosure, by definition, is more concerned with bad news. In this case, the negative effect of risk disclosure on volatility can be attributed to increased uncertainty. As argued above, the negative relation would also be observable mainly for idiosyncratic volatility as firm-specific risk information is revealed. However, we formulate the hypotheses in a more general way and will provide tests for total, systematic, and idiosyncratic volatility to provide a full picture of the results.

Based on the above reasoning, we formulate the "Bad News Hypothesis" as follows:

H2 (*Bad News Hypothesis*)**.** Increased risk disclosure within the annual report is related to higher volatility.

Of course, the reasons for a negative or positive relationship are not mutually exclusive. Therefore, the reason for a positive effect of risk disclosure (e.g. through signaling) can be outweighed by the reason for a negative effect (e.g. through revealing a new and substantial risk). In this case, we will find support for neither H1 nor H2, or results that differ strongly between risk categories and/or different research design choices.

Although risk disclosure is mandatory, it is also highly discretionary, meaning that companies can choose the form and specific content of their risk disclosure. For example, companies can be unspecific (Hope et al., 2016), they can engage in cheap talk (Dobler, 2008), or they can decide how to use graphics (Jones et al., 2018) or number formats, such as dollar amounts versus percentage values (Nelson and Rupar, 2015). This raises the question of how risk disclosure is, over all, perceived by

investors. Considering that risk exposure is highly industry-specific, a focus on one sector is useful for such an analysis.

Risk disclosure depends on the context of the business environment of a company. For a meaningful analysis of the content of the risk disclosure, we therefore focus on the energy sector. The variety of different risks within the sector (Wei et al., 2019b), its systemic relevance, and also its relative importance from a financial market perspective,[4] which makes it an interesting case. Many risks are specific to the energy sector. For example, firms in the energy sector face increased regulatory uncertainty due to the energy sector's huge impact on climate change, the risks related to oil price changes, and the risks stemming from the complexities of the energy markets.

3. Methods & data

3.1. Measurement of risk disclosure via latent Dirichlet allocation

We use a statistical topic model, namely the Latent Dirichlet Allocation (Blei et al., 2003), to obtain our measure of risk disclosure. This computational linguistic method is increasingly being used to assess information disclosure (Bao and Datta, 2014; Huang et al., 2017; Dyer et al., 2017; Brown et al., 2020). The advantages of LDA, compared to the widely used dictionary approaches or to manually coding documents, are straightforward. First, processing a large collection of documents is costly to do manually, while LDA offers automated coding, which can be easily scaled to assess larger data sets. Second, manual coding is based on subjective judgment of human coders, which inhibits its reliability and replicability. Third, LDA is an unsupervised machine learning algorithm which does not require pre-specification of the rules or keywords for the underlying taxonomy of the categories. The topics and their probabilistic relations with the keywords are discovered by LDA by fitting the assumed statistical model to an entire textual corpus. In contrast, manual coding or dictionary methods require researchers to pre-specify a deterministic set of rules or keywords to categorize the topics. It is almost impossible to determine a priori the topics across all documents, the keywords that identify each topic for an entire textual corpus, or the probabilistic relation between keywords and topics.

With LDA, the textual corpus is represented as a matrix of probabilities of words in a document. The goal of LDA is to infer a set of topics that splits the word–document relationship into a word–topic relationship and a topic–document relationship. LDA assumes a generative statistical process of how words in documents are created. The word generation of a word in a document consists of two steps: First, it assumes that each document has its own topic distribution. From this, a topic is drawn randomly. Second, each topic is assumed to have its own distribution over the words. From the topic of the first step, a word is randomly drawn. Repeating these two steps word by word generates a document.

The choice of probability distributions is important because it allows the same term to appear on different topics with potentially different weights. LDA is a mixed-membership model in which each document can belong to multiple topics. The word–topic relationship is later used for the interpretation of the topics. The topic–document relationship reduces the dimensionality of each document from many thousands (the number of words) to K (the number of topics). We estimated both probability matrices using Gibbs sampling with 1000 iterations.

Our data include the financial risk reports presented in the notes to the financial statements of 116 companies. After matching these observations with financial data (as described below), we arrive at an unbalanced panel that covers 96 firm and 752 firm-year observations

from 2007 to 2017. The reports are extracted from the respective pdf files, while some of them are based on OCR transcription. An overview of the available reports can be found in Table 2. A missing value heatmap is provided in Appendix A.5.

We then split the documents into pages. This produced 5303 pages, where pages with less than 50 words were deleted. To generate our features for later analysis, we preprocessed the linguistic data. We prepare the textual data using the following four steps:

1. We replaced each word with its inflected form, the so-called lemma, for example, by changing 'had' to 'have'.
2. We extracted ngrams (multi-word units, in our case using bigrams and trigrams). In this way, we could identify words like 'energy market' and 'exchange rate risk' instead of treating them as distinct words. This significantly improves the interpretability of the topic model that is used later.
3. We removed the stop words, frequently used English words without significant additional interpretational value. These are words such as 'and' and 'of'. We also removed the list of company names to abstract from companies naming themselves in the report.
4. To reduce the vocabulary, we rank words according to the information measure 'term frequency-inverse document frequency' (tf-idf) and choose the 5000 most informative words (for a more detailed explanation, see Appendix A.1).

For LDA, there are two ways to choose the appropriate number K of topics. The first is to choose K according to the interpretability (Hansen et al., 2018). Although this is highly subjective, Blei (2012) notes that interpretability can legitimize the choice of a particular K.[5] The second way to determine K is through an evaluation measure (Huang et al., 2018). We use the former for the main analysis and the latter as a robustness check.

The subjectively optimal K is the one with the highest interpretability of the topics. If K is chosen too high, one finds that the topics of interest are too divided into different parts. If K is too low, the topics of interest are likely to be mixed with other topics. We inspect several models based on configurations of K such as 10, 20, 30, 40, 50, and 60.[6] Finally, we choose K to be 30, leading to the topic model with the most interpretable topics. We evaluate topics according to term probability, a measure called salience (Chuang et al., 2012) and a weighted average of both, called the relevance measure (Sievert and Shirley, 2014). We conducted the labeling process of the topics as follows. First, two scholars independently interpreted the topics. In the event of similar interpretations, the topics are labeled accordingly. In case of slightly different interpretations, we discussed the topics and agreed on one interpretation.[7]

In the final step, we consolidated the identified topics into risk categories. Appendix A.3 describes the procedure which yields six risk categories (market risk, credit risk, risk management, country risk, economic risk, and accounting Risk) and one residual risk category, called 'other risk'. We multiply the weights assigned by the topic model approach to each risk category by the total number of pages of the risk disclosure.

Interestingly, while we expected to find some category of risks related to climate-related risks, the topic model algorithm could not

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[4] For example, the EURO STOXX 50® index includes 5 energy utilities (Engie, Enel, Eni, Iberdrola, and Total) with an index share of more than 10% (as of April 2020). See https://www.stoxx.com/index-details?symbol=SX5E.

[5] Blei (2012) notes a "disconnect between how topic models are evaluated and why we expect topic models to be useful".

[6] For inspection, we used the LDAvis package of R: https://cran.r-project.org/web/packages/LDAvis/index.html.

[7] As a robustness check, we used a number of topics K according to the coherence score suggested by Mimno et al. (2011) (see Appendix A.4). The optimal coherence score is given by a model with $K = 10$ topics. We perform the same analysis as for the actual model with $K = 30$ topics. The results are qualitatively similar.

Table 2
Development of reports per firms per year.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Available reports	52	59	69	74	78	87	93	97	99	105	92	905
Pages	245	309	396	404	473	553	558	548	609	659	549	5,303
Average pages	4.7	5.2	5.7	5.5	6.1	6.4	6.0	5.6	6.2	6.3	6.0	6.0

identify such a topic. A look at the individual item count for 'climate change' reveals that in our final sample of 913 reports, the item only appears 12 times.

3.2. Data

Our sample consists of firms from the ICB sectors 7530 (Electricity), 530 (Oil & Gas Producers), 570 (Oil Equipment & Services), and 7570 (Gas, Water & Multiutilities).[8] Data for dependent and independent variables (except *RiskDisc*) have been retrieved from Refinitiv (formerly ThomsonReuters Datastream, Worldscope, and Asset4), which provides data on firms' share prices, fundamentals, and environmental performance. It is often used in empirical studies with a focus on firm-level data (e.g., Benlemlih et al., 2018; Berkman et al., 2021; Elshandidy et al., 2013; Schiemann and Sakhel, 2019).

To assess the effects of risk disclosure on stock volatility, we derive three firm-level volatility measures. The total volatility of the firm i is measured by the annualized standard deviation of the daily stock returns. To further distinguish between systematic and idiosyncratic risk, we follow Bekaert et al. (2012) and run a Fama and French (1996, FF) regression per firm per year on daily excess returns and daily factors for market premia ($R_M - R_f$), size factor (SMB), and book-to-equity factor (HML).[9] The regression reads as follows:

$$R_i - R_f = \beta_1 \left(R_M - R_f \right) + \beta_2 SMB + \beta_3 HML + \varepsilon_i. \tag{1}$$

For the idiosyncratic risk, we take the annualized standard deviation of the residual ε_i per year. Our proxy for the systematic risk for firm i for a particular year is the square root of the difference between the total variance and the idiosyncratic variance. To account for the skewness of the volatility measures, we take the natural logarithm:

$$Vol_i^T = \ln \left(\sigma \left(R_i \right) \cdot \sqrt{250} \right) \tag{2}$$

$$Vol_i^I = \ln \left(\sigma \left(\varepsilon_i \right) \cdot \sqrt{250} \right) \tag{3}$$

$$Vol_i^S = \ln \left(\sqrt{\sigma^2 \left(R_i \right) - \sigma^2 \left(\varepsilon_i \right)} \cdot \sqrt{250} \right). \tag{4}$$

We also apply a range of control variables, covering the Market-to-Book Ratio, asset growth, firm size, leverage, firm profitability, a readability score regarding the risk disclosure text, and firm ESG performance provided by Refinitiv, which is based on an aggregate score of environmental, social and governance factors and ranging from 0 (worst) to 100 (best). Detailed descriptions of the variables and their sources are provided in Table 3. Our regression models contain only observations for which all relevant variables are available. In particular, we started with 1573 firm-year observations and lost 660 (239) of them due to unavailable risk disclosure data (financial data). This results in a final sample of 674 firm-year observations. Table 4 summarizes the selection.[10]

Table 5 summarizes the descriptive statistics of our variables, including the risk disclosure measures from automated textual analysis.

On average, during the period 2007–2017, European energy utilities use around 6 pages to disclose risk-related information in the annual reports. Although 95% of the firms in our sample report at least two pages, the top 5% provide 14 pages and more. Fig. 1 shows the geographical distribution of firm-years in our sample. The majority of the firms come from Italy and the United Kingdom. On average, the largest and most profitable companies are located in Russia. The least profitable firms are from Norway, while the smallest firms (on average) are from Ireland. Lastly, we find firms from Denmark and Poland (Sweden) to report the most (fewest) pages in the risk sections.

Topic-wise, credit risk takes the largest share. The mean number of pages is about 1.5 per annual report. The second largest share is taken by disclosure regarding risk management. Roughly 1.1 pages per document provide an explanation of the firm's measures and methods for coping with risk exposures. Interestingly, with only half a page, the disclosure of market risk exposure is on average the smallest section. Half of the sample documents contain even less than 0.3 pages (median) on market risk. In Fig. 2, we show the distribution of topics per report over time. Although the average number of pages increases over time from 4.5 to 6, the share of topics remains almost constant.

Turning to the correlations between the variables (Table 6), we find that most of the explanatory variables are statistically significantly correlated with the volatility measures. There is some dependence between individual risk disclosure measures. We find positive correlations between market risk, credit risk, and risk management in a range of 0.4 to 0.6, and other risk categories are also significantly correlated. Due to the rather high correlations among some of the most reported risk categories (see Table 5), we argue against a model that includes all individual risk categories, in order to avoid multicollinearity. Multicollinearity would impact the coefficients of our variables of interest and thereby interfere with our hypothesis tests. However, we use the aggregated risk disclosure measure RD, which allows us to infer the general effect of risk disclosure at the cost of not being able to identify the effects of the individual risk category in the presence of other risk categories. To further check for potential issues with multicollinearity, we report the maximum Variance Inflation Factor (VIF) for all variables of interest and control variables across all models in the respective tables. Only VIFs above 10 indicate potential multicollinearity problems. In all our regressions, the VIF is way below 10.

4. Results & discussion

In our first analysis, we examine the effect of total risk disclosure on the three different volatility proxies. In particular, our panel regression is

$$Vol_{i,t} = \alpha_0 + \alpha_1 RD_{i,t-1} + \alpha_2 Controls_{i,t-1} + u_{i,t}, \tag{5}$$

where $Vol_{i,t}$ is one of the three volatility proxies (i.e., total, systematic, or idiosyncratic volatility) for firm i and year t.[11] $RD_{i,t-1}$ is the number

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[8] We also analyze industry-specific subsamples and find qualitatively similar results for each subsample. For this reason, we combine observations from ICB sectors 530 and 570, because they are rather similar. Results are available upon request.

[9] The return data is calculated as percentage change from daily Total Return Index (RI) for each stock available from Refinitiv (DataStream). The three factors and the risk-free rate are retrieved from Kenneth French's website

(Fama/French European 3 Factors [Daily]): http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10] Note that we do not reduce our sample due to missing ESG score ratings. Missing values are imputed with zeros. For reasons of robustness, we also checked a reduced sample and re-estimated our models without ESG scores as an independent variable. The results remain qualitatively the same and are available on request.

[11] We consider a time lag of one year between the dependent and independent variables to clearly place risk disclosure before the measurement of volatility, and avoid issues of reversed causality.
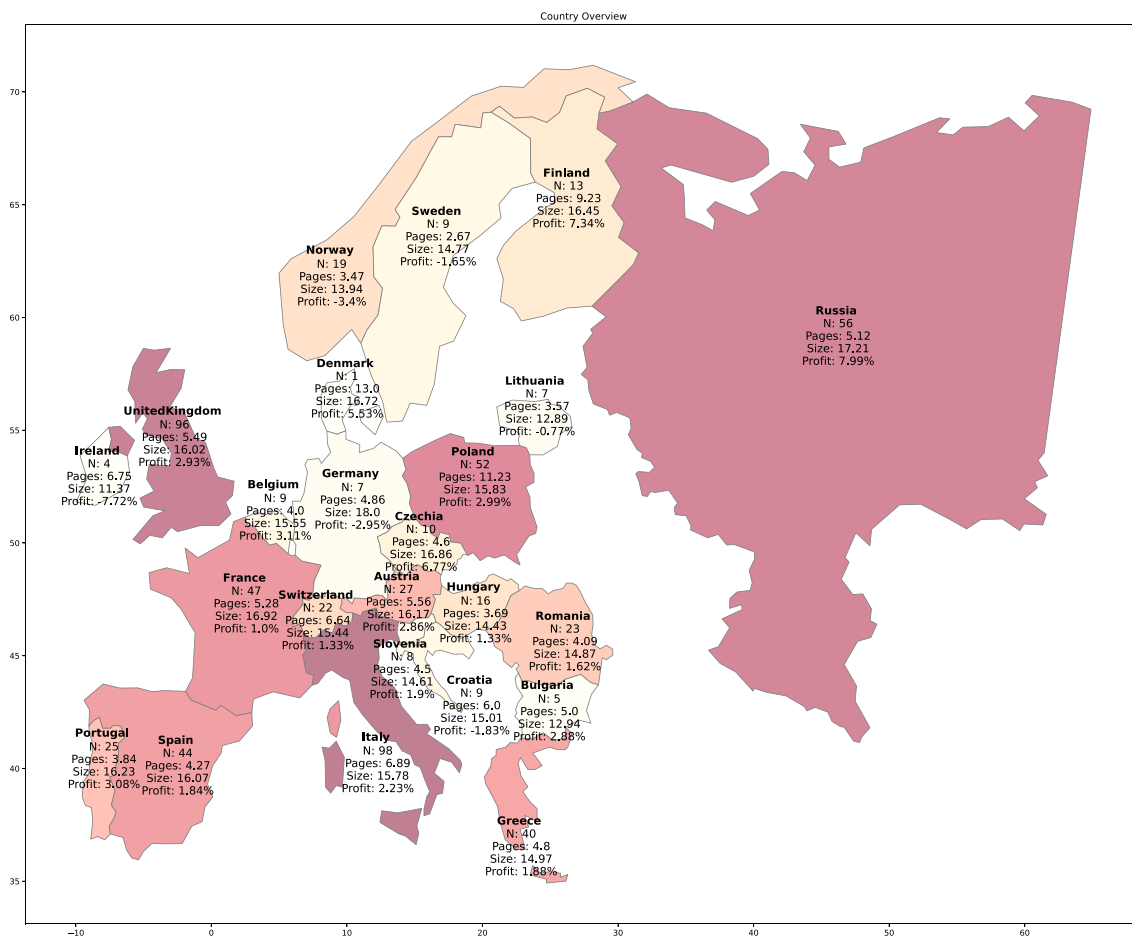
Fig. 1. Overview of countries in the sample with number of firm-years per country and mean statistics of annual pages of risk disclosure, log firm size and profit (Return on Assets in percentages). Color shades of red indicates the number of firms per country in the sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
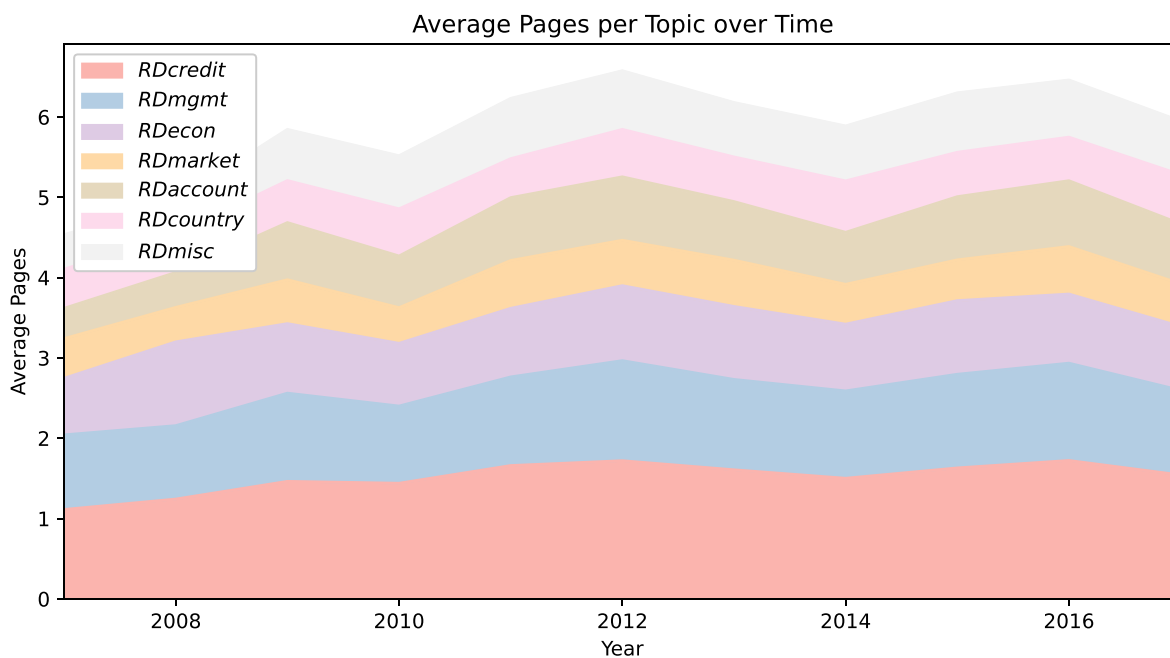

Fig. 2. Average pages per topic over time.

Table 3
Variable definitions.

Name	Label	Measurement	Data source
Dependent variables			
Total volatility	Vol^T	Natural logarithm of the standard deviation of daily stock returns	Own calculations[9]
Systematic risk	Vol^S	Natural logarithm of square root of the difference between the variance of daily stock returns and the variance of the residual from the FF regression	Own calculations
Idiosyncratic risk	Vol^I	Natural logarithm of the standard deviation of the residual of FF regression	Own calculations
Firm value	$Firmval$	Natural logarithm of the market value of equity	Refinitiv
Risk disclosure measures			
Risk disclosure	RD	Number of pages with risk-related information	Textual analysis
Market-related risk	$RDmarket$	Number of pages which contain risks related to the firm's market environment	Textual analysis
Credit-related risk	$RDcredit$	Number of pages of risk disclosure related to credits	Textual analysis
Risk management-related	$RDmgmt$	Number of pages with disclosure relating to risk management	Textual analysis
Country-specific risk	$RDcountry$	Number of pages with country-specific risk disclosures	Textual analysis
Economy-related risk	$RDecon$	Number of pages with risk disclosures related to economic environment	Textual analysis
Accounting-related risk	$RDaccount$	Number of pages with risk disclosures related to accounting-specific topics	Textual analysis
Miscellaneous risk	$RDmisc$	Number of pages with risk disclosure related to other topics	Textual analysis
Firm controls			
Readability score	$Readability$	Flesh-Kincaid grade level based on sentences as measurement scope	Risk-related text
Market-to-book ratio	MTB	Market value of equity divided by book value of equity	Refinitiv
Asset growth	$Growth$	Change in total assets from year $t-1$ to t divided by total assets in year $t-1$	Refinitiv
Firm size	$Size$	Natural logarithm of the book value of total assets	Refinitiv
Leverage	Lev	Total liabilities divided by total assets	Refinitiv
Profitability	$Profit$	Return on assets measured as the net income before extraordinary items divided by total assets	Refinitiv
ESG performance score	ESG	Asset 4 Environmental, Social, and Corporate Governance (ESG) performance score	Refinitiv

Table 4
Selection of firms and firm-years.

	Firms	Firm-years
Number of firms/firm-years	143	1,573
Firms/firm-years lost due to unavailable risk disclosure data	28	668
Number of firms/firm-years with risk disclosure data	115	905
Firms/firm-years lost due to unavailable financial data	18	153
Number of firms/firm-years in sample	97	752

Table 5
Descriptive statistics.

	Mean	Std.Dev.	5-perc.	Median	95-perc.
Dependent variables					
Vol^T	3.4328	0.4407	2.7718	3.3904	4.1829
Vol^S	2.4189	0.6856	1.2120	2.4436	3.4601
Vol^I	3.3057	0.4592	2.6367	3.2626	4.0507
$Firmval$	8.0895	1.7749	5.0358	8.0097	11.0060
Risk disclosure measure					
RD	5.9574	3.7085	1.0000	5.0000	14.0000
$RDmgmt$	1.0975	1.0021	0.1579	0.7773	3.2444
$RDcredit$	1.5429	1.0068	0.2901	1.3693	3.4654
$RDmarket$	0.5311	0.6669	0.0195	0.2882	1.8323
$RDcountry$	0.5570	0.9373	0.0325	0.1847	2.3154
$RDecon$	0.8647	1.0118	0.1121	0.6587	1.9860
$RDaccount$	0.7011	0.7098	0.0605	0.4582	2.1371
$RDmisc$	0.6632	1.2999	0.0260	0.3283	2.1530
Firm controls					
$Readability$	22.4191	5.2138	17.0037	21.4298	33.0904
MTB	1.3970	1.7564	0.3108	1.0892	3.9449
$Growth$	0.0818	0.3461	−0.1429	0.0357	0.3884
$Size$	15.8316	1.7315	13.1923	15.7728	18.9553
Lev	0.5582	0.1861	0.2350	0.5733	0.8441
$Profit$	0.0282	0.0592	−0.0717	0.0294	0.1184
ESG	2.7494	1.9078	0.0000	3.9646	4.3795

of pages of risk disclosure in the previous year, and $Controls_{i,t-1}$ is a vector of firm-level controls including readability of the disclosure, the market-to-book ratio, the growth rate of total assets, firm size, leverage, profitability, and environmental, social, and governance score. We also include fixed effects for year, industry, and country.

According to our hypotheses, we find support for H1 (signaling hypothesis) if β_1 is positive and significant for the corresponding risk disclosure category, because this indicates that more disclosure regarding the risk category analyzed is related to higher firm values. A negative and significant coefficient β_1 indicates support for H2 (bad news hypothesis), which means a decrease in firm value for companies that provide more risk disclosure.

The results, presented in Table 7, show that total risk disclosure has a significantly negative relationship with idiosyncratic volatility, but not with total or systematic volatility. This result is in line with H1, the signaling hypothesis. More risk disclosure leads to less uncertainty about firms' future cash flow expectations, which materializes in lower idiosyncratic volatility. The fact that we find significant results only for idiosyncratic risk is also in line with the argument that risk disclosure primarily reveals firm-specific risks to (potential) investors. If more general information (e.g., market development) were derived from risk reporting, then systematic (or total) volatility would also become significant.

Having established empirical support for the negative relationship between total risk disclosure and idiosyncratic volatility, we further examine the relationship between idiosyncratic risk and the risk categories along which the energy utility reported. Table 8 reports the results along the seven risk categories with idiosyncratic volatility as a dependent variable.

The significantly negative relationship is reported for four risk categories (i.e., credit risk, risk management, economic risk, accounting risk), which supports the signaling hypothesis H1. We also find that the "other risk" has a significantly positive coefficient. This finding is in line with H2 and indicates that increased reporting about "other risks" leads to increased uncertainty about a firm's future cash flows. In general, we find different results along the seven risk categories, which reveals that, indeed, not all risk categories are perceived homogeneously by investors.

Table 6
Correlation (Pearson) between variables.

	Vol^T	Vol^S	Vol^I	RD	RD market	RD credit	RD mgmt	RD country	RD econ	RD account	RD misc	Read-ability	MTB	Growth	Size	Lev	Profit	ESG
Vol^T	1																	
Vol^S	0.61***	1																
Vol^I	0.96***	0.42***	1															
RD	−0.17***	−0.12***	−0.17***	1														
RDmarket	−0.14***	0.05	−0.22***	0.54***	1													
RDcredit	−0.19***	−0.09*	−0.21***	0.78***	0.57***	1												
RDmgmt	−0.24***	−0.14***	−0.25***	0.62***	0.40***	0.45***	1											
RDcountry	0.14***	−0.02	0.18***	0.28***	−0.09*	0.10**	−0.06	1										
RDecon	−0.05	−0.01	−0.06	0.60***	0.30***	0.37***	0.31***	0.01	1									
RDaccount	−0.13***	−0.22***	−0.08*	0.62***	0.19***	0.45***	0.30***	0.25***	0.21***	1								
RDmisc	−0.08*	−0.05	−0.07*	0.49***	0.01	0.20***	0.08*	−0.06	0.12**	0.20***	1							
Readability	−0.05	−0.00	−0.07*	0.08*	0.01	0.04	0.08*	−0.00	0.07*	0.01	0.08*	1						
MTB	−0.05	0.11**	−0.10*	0.01	0.04	−0.01	0.07*	0.04	−0.02	−0.07	−0.02	0.05	1					
Growth	0.18***	0.19***	0.15***	−0.06	−0.05	−0.03	−0.03	0.00	−0.03	−0.06	−0.04	−0.07	0.07	1				
Size	−0.40***	0.06	−0.51***	0.20***	0.32***	0.22***	0.23***	−0.11**	0.08*	0.04	0.08*	0.10**	0.03	−0.06	1			
Lev	−0.16***	0.06	−0.20***	−0.05	0.13***	−0.05	0.10**	−0.19***	−0.00	−0.06	−0.07	0.08*	0.03*	−0.05	0.27***	1		
Profit	−0.24***	−0.10*	−0.26***	0.11**	0.06	0.09*	0.06	0.13***	−0.01	0.04	0.04	−0.01	0.21***	0.07	0.21***	−0.24***	1	
ESG	−0.20***	0.18***	−0.29***	0.20***	0.24***	0.13***	0.18***	−0.01	0.11**	0.06	0.10**	0.09*	0.15***	−0.05	0.60***	0.18***	0.16***	1

Asterisks ∗, ∗∗, and ∗∗∗ indicate statistical significance at 5%, 1%, and 0.1%, respectively.

Table 7
Results of the panel regression for three volatility measures with fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables shown is 4.20 across all three models (for $Size_{t-1}$).

	Vol_t^T	Vol_t^S	Vol_t^I
RD_{t-1}	−0.0067	−0.0038	−0.0104
	(0.0035)	(0.0058)	(0.0034)**
$Readability_{t-1}$	−0.0006	−0.0049	0.0001
	(0.0017)	(0.0029)	(0.0017)
MTB_{t-1}	−0.0148	0.0054	−0.0197
	(0.0067)*	(0.0090)	(0.0078)*
$Growth_{t-1}$	0.0867	0.1153	0.0868
	(0.0260)***	(0.0358)**	(0.0291)**
$Size_{t-1}$	−0.0726	0.0536	−0.1113
	(0.0133)***	(0.0173)**	(0.0130)***
Lev_{t-1}	0.0777	−0.2791	0.1771
	(0.0781)	(0.1178)*	(0.0774)*
$Profit_{t-1}$	−1.2812	−1.1988	−1.4010
	(0.2326)***	(0.3331)***	(0.2362)***
ESG_{t-1}	0.0156	0.0255	0.0161
	(0.0084)	(0.0140)	(0.0084)
Constant	3.6851	1.2510	4.0399
	(0.1786)***	(0.2471)***	(0.1776)***
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R^2_{adj}	0.60	0.60	0.64
F	24.58***	24.58***	28.82***
N	752	752	752

Standard errors are in parentheses. Asterisks ∗, ∗∗, and ∗∗∗ indicate statistical significance at 5%, 1%, and 0.1%, respectively.

5. Additional analyses

5.1. Reverse causality

A skeptical reader might view risk disclosure as endogenous to the risk of a company. To alleviate this concern to some extent, we approach reverse causality by regressing the volatility of a company on the risk reporting. In particular, our regression reads as follows:[12]

$$RD_{i,t} = \alpha_0 + \alpha_1 Vol_{i,t-1} + \alpha_2 Controls_{i,t-1} + u_{i,t}. \qquad (6)$$

---

[12] Note that *Readability* is not lagged.

Our results presented in Table 9 show no indication of reverse causality. This means that the results indicate that, for energy utilities, risk reporting cannot be explained by total volatility, systematic volatility, or idiosyncratic volatility of its stock the year before reporting.

5.2. Firm value effects

In addition to the effect of risk disclosure on volatility, we also examine whether risk disclosure is related to firm value. As the main results showed, (potential) investors perceive risk disclosure as an uncertainty reducing signal. Ceteris paribus, lower uncertainty leads to lower cost of capital and, in term, to higher firm values. With our firm value analysis, we test whether this potential cause-and-effect chain can be observed in practice.

Our dependent variable on the firm valuation model is *Firmval*, and is measured as the natural logarithm of the market value of the equity. The model uses a similar set of control variables with one exception. We also add a control variable to capture uncertainty about the company firm value (Vol^T), i.e. the firm's stock volatility. We also include fixed effects by year, industry, and country. The firm valuation model takes the following form:

$$Firmval_{i,t} = \alpha_0 + \alpha_1 RD_{i,t-1} + \alpha_2 Controls_{i,t-1} + u_{i,t}, \qquad (7)$$

Table 10 presents the results. We set up eight models, where we regress our measure of total risk disclosure *RD* and the seven specific risk disclosure measures (for market risk, credit risk, risk management, country risk, economic risk, accounting risk, and other risks) individually on the value of the company.

Model (1) assesses whether risk disclosure, in general, contributes to the firm value of an energy utility. We find that an additional page of risk reporting is associated with a 2.9% increase in firm value. Thus, our results echo the literature on the positive effects of disclosure (Rajgopal, 1999; Hope et al., 2016) and are in line with our previous results on idiosyncratic volatility. More disclosure of risks leads to lower idiosyncratic volatility and to higher firm valuations. Again, it is important to note that risk disclosure reveals rather negative information. Therefore, finding a significant positive–rather than a negative–relation between risk disclosure and firm value provides strong additional support of the signaling hypothesis.

Turning to the specific risk disclosure models, we find positive and statistically significant coefficients for the disclosure of market risk (co-eff. 0.1724, $p < 0.01$), credit risk (0.0930, $p < 0.01$), risk management (0.0951, $p < 0.01$), and risk related to the economy (0.0385, $p < 0.05$). Note that we do not find any negative coefficients for risk disclosure

Table 8

Results of the panel regression for idiosyncratic volatility with fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables shown is 4.33 across all models (for $Size_{t-1}$).

Vol_t^I	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$RDmarket_{t-1}$	−0.0215						
	(0.0174)						
$RDcredit_{t-1}$		−0.0472					
		(0.0114)***					
$RDmgmt_{t-1}$			−0.0512				
			(0.0142)***				
$RDcountry_{t-1}$				−0.0029			
				(0.0225)			
$RDecon_{t-1}$					−0.0159		
					(0.0080)*		
$RDaccount_{t-1}$						−0.0593	
						(0.0181)**	
$RDmisc_{t-1}$							0.0216
							(0.0080)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}	0.65	0.66	0.65	0.65	0.65	0.65	0.65
F	28.36***	29.36***	29.11***	28.29***	28.40***	28.88***	28.47***
N	752	752	752	752	752	752	752

Standard errors are in parentheses. Asterisks *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%, respectively.

Table 9

Panel regression results for three models with RD as a dependent variable, fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 4.55 for the three models (for $Size_{t-1}$).

RD_t	(1)	(2)	(3)
Vol_{t-1}^T	−0.2316		
	(0.4015)		
Vol_{t-1}^S		0.2373	
		(0.2602)	
Vol_{t-1}^I			−0.6828
			(0.3986)
$Readability_t$	0.0027	0.0024	0.0028
	(0.0251)	(0.0251)	(0.0249)
MTB_{t-1}	0.0787	0.0883	0.0692
	(0.0652)	(0.0693)	(0.0605)
$Growth_{t-1}$	0.3234	0.3320	0.3469
	(0.8101)	(0.7987)	(0.8208)
$Size_{t-1}$	0.2733	0.2788	0.2132
	(0.1366)*	(0.1311)*	(0.1410)
Lev_{t-1}	−0.6995	−0.6253	−0.6272
	(0.8164)	(0.8139)	(0.8234)
$Profit_{t-1}$	1.5823	2.4181	0.8647
	(2.0207)	(2.0082)	(2.0262)
ESG_{t-1}	0.2753	0.2544	0.2805
	(0.1033)**	(0.1052)*	(0.1033)**
Constant	4.6482	0.0290	7.7057
	(3.2902)	(2.0720)	(3.3802)*
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R^2_{adj}	0.38	0.38	0.38
F	10.19***	10.21***	10.29***
N	689	689	689

Standard errors are in parentheses. Asterisks *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%, respectively.

variables. In particular, disclosure of market risk has a high coefficient, which results in a 12% $((\exp(0.1724 \cdot 0.6669) - 1)$ increase per unit of standard deviation (0.6669). We note that the average amount of

market risk disclosed in our sample is approximately 0.53 pages, and 5% of the annual reports disclose more than 1.83 pages. Overall, the regressions produce very high adjusted R^2's, which is typical for firm value regressions (Barth and McNichols, 1994; Campbell et al., 2003).

In summary, we find that the disclosure of risk-related information is positively associated with firm value. Therefore, the more transparent an energy utility is compared to its peers, the higher its observed firm value.

5.3. Robustness tests

We carried out some additional tests to ensure the robustness of our results against alternative research design decisions. First, companies may behave differently during the years in which they report negative earnings (i.e., loss years). Furthermore, investors may react differently to the rather negative content of risk disclosure during the loss years. Therefore, we added a dummy variable which equals one for firm-years with negative income and is zero otherwise. We also interact the loss variable with the risk disclosure variables. The results are provided in Table A.3. We find qualitatively very similar results to those reported in our main analyzes of idiosyncratic volatility. The loss variable is positive and in many (but not all) cases significant, which is in line with the notion that after a loss year, investors are more uncertain about the future prospects of a firm. The interaction of loss and risk disclosure does not reach significance for total risk disclosure or any risk disclosure category, further demonstrating that the relationship between idiosyncratic volatility and risk disclosure is not moderated by the occurrence of loss years.

Second, volatility can be seen as a rather persistent firm characteristic that does not vary considerably over time. In this case, it would be useful to include lagged volatility as an additional control variable. However, the results in Table A.4 show that hypothesis H1 is still supported, which means that the disclosure of total risk is still significantly and negatively related to the idiosyncratic volatility.

Third, most of the variables in our models are built on logarithmic values or, in the case of the ESG score, occur only within a restricted range of values, which minimizes the impact of extreme values on our results. For the exceptions (i.e. Lev and $Profit$), we apply winsorizing at the lowest and highest percentile. In robustness tests, we also analyze

Table 10
Panel regression results for firm value with fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 4.51 across all models (for $Size_{t-1}$).

$Firmval_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD_{t-1}	0.0276							
	(0.0061)***							
$RDmarket_{t-1}$		0.1724						
		(0.0361)***						
$RDcredit_{t-1}$			0.0930					
			(0.0198)***					
$RDmgmt_{t-1}$				0.0951				
				(0.0229)***				
$RDcountry_{t-1}$					0.0780			
					(0.0492)			
$RDecon_{t-1}$						0.0385		
						(0.0187)*		
$RDaccount_{t-1}$							0.0225	
							(0.0340)	
$RDmisc_{t-1}$								0.0028
								(0.0201)
$Readability_{t-1}$	0.0020	0.0052	0.0023	0.0015	0.0015	0.0016	0.0017	0.0018
	(0.0036)	(0.0037)	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
MTB_{t-1}	0.0764	0.0729	0.0777	0.0759	0.0789	0.0783	0.0790	0.0788
	(0.0323)*	(0.0318)*	(0.0322)*	(0.0328)*	(0.0332)*	(0.0333)*	(0.0337)*	(0.0335)*
$Growth_{t-1}$	−0.1054	−0.0883	−0.1063	−0.1093	−0.1077	−0.0991	−0.0985	−0.0967
	(0.0899)	(0.0885)	(0.0906)	(0.0911)	(0.0981)	(0.0969)	(0.0980)	(0.0984)
$Size_{t-1}$	0.8537	0.8399	0.8511	0.8605	0.8643	0.8628	0.8626	0.8618
	(0.0216)***	(0.0223)***	(0.0217)***	(0.0214)***	(0.0215)***	(0.0213)***	(0.0214)***	(0.0215)***
Lev_{t-1}	−0.7012	−0.7415	−0.6698	−0.7761	−0.6678	−0.7379	−0.7180	−0.7157
	(0.1695)***	(0.1682)***	(0.1707)***	(0.1688)***	(0.1795)***	(0.1710)***	(0.1720)***	(0.1736)***
$Profit_{t-1}$	3.5069	3.5016	3.4868	3.4830	3.4835	3.5255	3.5155	3.5058
	(0.5323)***	(0.5239)***	(0.5298)***	(0.5343)***	(0.5393)***	(0.5399)***	(0.5404)***	(0.5398)***
ESG_{t-1}	0.0821	0.0816	0.0881	0.0796	0.0872	0.0867	0.0861	0.0877
	(0.0160)***	(0.0162)***	(0.0162)***	(0.0164)***	(0.0162)***	(0.0165)***	(0.0167)***	(0.0165)***
Vol^T_{t-1}	−0.3986	−0.4221	−0.3942	−0.3912	−0.4109	−0.4073	−0.4094	−0.4132
	(0.0840)***	(0.0836)***	(0.0834)***	(0.0836)***	(0.0858)***	(0.0851)***	(0.0852)***	(0.0856)***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
F	172.52***	174.02***	173.09***	171.39***	168.78***	168.62***	167.91***	167.81***
N	741	741	741	741	741	741	741	741

Standard errors are in parentheses. Asterisks ∗, ∗∗, and ∗∗∗ indicate statistical significance at 5%, 1%, and 0.1%, respectively.

models where all variables and where no variables were winsorized. The results are provided in Table A.5 in Panels A and B, respectively. In both cases, our results remain qualitatively very similar to our basic analyses. The signs and significance levels for our variables of interest remain unchanged.

6. Conclusions & policy implications

We find strong empirical support for the signaling hypothesis of risk disclosure due to a significantly negative relationship between risk disclosure and idiosyncratic volatility and a significantly positive relationship between risk disclosure and firm value. More detailed analyzes show that the relationships are not observable for all risk categories, but they are observable for total risk disclosure and most of the risk categories. In additional analyses, we ruled out that reverse causality drives our results, meaning that firm's lower or higher volatility is not found to provide more or less risk disclosures.

The findings of our study have at least two important practical implications.

1. From a regulatory perspective, risk reporting, in particular for energy utilities, which are systemically important, is an effective tool to increase transparency. Despite criticism that corporate risk disclosure is often ambiguous, unspecific, and characterized

by boilerplate statements, the capital market seems to appreciate the increased transparency that is provided. This is especially evident for disclosure of Credit Risks, as well as disclosure of Risk Management activities. Our findings indicate that risk disclosure in its current form is related to reduced idiosyncratic volatility and increased firm value. Therefore, regulators can build on existing risk disclosure regulations and could aim to further increase the specificity of such disclosures. Companies should take our findings as an encouragement to voluntarily disclose more information on their risk exposure and management.

2. On another note, we are quite surprised that even in light of the Paris Agreement on Climate Change, the industry that is probably the most influenced and influencing in this regard does not report on climate change-related risk at a detectable level. We cannot identify a separate risk reporting category, nor can we find considerable discussions of such risks in annual reports when looking at them manually. In our opinion, this finding shows that all stakeholders are at high risk. If firms do not deliberately provide such information, the market can only infer it from publicly available information, with a lot of uncertainty and information asymmetries, eventually reducing the market valuation of such a firm. For example, Schiemann and Sakhel (2019) show that some forms of climate-related risk disclosure are associated with lower information asymmetry. Although

awareness of climate-related risks for energy utilities appears to be increasing, it is still not spread throughout Europe[13] Of course, the increased focus on the climatic effects of companies has already led to increased scrutiny and the development of related disclosure guidelines, for example, by the TCFD (Eccles and Krzus, 2018). This means that policy makers are interested in companies' disclosures of climate-related risks in order to assess the industry's vulnerability to climate change. Although companies can choose to report their exposure in their voluntary sustainability reports, it appears that energy companies perceived the financial implications of climate-related risks to be rather low, at least until 2017, the end of our sample period.[14]

As with every empirical study, there are some limitations which must be considered when interpreting the results. First, our focus is on companies in the energy sector within the EU. Although this allows us to better interpret the results from the content analysis, due to the rather homogeneous setting within a specific sector and region, our results are not necessarily transferable to other sectors and/or regions. Indeed, a focus on different regions (with different regulations on risk disclosure) for the same sector might be useful in order to investigate whether the positive relation between risk disclosure and idiosyncratic volatility depends on the regulations and institutional setting.

Second, our methodological focus is on an automated content analysis based on LDA (Blei, 2012). Although this allows for the analysis of many reports and a thematic interpretation of risk disclosure, we do not aim to analyze further aspects of such disclosures (e.g., quantitative versus qualitative disclosure, use of boilerplate statements, or the tone of the statements). Therefore, our results are only applicable to the extent of risk disclosure. If other aspects of risk disclosure are of interest, other methods must be employed.[15]

Our study contributes to the literature by focusing on risk disclosure, as one building stone of corporate governance. Therefore, we do not only support the findings of Srivastava and Kathuria (2020), which show that high-quality corporate governance systems are related to better firm performance. We also extend Srivastava and Kathuria (2020) through our focus on risk disclosure and its perception in the capital market. Furthermore, we complement the literature on risk management in the energy sector (e.g., Kim and Choi, 2019; Nguyen et al., 2021; Sadorsky, 2001) focusing on the consequences of the actual reporting behavior of companies. More specifically, we contribute to the literature that focuses on the usefulness of risk disclosure. Although the literature reports some critical issues related to risk disclosure, such as an indication of more boilerplate disclosures (Kravet and Muslu, 2013), higher audit fees related to more extensive risk disclosure (Yang et al., 2018), or negative short-term market reactions to considerable increases in a company's risk disclosure (Campbell et al., 2014), we find support for risk disclosures being useful for (potential) investors and generally regarded as a signal of a high quality of company risk management, at least in the energy sector.

It remains for future research to examine whether the increasing focus on sustainability reporting, for example, the publication of the SASB Materiality Map (TM) in the USA or the current developments on sustainability-related disclosure of the ISSB (International Sustainability Standards Board) and the ESRS (European Sustainability Reporting Standards), have an effect on the risk reporting, especially on climate-related risks, of their energy utilities.

CRediT authorship contribution statement

Maximilian Düsterhöft: Methodology, Software, Investigation, Data curation, Writing – review & editing. **Frank Schiemann:** Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Thomas Walther:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

Appendix A

A.1. Feature selection

To reduce the vocabulary, we classify words according to an information measure called tf-idf:

$$\text{tf-idf} = \frac{tf}{\log(df)},$$

where tf is the frequency of the term and has a positive impact on this measure. The inverse document frequency idf has a negative impact, i.e., if a term is used in more documents, it is less informative. We trim the vocabulary according to tf-idf. We use the 5000 most informative words to obtain the vocabulary for our topic model (see Table A.1).

A.2. Latent Dirichlet allocation

The LDA approach models the probability of each word in a document as the product of the probabilities of the word within a given topic $k = P(w_i|z_i = k)$ with the probabilities of a topic within a given document $\theta_d = P(z_i = k|D = d)$. That is,

$$P(w_i|D = d) = \sum_{k=1}^{K} P(w_i|z_i = k)P(z_i = k|D = d)$$

LDA assumes a number K of latent topics. Informally, a topic can be thought of as a weighted word list that groups words that express the same underlying theme. Each topic is a probability vector $\beta_k \in \Delta^{V-1}$ over V.

LDA assumes the following generative process for a document $w = (w1, \dots, wN)$ of a corpus D containing N words from a vocabulary consisting of V different terms, $w_i \in \{1, \dots, V\} \quad \forall i = 1, \dots, N$. The generative model consists of the following three steps.

- Step 1: The distribution β of the terms is determined for each topic by $\beta \sim Dirichlet(\delta)$.
- Step 2: The proportions θ of the distribution of the topics of the document w are determined by $\theta \sim Dirichlet(\alpha)$.
- Step 3: For each of the N words w_i,
    - Choose a topic $z_i \sim Multinomial(\theta)$.
    - Choose a word w_i from a multinomial probability distribution conditioned on the topic $z_i : p(w_i|z_i\beta)$. The distribution β of terms in a topic contains the probability that each word occurs in the given topic.

The Gibbs sampling in the LDA model draws from the posterior distribution $p(z|w)$ is obtained by sampling from Griffiths et al. (2004):

$$p(z_i = K|w, z_{-i}) \propto \frac{n_{-i,K}^{(j)} + \delta}{n_{-i,K}^{(.)} + V\delta} \cdot \frac{n_{-i,K}^{d_i} + \alpha}{n_{-i,.}^{d_i} + k\alpha}.$$

Here, z_{-i} is the vector of current topic memberships of all words without the ith word w_i. The index j indicates that w_i is equal to the

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[13] As of March 2020, only 15 European energy companies were listed as supporters by the Task Force on Climate-related Financial Disclosure (https://www.fsb-tcfd.org/tcfd-supporters/).

[14] First studies identify climate risk disclosure in annual reports in SEC fillings (Berkman et al., 2021; Kölbel et al., 2022) and for the largest European firm (Friederich et al., 2021).

[15] While LDA decomposes documents into topics and therefore shows what is talked about, it does not provide insights into how these topics are discussed. Sentiment analysis could provide further insight into the issue of tone and its extent. Since LDA uses the bag-of-word assumption, neglecting the structure of a sentence, it does not discriminate between active and passive language or tenses. A more extensive use of the methods of text mining would enable a more holistic picture of not only the 'what' that is written in the risk report, but also 'how' it was written.

Table A.1
Preprocessing steps. In each step, the size of vocabulary (Types) and the total number of words (Tokens) evolves.

	Raw text	Remove stopwords + non-words	Lemmatization	Obtaining ngrams	TF-IDF adjustment
Tokens	981 074	804 008	755 473	1 984 397	707 101
Types	16 255	16 085	14 023	235 457	5 000

Table A.2
Example list of topics and related words from LDA Topic Model with $K = 30$.

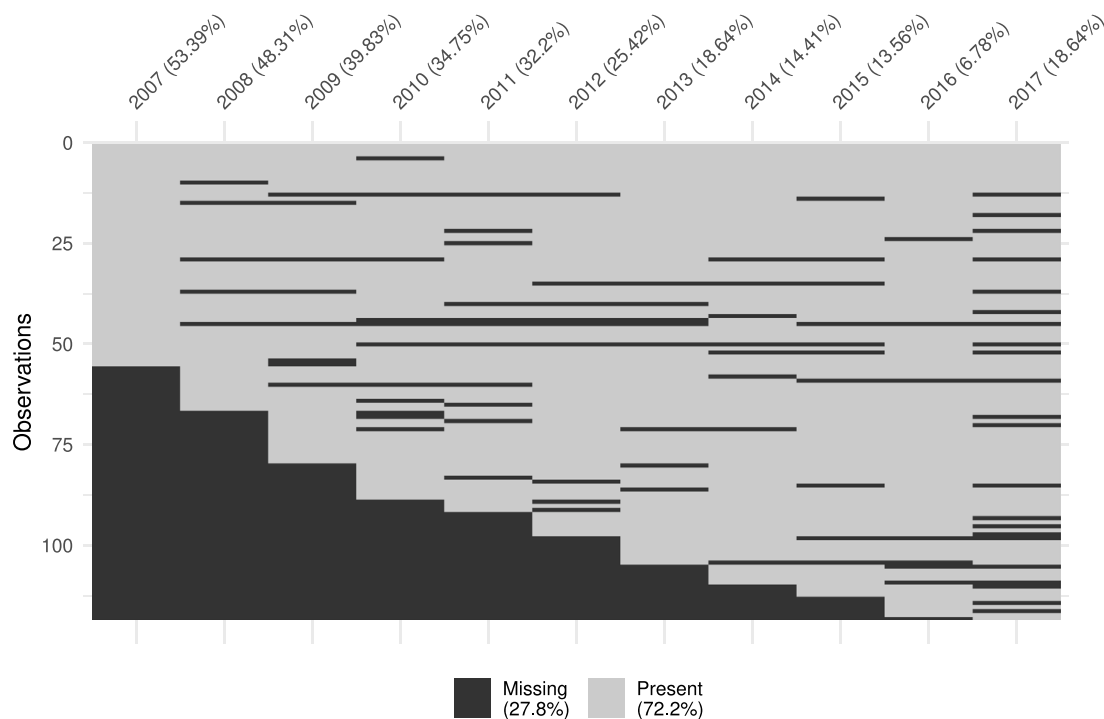| Topic name	Market risk	Credit risk	Risk management	Country risk	Economic risk	Accounting risk	Other risks
Words	price	credit	risk	group	rate	value	pln
	oil	risk	group	december	interest	fair	financial
	gas	credit_risk	management	financial	interest_rate	fair_value	risk
	risk	group	financial	russian	rate_risk	level	december
	commodity	financial	limit	million	risk	market	group
	market	exposure	risk_management	note	interest_rate	financial	result
	product	counterparty	potential	consolidated	fix	asset	pge
	crude	counterparties	market	rub	float	instrument	change
	group	customers	december	consolidated_ financial	debt	price	statement
	crude_oil	rating	risk_limit	cash	change	use	currency
Number of topics	2	8	5	4	4	4	3

Fig. A.3. Data Heatmap — Data availability of risk disclosures across the sample period.

jth term in the vocabulary. $n_{-i,K}^{(j)}$ is defined as the number of times the jth term of the vocabulary is currently assigned to topic K without the ith word. The dot implies that a summation is performed on this index. d_i indicates the document in the corpus to which w_i belongs. In the formulation of the Bayesian model, δ and α are the parameters of the prior distributions for the term distribution β of each topic and the topic distribution θ of each document, respectively. The predictive distributions of the parameters θ and β given by w and z are given by

$$\beta_K^{(j)} = \frac{n_K^{(j)} + \delta}{n_K^{(\cdot)} + V\delta}$$

$$\widehat{\theta}_K^{(d)} = \frac{n_K^{(d)} + \alpha}{n_{\cdot}^{(d)} + k\alpha}$$

for $j = 1, \dots, V$ and $d = 1, \dots, D$.

Table A.3

Panel regression results for idiosyncratic volatility with loss-year interaction with fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 6.09 across all models (for $Loss$).

Vol_t^I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD_{t-1}	−0.0105							
	(0.0036)**							
RD_{t-1} * Loss	−0.0051							
	(0.0074)							
$RDmarket_{t-1}$		−0.0217						
		(0.0177)						
$RDmarket_{t-1}$ * Loss		−0.0182						
		(0.0438)						
$RDcredit_{t-1}$			−0.0468					
			(0.0126)***					
$RDcredit_{t-1}$ * Loss			−0.0153					
			(0.0242)					
$RDmgmt_{t-1}$				−0.0508				
				(0.0145)***				
$RDmgmt_{t-1}$ * Loss				−0.0050				
				(0.0401)				
$RDcountry_{t-1}$					−0.0148			
					(0.0222)			
$RDcountry_{t-1}$ * Loss					0.0462			
					(0.0535)			
$RDecon_{t-1}$						−0.0116		
						(0.0121)		
$RDecon_{t-1}$ * Loss						−0.0132		
						(0.0165)		
$RDaccount_{t-1}$							−0.0724	
							(0.0207)***	
$RDaccount_{t-1}$ * Loss							0.0418	
							(0.0332)	
$RDmisc_{t-1}$								0.0201
								(0.0083)*
$RDmisc_{t-1}$ * Loss								0.0070
								(0.0253)
Loss	0.1510	0.1248	0.1462	0.1152	0.0915	0.1269	0.0859	0.1040
	(0.0657)*	(0.0513)*	(0.0578)*	(0.0616)	(0.0509)	(0.0466)**	(0.0505)	(0.0448)*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}	0.64	0.64	0.65	0.65	0.64	0.64	0.64	0.64
F	28.13***	27.62***	28.66***	28.32***	27.58***	27.67***	28.20***	27.67***
N	752	752	752	752	752	752	752	752

Standard errors are in parentheses. Asterisks *, **, and *** indicate statistical significance at 5%, 1%, and 0.1%, respectively.

A.3. Word–topic assignments

Table A.2 shows the most probable assignments of words and topics. Two people interpreted these to guarantee their intersubjective reliability. After subjective assignment of a label to each of the 30 topics, we grouped the topics into 6 categories, namely market risk, credit risk, risk management, country risk, economic risk, and accounting risk. Topics for which we were unable to find appropriate labels are grouped into Other Risks. Grouping topics into categories can lead to some generalization of specific risks; for example, economic risk includes the risk of a change in interest rates (as shown in Table A.2) and also exchange rate risk. Similarly, Credit Risk pools risks from counterparties as well as debt-specific risks such as liquidity.

A.4. Using topic coherence as a robustness check

Not only to use subjective judgment to determine the number of topics K, we also used the topic coherence measure suggested by Mimno et al. (2011). The coherence score counts how often highly probable terms from a single topic, which by the interpretation of

the model should represent semantic coherence, co-occur with each other in documents. Using the same preprocessing chain as in the main analysis, we ran the models from $K = 10$ to $K = 60$ in steps of 5. The coherence score was found to be the highest (and therefore the best) with $K = 10$.

The number of topics strongly differs from the model used in the main analysis, being more coarse-grained. We interpret the topics and link them to the topics of the main analysis.

A.5. Data Heatmap

See Fig. A.3.

A.6. Additional analyses

See Tables A.3–A.5.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106794.

Table A.4

Panel regression results for three measures of volatility with controlling for lagged volatility fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 4.31 across all models (for $Size_{t-1}$).

	Vol_t^T	Vol_t^S	Vol_t^I
RD_{t-1}	−0.0048	−0.0024	−0.0086
	(0.0032)	(0.0056)	(0.0030)**
Vol_{t-1}^T	0.4174	0.4476	0.4304
	(0.0385)***	(0.0579)***	(0.0364)***
$Readability_{t-1}$	0.0002	−0.0043	0.0009
	(0.0017)	(0.0029)	(0.0016)
MTB_{t-1}	−0.0040	0.0165	−0.0083
	(0.0049)	(0.0121)	(0.0049)
$Growth_{t-1}$	0.0706	0.1366	0.0658
	(0.0464)	(0.0761)*	(0.0406)
$Size_{t-1}$	−0.0409	0.0889	−0.0788
	(0.0115)***	(0.0166)***	(0.0113)***
Lev_{t-1}	0.0265	−0.3293	0.1252
	(0.0664)	(0.1137)**	(0.0646)
$Profit_{t-1}$	−0.7202	−0.6317	−0.8184
	(0.2108)***	(0.3270)	(0.2088)***
ESG_{t-1}	0.0105	0.0190	0.0106
	(0.0081)	(0.0138)	(0.0082)
Constant	2.2122	−0.3512	2.5231
	(0.2038)***	(0.3227)	(0.2009)***
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R_{adj}^2	0.66	0.64	0.70
F	30.78***	27.35***	36.64***
N	743	743	743

Standard errors are in parentheses. Asterisks ∗, ∗∗, and ∗∗∗ indicate statistical significance at 5%, 1%, and 0.1%, respectively.

Table A.5

Panel regression results for idiosyncratic volatility with all variables winsorized (Panel A) and no variable winsorized (Panel B) with fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 4.42 across all models (for $Size_{t-1}$).

Vol_t^I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All variables winsorized								
RD_{t-1}	−0.0100							
	(0.0035)**							
$RDmarket_{t-1}$		−0.0127						
		(0.0182)						
$RDcredit_{t-1}$			−0.0449					
			(0.0112)***					
$RDmgmt_{t-1}$				−0.0461				
				(0.0144)**				
$RDcountry_{t-1}$					−0.0011			
					(0.0238)			
$RDecon_{t-1}$						−0.0245		
						(0.0139)		
$RDaccount_{t-1}$							−0.0728	
							(0.0190)***	
$RDmisc_{t-1}$								0.0241
								(0.0099)*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}	0.64	0.63	0.64	0.64	0.63	0.63	0.64	0.63
F	28.35***	27.92***	28.84***	28.50***	28.89***	28.03***	28.65***	28.07***
N	752	752	752	752	752	752	752	752
Panel B: No variables winsorized								
RD_{t-1}	−0.0103							
	(0.0034)**							
$RDmarket_{t-1}$		−0.0219						
		(0.0175)						
$RDcredit_{t-1}$			−0.0470					
			(0.0114)***					
$RDmgmt_{t-1}$				−0.0518				
				(0.0142)***				
$RDcountry_{t-1}$					−0.0018			
					(0.0226)			
$RDecon_{t-1}$						−0.0150		
						(0.0079)		
$RDaccount_{t-1}$							−0.0582	
							(0.0181)**	
$RDmisc_{t-1}$								0.0213
								(0.0081)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj}	0.64	0.63	0.64	0.64	0.63	0.63	0.64	0.63
F	28.41***	27.98***	28.94***	28.73***	27.90***	28.00***	28.45***	28.07***
N	752	752	752	752	752	752	752	752

Standard errors are in parentheses. Asterisks ∗, ∗∗, and ∗∗∗ indicate statistical significance at 5%, 1%, and 0.1%, respectively.

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