Let's Talk About Risk! Stock Market Effects of Risk Disclosure for European Energy Utilities[☆]

Maximilian Düsterhöft[a], Frank Schiemann[b], Thomas Walther[a,c,*]

[a]*Faculty of Business and Economics, Technische Universität Dresden, Germany*
[b]*Faculty of Social Sciences, Economics and Business Administration, University of Bamberg, Germany*
[c]*Utrecht School of Economics, Utrecht University, The Netherlands*

Abstract

We analyse whether risk reporting by European energy utilities is positively or negatively 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 in 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. In additional analyses, we show that reverse causality does not explain our results. We also find 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. Our findings imply that current risk disclosure regulation is useful in the sense that it provides information, which decreases idiosyncratic volatility, and which is reflected in the firm value. Interestingly, we are not able to identify a climate-related risk topic, and further tests show only 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.

Keywords: Climate Change, Risk Reporting, Risk Disclosure, Energy Utilities, Topic Modelling

JEL classification: G32; M41; M48

[☆]We are thankful to Lance Bachmeister (handling editor), two anonymous referees, Michael Dobler, Robert Gutsche, Ronald Huisman, and Eric Schmiedchen for useful comments on an earlier version of this manuscript. A former version of this paper was circulated under the title "Let's Talk About Risk! The Firm Value Effects of Risk Disclosure for European Energy Utilities." We gratefully acknowledge the assistance of Leif Hansen and Phillipp Henschke. Part of the work was conducted during Thomas Walther's research time as Assistant Professor at the University of St. Gallen, the Institute for Operations Research and Computational Finance. This publication is part of SCCER CREST, which is supported by Innosuisse. Thomas Walther is grateful for the funding received for conducting this research.

*Corresponding Author, Mail: t.walther@uu.nl

First Version: Sep 2020 – This Version: March 29, 2023 – Latest Version: SSRN

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 & Yun, 2013), (climate change induced) policy uncertainty (Tulloch et al., 2017, Breitenstein et al., 2022), and geopolitical risk (Finon & Locatelli, 2008). Risk disclosure is an important tool for listed firms to transparently communicate their known risks and risk management procedures. It can help (potential) investors to make more precise cash flow estimates and regulators to 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. Accordingly, risk disclosure tends to be rather opaque (Dobler et al., 2011, Kravet & Muslu, 2013), which inhibits its usefulness for investors and might even increase stock market volatility due to the implied uncertainty about future cash flows. Against the background of high risk exposures of energy utilities and the ambiguous role of risk disclosure, we analyse 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 disclosed information in annual reports, risk disclosure plays a special role (Kravet & Muslu, 2013). Managers of the utilities 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, the transparency and communication of risks and risk management appear to be the main goals of risk disclosures.[1] This information is also important to regulators and rating agencies for their duty to supervise and monitor risk levels (Healy & Palepu, 2001).

[1] Regulators and supervisors are aware of the challenges to informative risk disclosure. The International Accounting Standards Board (IASB) developed standards, such as the IFRS 7, to build the foundation for transparent and comparable disclosures. Mandatory since 2007, the IFRS 7 covers the disclosure of financial instruments and consequently the 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.

Risk disclosure contains a forward-looking perspective, and is more qualitative in nature. Forward-looking information contains expectations, which are difficult to quantify, and quantified forward-looking information about a company's risks is often connected with the high indirect costs of disclosure (Leuz & Wysocki, 2016) when competitors are likely to use such information against the disclosing company. Indeed, the empirical literature finds that companies refrain from disclosing forward-looking and quantitative information (Linsley & Shrives, 2006), risk disclosures lack transparency and clarity (Dobler et al., 2011), or only provide boilerplate statements and cheap talk (Dobler, 2008, Kravet & Muslu, 2013). However, empirical studies confirm the usefulness of risk disclosure for capital market participants (Campbell et al., 2014, Elshandidy & Shrives, 2016). Hence, interested readers of risk disclosures need to tackle the challenge of filtering relevant information about risks, so as to interpret this information correctly and, finally, to 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 of accounting, finance (Loughran & 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). LDA allows to detect hidden topics in a text by probability weighting of single or multiple words within a topic, and topics within a text. Unlike supervised text analysis techniques, LDA does not need predefined labels or list of words to define topics. The closest to our study is Wei et al.

[2]With the inclusion of word lists (Frankel et al., 2022), topic modelling (Hannigan et al., 2019), or supervised machine learning (Wei et al., 2019a), scholars are able to generate quantitative evidence out of narrative textual communication. For example, Bybee et al. (2021) use LDA to measure the structure of newspaper topics over time and relate it to the business cycle. Sautner et al. (2021) use the number of occurrences of bigrams in conference earnings calls to measure climate change exposure, which the authors relate to risk premia in Sautner et al. (2021). Maybe the most prominent example is Baker et al. (2016), who use 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 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 & Xue (2021) use LDA to define news topics, which are later on used for a sentiment analysis. Polyzos & Wang (2022) employ LDA to extract the topics from energy market related tweets to further on test for market efficiency.

(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 analysing a firm's practice of disclosing risks has focused on either particular countries or regions (e.g. Amran et al., 2009) or on specific branches (e.g. Dobler et al., 2011, on the manufactoring sector). As far as our knowledge extends, the present study is the first to examine the risk disclosure practices of energy utilities by themselves. We consider the risk reports presented in the notes to the financial statements and apply a topic model, which identifies 6 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 & Malkiel, 2003, Wei & Zhang, 2006). In the context of energy companies, studies usually look at market risk exposure (Mohanty & Nandha, 2011, Sadorsky, 2012). In addition to oil and gas risk exposure, Lyocsa & Todorova (2021) also investigate the risk spillover from the financial markets in terms of world-, country-, and industry-wide 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 four ways.

1. Our focus on the relation between risk disclosure and stock volatility enhances the understanding of company-focused regulation and its impact on volatility. The previous literature has found evidence for a negative association between extensive risk disclosure and firm risk (Kim & 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 speak 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, something which contains the market's expectations about a firm's future performance. Thus, we not only show that higher transparency (more risk disclosure)

leads to less uncertainty (lower risk), 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 aiming to measure 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 & 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 analyse 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 take a broader focus across different sectors or focus on the financial sector. Our focus on energy utilities allows a more specific interpretation of the content analysis and of our results.

Our study's main practical implications is to underpin the usefulness of risk disclosure regulation by establishing a positive relation 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 analyses 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 such 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 more specific climate-related risk disclosure regulation[3] could be beneficial for energy

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

utilities.

2. Literature Review and Development of the Hypotheses

2.1. Literature Review

Over the last years a substantial body of literature focusing on risk disclosure has evolved. 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.

The vast majority of studies have, with few exceptions, undertaken research on developed countries (the U.S., European countries, Australia, Canada, Japan) (i.e. Amran et al., 2009, Hassan, 2009, Mokhtar & Mellett, 2013). Only very few studies aim at specific sectors: the majority focus on either non-financial or financial companies. The type of risks 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. There are a few studies with a focus on a concrete sector: on commercial banks (Oliveira et al., 2011b), high-polluting industries (Dobler et al., 2014), and manufacturing firms (Dobler et al., 2011, Lajili et al., 2012).

The methods applied by previous research can be classified into three categories: content analysis, disclosure index, and other methods. The majority of recent studies apply content analysis to risk disclosure and measure the quantity of disclosed risk-related information (among others Dobler et al., 2014, 2011, Abraham & Cox, 2007, Linsley & Shrives, 2006). Content analyses focuses on code words, phrases, sentences, or 'thought units' (Srnka & 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 analysed and hypotheses can

fsb-tcfd.org

be tested by means of regression models. Few studies concentrate solely on parts of the reports, such as management reports or notes (Dobler et al., 2011). Usually, the coding and analysing is conducted manually. However, more recently studies rely on automated (software based) content analysis (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 which represents the level of disclosure of a report, where higher scores indicate more and/or better disclosure. This score can be either weighted or unweighted to control the importance of different items of the index (Marston & Shrives, 1991, Cooke, 1989). This technique is used by some studies to measure the level of risk disclosure as well (among others Mokhtar & Mellett, 2013, Hassan, 2009). A few studies employ other methods. For example, Filzen (2015) and Brown et al. (2018) rely on word counts, simply focusing on the number of occurrences of certain, pre-defined 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 before, most research articles are limited to companies of a specific region or country. A reason for this restriction can been seen in regulatory differences between countries (e.g. different accounting standards might apply in different countries). For example, Kravet & 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 U.S., 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 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

Authors	Sample	# Firms	Region	Branch	Method	Sub-method
Beretta & Bozzolan (2004)	2001	85	Italy	non-financial	CA	manual
Chalmers & Godfrey (2004)	1992–1996	199	Australia	non-financial	DI	unweighted
Lajili & Zéghal (2005)	1999	228	Canada		CA	manual
Linsley & Shrives (2005)	2000	79	UK	non-financial	CA	manual
Linsley & Shrives (2006)	2000	79	UK	non-financial	CA	manual
Linsley et al. (2006)	2001	18	Canada, UK	banks	CA	manual
Abraham & Cox (2007)	2002	71	UK	non-financial	CA	manual
Lopes & 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 & 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 & Hussainey (2012)	2009	72	UK	non-financial	CA	manual
Elshandidy et al. (2013)	2005–2009	290	UK	non-financial	CA	automated
Mokhtar & Mellett (2013)	2007	105	Egypt	non-financial	CA, DI	manual, unweighted
Barakat & Hussainey (2013)	2008–2010	85	European Union	banks	DI	unweighted
Kravet & Muslu (2013)	1997–2007	4,315	USA		CA	automated
Bao & 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 & 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

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

environmental performance. Nonetheless, the authors state that energy and utility firms 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. In addition, we build on the question how risk disclosures are perceived by capital market participants. 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.

While 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 & Muslu, 2013, Bao & 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. Thereby, 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 upon, and the extent of risk disclosure on these specific risk categories.

2.2. Hypothesis Development

Regarding the relation between risk disclosure and firm volatility, there are three possible relations: (1) no relation, (2) a positive relation, or (3) a negative relation (Bao & Datta, 2014). If risk disclosure is not related to volatility, then the content of the risk disclosure might be irrelevant. This is the case if 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 to 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). In line with this argument, Schiemann & Sakhel (2019) report that for companies in carbon-intensive sectors 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 relation 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 signalling effect. Through risk disclosure, firms signal the high quality of their risk management system and their expectations of relevant risks. For example, firms reporting about environmental risks not only show that they are aware of those 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 & Yun (2013) show that risk management can increase the firm value, specifically for energy utilities. Note that a prerequisite for finding a positive relation is that the disclosed risk information is useful and new to the capital market. Empirical research provides some evidence that risk disclosure is indeed interpreted favourably by capital market participants. For example, Rajgopal (1999) find evidence that the 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 to be related to positive capital market reactions. Based on this explanation, we formulate H1, which we refer to as the 'Signalling Hypothesis':

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

There are also theoretical arguments supporting a negative relation 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 about what and how to disclose. For example, managers might decide to obfuscate risk disclosure by including unspecific, boilerplate statements. More concrete and/or thorough risk disclosure might then reveal additional risks. Indeed, previous research shows that capital market participants can become more uncertain about a firm's future prospects 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 the increased uncertainty. As argued above, the negative relation would also be observable mainly for idiosyncratic volatility as firm-specific risk information would be 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 results.

According to 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 relation or for a positive relation are not mutually exclusive. Therefore, the reason for a positive effect of risk disclosure (e.g. through signalling) 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 differing 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, firms can be unspecific (Hope et al., 2016), they can engage in cheap talk (Dobler, 2008), or they can decide in which way to use graphics (Jones et al., 2018) or number formats, such as dollar amounts vs percentage values (Nelson & Rupar, 2015). This raises the question, 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 a company's business environment. 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, but also its relative importance from a financial market perspective[4], make 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 method from computational linguistics is increasingly used in assessing information disclosure (Bao & Datta, 2014, Huang et al., 2017, Dyer et al., 2017, Brown et al., 2019). 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 an automated coding which can easily be scaled to assess larger data sets.

[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.

Second, manual coding relies on the human coders' subjective judgment, 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 from 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 randomly drawn. 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 in 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 includes 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 covering 96 firm and 676 firm-year observations from 2007 to 2017. The reports are extracted from the respective pdf files,

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Available Reports	53	59	69	75	79	88	94	98	100	106	92	913
Pages	248	309	396	407	476	556	562	552	613	662	549	5,330
Average Pages	4.7	5.2	5.7	5.4	6.0	6.3	6.0	5.6	6.1	6.2	6.0	5.8

Table 2: Development of reports per firms per year

while some of them are based on OCR transcription. An overview of the available reports can be seen in Table 2. A missing value heatmap is provided in the Appendix A.5.

We then split the documents into pages. This produced 5,330 pages, where pages with less than 50 words were deleted. To generate our features for later analysis, we preprocessed the linguistic data. We prepared the textual data using the following four steps:

1. We replaced each word with its inflected form—the so called lemma—for example, in changing 'had' to 'have'.
2. We extractd ngrams (multi-word units, in our case using bi- and trigrams). In this way, we could identify words like 'energy market' and 'exchange rate risk' instead of treating them as distinct words. This improves significantly 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 further removed the list of company names to abstract from companies naming themselves in the report.
4. In order to reduce the vocabulary, we ranked words according to the information measure 'term frequency-inverse document frequency' (tf-idf) and choose the 5000 most informative words (for further 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 interpretability (Hansen et al., 2018). Even though this is highly subjective, Blei (2012) notes that interpretability can legitimize the choice of a particular K.[5] The second way of determining K is via an evaluation measure (Huang

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

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 the topics of interest too split up into different parts. If K is too low, the topics of interest are likely to be mixed up with other themes. We inspected several models based on configurations of K as 10, 20, 30, 40, 50, and 60.[6] Finally, we chose 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 relevance-measure (Sievert & Shirley, 2014). We conducted the labelling process of the topics as follows. First, two scholars independently interpreted the topics. In case of similar interpretations, the topics were labelled 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 outlines the procedure which yields 6 risk categories (Market Risk, Credit Risk, Risk Management, Country Risk, Economic Risk, and Accounting Risk) and one residual risk category, called 'Other Risk'. We multiplied the weights assigned by the topic model approach to each risk category with the total number of pages of the risk disclosure.

Interestingly, while we expected to find some risk category regarding climate-related risk, the topic model algorithm could not identify such a topic. A look at the individual item count for 'climate change' reveals that in our final sample of 676 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]

[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 ran the same analysis as for the actual model with $K = 30$ topics. The results are qualitatively similar.

[8] We also analyse 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.

The data for the 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., Berkman et al., 2021, Elshandidy et al., 2013, Schiemann & Sakhel, 2019)

In order to assess the effects of risk disclosure on stock volatility, we derive three firm-level volatility measures. The total volatility of firm i is measured by the annualized standard deviation of daily stock returns. To further distinguish between systematic and idiosyncratic risk, we follow Bekaert et al. (2012) and run a Fama & French (1996, FF) regression per firm per year on the 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

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

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 firms ESG performance based on an aggregate score provided by Refinitiv. A detailed description of the variables and their sources is provided in Table 3. Our

Results are available upon request.

[9] We retrieve the data for the three factors and the risk free rate from Kenneth French's webpage (Fama/French European 3 Factors [Daily]): `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

regression models contain only observations for which all relevant variables are available. In particular, we started with 1,573 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]

Name	Label	Measurement	Data Source
Dependent Variables			
Total Volatility	Vol^T	Natural logarithm of the standard deviation of daily stock returns	Own calculations
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	Worldscope
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	Worldscope
Asset Growth	*Growth*	Change in total assets from year t-1 to t divided by total assets in year t-1	Worldscope
Firm size	*Size*	Natural logarithm of the book value of total assets	Worldscope
Leverage	*Lev*	Total liabilities divided by total assets	Worldscope
Profitability	*Profit*	Return on assets measured as the net income before extraordinary items divided by total assets	Worldscope
ESG Performance Score	*ESG*	Asset 4 Environmental, Social, and Corporate Governance (ESG) performance score	Asset4

Table 3: Variable definitions

Table 5 summarizes the descriptive statistics of our variables, including the risk disclosure measures from the automated textual analysis. On average over the period 2007–2016, European energy utilities use around 6 pages to disclose risk related information in the annual reports. While 95% of the firms in our sample report at least two pages, the top 5% provide 14 pages and more. Figure 1 depicts the geographical distribution of the

[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 upon request.

	Firms	firm-year observation
Number of firms/firm-years	143	1,573
Firms/firm-years lost due to unavailable risk disclosure data	27	660
Number of firms/firm-years with risk disclosure data	116	913
Firms/firm-years lost due to unavailable financial data	21	239
Number of firms/firm-years in sample	95	674

Table 4: Selection of firms and firm-years.

firms in our sample. A majority of the firms come from Italy and the United Kingdom. On average the largest and most profitable firms are situated 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.

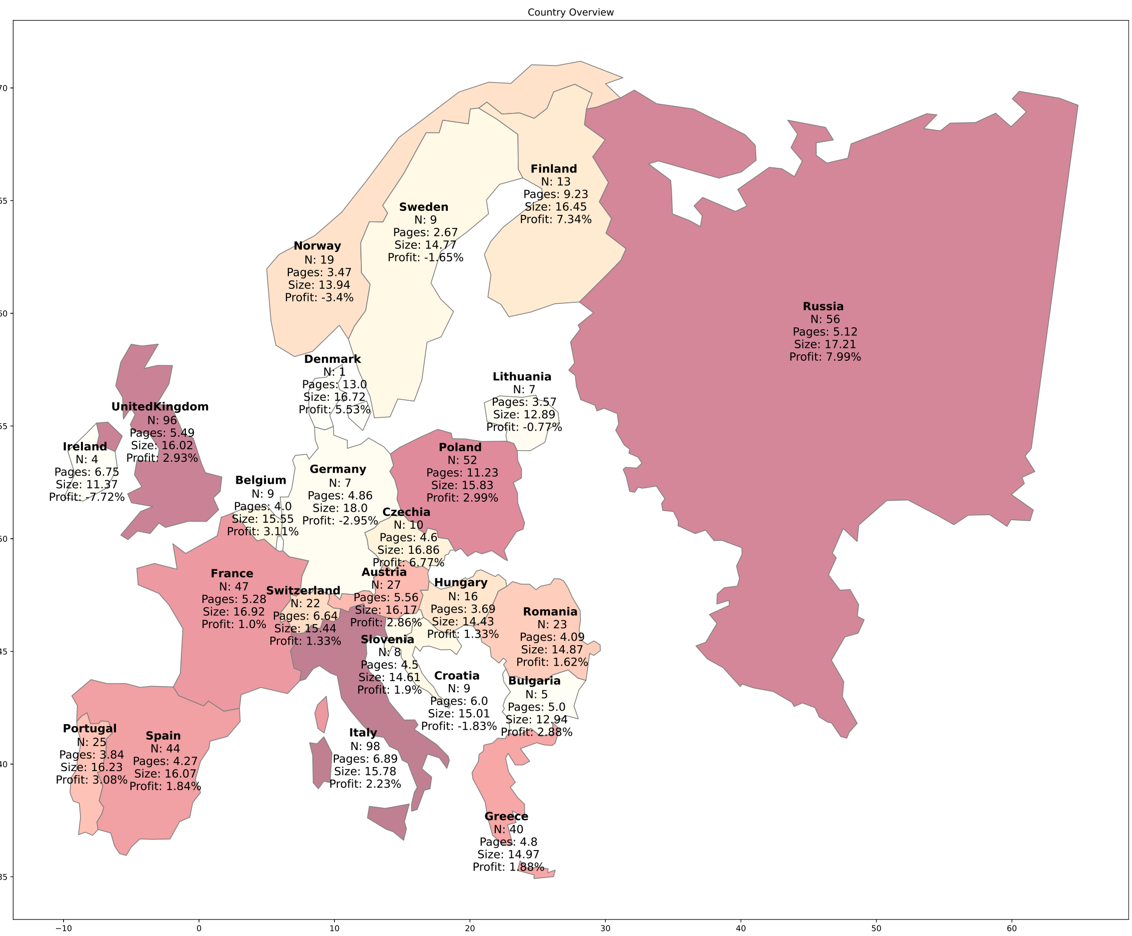

Figure 1: Overview of countries in the sample with number of firms per country and mean statistics of annual pages of risk disclosure, log firm size and profit (Return on Assets in percentages). Color shades of red indicates the number of firms per country in the sample.

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 Figure 2, we show the distribution of the topics per report over time. While the average number of pages increases over time from 4.5 to 6.5, the share of topics remain almost constant.

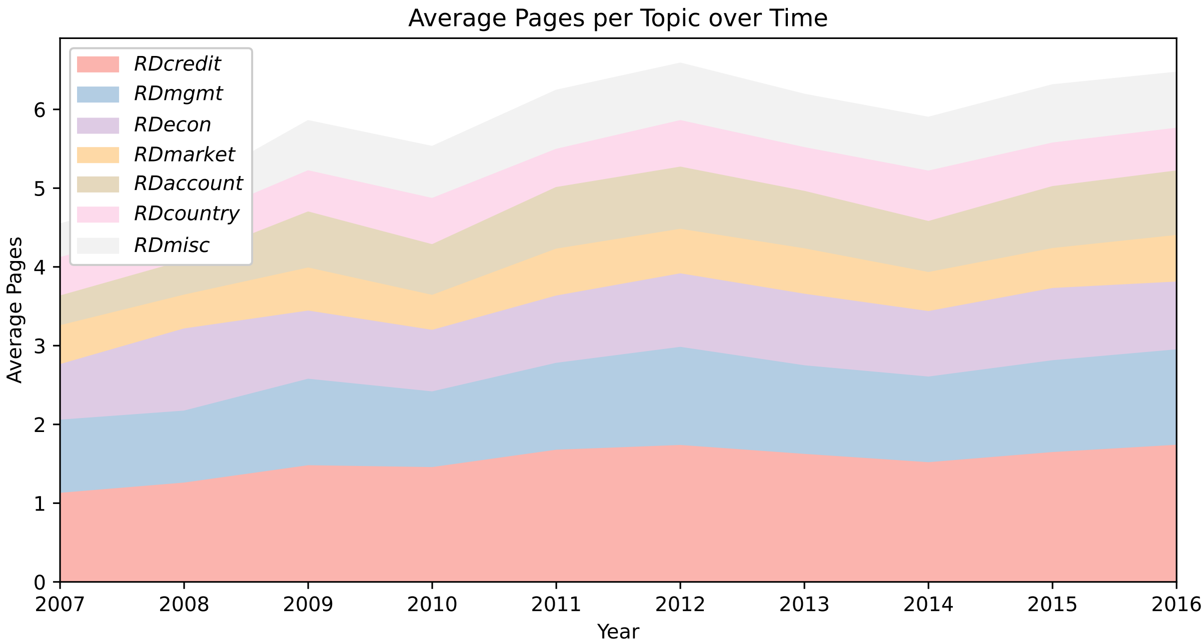

Figure 2: Average pages per topic over time.

Turning to the correlations between the variables (Table 6), we find most of the explanatory variables to be statistically significantly correlated with the volatility measures. There is some dependence between the 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 which includes all individual risk categories, in order to avoid multicollinearity. Multicollinearity would impact the coefficients of our variables of interests, and thereby interfere with our hypothesis tests. However, we use the aggregated risk disclosure measure *RD* instead, which allows us to infer the overall risk disclosure effect at the cost of not being able to identify individual risk category effects 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 issues.

	Mean	Std.Dev.	5-perc.	Median	95-perc.
Dependent Variables					
Vol^T	3.4394	0.4482	2.7541	3.3965	4.1990
Vol^S	2.4501	0.6918	1.2133	2.4985	3.5014
Vol^I	3.3060	0.4672	2.6293	3.2585	4.0820
$Firmval$	8.0788	1.8132	4.9929	7.9661	11.1072
Risk Disclosure Measure					
RD	5.9585	3.7509	1.0000	5.0000	14.0000
$RDmgmt$	1.1026	1.0176	0.1561	0.7773	3.3159
$RDcredit$	1.5429	1.0162	0.2859	1.3763	3.4733
$RDmarket$	0.5311	0.6713	0.0184	0.2840	1.8323
$RDcountry$	0.5505	0.9263	0.0317	0.1841	2.4094
$RDecon$	0.8727	1.0455	0.1106	0.6587	2.0429
$RDaccount$	0.6959	0.7084	0.0618	0.4476	2.1129
$RDmisc$	0.6628	1.3101	0.0246	0.3328	2.1530
Firm Controls					
$Readability$	22.3918	5.2899	16.9907	21.4080	32.7037
MTB	1.4334	1.5833	0.3151	1.0841	3.9720
$Growth$	0.0898	0.3630	-0.1429	0.0401	0.4181
$Size$	15.8282	1.7304	13.1962	15.7638	18.9553
Lev	0.5574	0.1854	0.2338	0.5732	0.8441
$Profit$	0.0267	0.0599	-0.0761	0.0282	0.1186
ESG	2.7693	1.8965	0.0000	3.9646	4.3849

Table 5: Descriptive statistics

	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	0.63^{***}	1																
Vol^I	0.96^{***}	0.43^{***}	1															
RD	-0.17^{***}	-0.13^{***}	-0.18^{***}	1														
$RDmarket$	-0.13^{***}	0.05	-0.21^{***}	0.55^{***}	1													
$RDcredit$	-0.18^{***}	-0.09^{**}	-0.21^{***}	0.78^{***}	0.58^{***}	1												
$RDmgmt$	-0.24^{***}	-0.16^{***}	-0.25^{***}	0.63^{***}	0.41^{***}	0.46^{***}	1											
$RDcountry$	0.14^{***}	0	0.18^{***}	0.26^{***}	-0.09^{**}	0.08^{**}	-0.06	1										
$RDecon$	-0.05	-0.01	-0.06	0.6^{***}	0.3^{***}	0.37^{***}	0.32^{***}	0	1									
$RDaccount$	-0.14^{***}	-0.23^{***}	-0.08^{**}	0.61^{***}	0.19^{***}	0.44^{***}	0.3^{***}	0.24^{***}	0.2^{***}	1								
$RDmisc$	-0.09^{**}	-0.07^{*}	-0.07^{*}	0.49^{***}	0.01	0.21^{***}	0.09^{**}	-0.05	0.12^{***}	0.21^{***}	1							
$Readability$	-0.04	0.01	-0.07^{*}	0.07^{*}	0.01	0.03	0.09^{**}	-0.01	0.06	-0.01	0.06^{*}	1						
MTB	-0.05	0.15^{***}	-0.11^{***}	0.00	0.04	-0.02	0.07^{*}	0.06^{*}	-0.03	-0.10^{***}	-0.03	0.04	1					
$Growth$	0.18^{***}	0.19^{***}	0.16^{***}	-0.07^{*}	-0.05	-0.03	-0.03	0.01	-0.04	-0.07^{*}	0.07^{*}	-0.08^{*}	0	1				
$Size$	-0.39^{***}	0.06	-0.51^{***}	0.2^{***}	0.32^{***}	0.22^{***}	0.24^{***}	-0.12^{***}	0.08^{**}	0.02	0.08^{**}	0.12^{***}	0.03	-0.06	1			
Lev	-0.17^{***}	0.05	-0.22^{***}	-0.04	0.13^{***}	-0.04	0.12^{***}	-0.2^{***}	0	-0.05	-0.07^{*}	0.09^{**}	0.07^{*}	-0.05	0.28^{***}	1		
$Profit$	-0.24^{***}	-0.09^{**}	-0.27^{***}	0.1^{**}	0.05	0.08^{**}	0.06	0.13^{***}	-0.02	0.02	0.05	-0.02	0.26^{***}	0.06	0.21^{***}	-0.25^{***}	1	
ESG	-0.21^{***}	0.15^{***}	-0.3^{***}	0.22^{***}	0.25^{***}	0.15^{***}	0.2^{***}	-0.01	0.13^{***}	0.07^{*}	0.1^{***}	0.11^{***}	0.19^{***}	-0.05	0.61^{***}	0.18^{***}	0.18^{***}	1

Table 6: Correlation (Pearson) between variables. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

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

In accordance with our hypotheses, we find support for H1 (Signalling Hypothesis) if β_1 is positive and significant for the corresponding risk disclosure category because this indicates that more disclosure regarding the analysed risk category is related to higher firm values. A negative and significant coefficient β_1 indicates support for H2 (Bad News Hypothesis), meaning a decrease of the firm value for companies providing more risk disclosure.

The results, presented in Table 7, show that total risk disclosure has a significantly negative relation with idiosyncratic volatility, but not with total or systematic volatility. This result is in line with H1, the signalling 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 reveal firm-specific risks to (potential) investors. If more general information (e.g., market development) would be derived from risk reporting, then systematic (or total) volatility become significant as well.

[11] We consider a time lag of one year between the dependent and independent variables to clearly place risk disclosure before the measurement of firm value, and avoid issues of reversed causality.

	Vol_t^T	Vol_t^S	Vol_t^I
RD_{t-1}	-0.0056	-0.0023	-0.0092
	(0.0038)	(0.0061)	(0.0036)**
$Readability_{t-1}$	-0.0004	-0.0052	0.0003
	(0.0018)	(0.0029)	(0.0018)
MTB_{t-1}	-0.0189	0.0189	-0.0278
	(0.0092)**	(0.0104)*	(0.0098)***
$Growth_{t-1}$	0.0833	0.1118	0.0836
	(0.0272)***	(0.0338)***	(0.0300)***
$Size_{t-1}$	-0.0657	0.0628	-0.1075
	(0.0140)***	(0.0182)***	(0.0137)***
Lev_{t-1}	0.0444	-0.3357	0.1623
	(0.0854)	(0.1222)***	(0.0843)*
$Profit_{t-1}$	-1.3213	-1.3868	-1.4027
	(0.2643)***	(0.3704)***	(0.2633)***
ESG_{t-1}	0.0136	0.0223	0.0147
	(0.0094)	(0.0155)	(0.0096)
Constant	3.5996	1.1466	3.9902
	(0.1888)***	(0.2579)***	(0.1880)***
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R^2_{adj}	0.61	0.61	0.65
F	23.60***	23.59***	27.70***
N	674	674	674

Table 7: Panel regression results for three measures of 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 4.26 across all three models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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

The significantly negative relation is reported for four risk categories (i.e., credit risk, risk management, economic risk, accounting risk), which supports the signalling hypothesis, H1. We also find that ”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. Overall, we find different results along the seven risk categories, which reveals that indeed not all risk categories are perceived homogeneously by investors.

Vol^I_t	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$RDmarket_{t-1}$	−0.0134						
	(0.0185)						
$RDcredit_{t-1}$		−0.0447					
		(0.0121)***					
$RDmgmt_{t-1}$			−0.0458				
			(0.0148)***				
$RDcountry_{t-1}$				0.0000			
				(0.0247)			
$RDecon_{t-1}$					−0.0141		
					(0.0081)*		
$RDaccount_{t-1}$						−0.0606	
						(0.0200)***	
$RDmisc_{t-1}$							0.0227
							(0.0082)***
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	27.33***	28.21***	27.94***	27.30***	27.39***	27.87***	27.50***
N	674	674	674	674	674	674	674

Table 8: Panel regression results 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 4.39 across all models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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

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

Our results presented in Table 9 do not show any indication of reverse causality. That means, the results indicate that for energy utilities risk reporting can neither be explained by the total volatility, the systematic volatility, nor the idiosyncratic volatility of its stock the year prior to the 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

RD_t	(1)	(2)	(3)
Vol^T_{t-1}	-0.1186		
	(0.4442)		
Vol^S_{t-1}		0.2019	
		(0.2871)	
Vol^I_{t-1}			-0.3400
			(0.4366)
$Readability_{t-1}$	-0.0058	-0.0054	-0.0074
	(0.0227)	(0.0227)	(0.0228)
MTB_{t-1}	0.2873	0.2886	0.2634
	(0.0988)***	(0.0975)***	(0.0926)***
$Growth_{t-1}$	0.3685	0.3761	0.3882
	(0.8854)	(0.8851)	(0.8995)
$Size_{t-1}$	0.3017	0.2873	0.2559
	(0.1553)*	(0.1481)*	(0.1611)
Lev_{t-1}	-1.3942	-1.3377	-1.3132
	(0.8853)	(0.8663)	(0.8924)
$Profit_{t-1}$	1.2249	1.3774	0.5768
	(2.2094)	(2.1555)	(2.2396)
ESG_{t-1}	0.2474	0.2385	0.2558
	(0.1066)**	(0.1077)**	(0.1066)***
Constant	3.7509	3.8001	6.1501
	(3.1415)	(2.2995)*	(3.2695)*
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	9.23***	9.25***	9.25***
N	610	610	610

Table 9: Panel regression results for three models with RD as dependent variable, fixed effects for country, industry, and year and robust standard errors. The largest VIF for variables of interest and control variables is 4.86 across all three models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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 of the firm valuation model is *Firmval*, and is measured as the natural logarithm of the market value of 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 year, industry, and country fixed effects. The firm valuation model takes the following form:

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

Table 10 presents the results. We set up 8 models, where we regress our measure for 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 firm value.

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 risk disclosure leads to lower idiosyncratic volatility and to higher firm valuations. Again, it is important to point to the fact 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 signalling hypothesis.

Turning to the specific risk disclosure models, we find positive and statistically significant coefficients for disclosure on Market Risk (coeff. 0.1547, $p < 0.01$), Credit Risk (0.0889, $p < 0.01$), Risk Management (0.0836, $p < 0.01$), and Economy-related Risk (0.0310, $p < 0.1$). Note that we do not find any negative coefficients for risk disclosure variables. Especially the disclosure of Market Risk has a high coefficient, translating to a 17% ($(\exp(0.1547 \cdot 1.0176) - 1)$ increase per unit of standard deviation (1.0176). We note that the average amount of disclosed Market Risk in our sample is about 1.10 pages, and 5% of the annual reports disclose more than 3.32 pages. Overall, the regressions yield very high adjusted R^2's, which is typical for firm value regressions (Barth & McNichols, 1994, Campbell et al., 2003).

$Firmval_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD_{t-1}	0.0255 (0.0063)***							
$RDmarket_{t-1}$		0.1547 (0.0380)***						
$RDcredit_{t-1}$			0.0889 (0.0204)***					
$RDmgmt_{t-1}$				0.0836 (0.0231)***				
$RDcountry_{t-1}$					0.0807 (0.0504)			
$RDecon_{t-1}$						0.0310 (0.0163)*		
$RDaccount_{t-1}$							0.0195 (0.03448)	
$RDmisc_{t-1}$								0.0060 (0.0196)
$Readability_{t-1}$	0.0013 (0.0036)	0.0040 (0.0038)	0.0016 (0.0037)	0.0009 (0.0036)	0.0006 (0.0035)	0.0008 (0.0036)	0.0008 (0.0035)	0.0009 (0.0035)
MTB_{t-1}	0.1124 (0.0448)**	0.1087 (0.0446)**	0.1134 (0.0445)**	0.1130 (0.0454)**	0.1159 (0.0457)**	0.1155 (0.0459)**	0.1166 (0.0462)**	0.1163 (0.0461)**
$Growth_{t-1}$	−0.1231 (0.0874)	−0.1065 (0.0861)	−0.1230 (0.0876)	−0.1247 (0.0885)	−0.1236 (0.0945)	−0.1135 (0.0934)	−0.1125 (0.0941)	−0.1105 (0.0943)
$Size_{t-1}$	0.8633 (0.0232)***	0.8507 (0.0241)***	0.8605 (0.0235)***	0.8695 (0.0230)***	0.8734 (0.0230)***	0.8715 (0.0229)***	0.8717 (0.0232)***	0.8703 (0.0232)***
Lev_{t-1}	−0.8619 (0.1934)***	−0.8921 (0.1913)***	−0.8313 (0.1944)***	−0.9309 (0.1914)***	−0.8310 (0.2045)***	−0.8967 (0.1950)***	−0.8827 (0.1959)***	−0.8785 (0.1976)***
$Profit_{t-1}$	3.0981 (0.4923)***	3.0994 (0.4875)***	3.0672 (0.4908)***	3.0733 (0.4908)***	3.0564 (0.4978)***	3.1016 (0.4962)***	3.0808 (0.4952)***	3.0685 (0.4949)***
ESG_{t-1}	0.0855 (0.0169)***	0.0853 (0.0170)***	0.0915 (0.0172)***	0.0840 (0.0173)***	0.0912 (0.0169)***	0.0912 (0.0173)***	0.0907 (0.0177)***	0.0925 (0.0174)***
Vol^T_{t-1}	−0.3170 (0.0956)***	−0.3388 (0.0956)***	−0.3135 (0.0947)***	−0.3097 (0.0952)***	−0.3252 (0.0976)***	−0.3225 (0.0969)***	−0.3241 (0.0974)***	−0.3285 (0.0978)***
Constant	−4.3108 (0.4904)***	−4.0338 (0.5105)***	−4.3613 (0.4857)***	−4.3424 (0.4904)***	−4.4142 (0.4970)***	−4.3844 (0.4945)***	−4.3792 (0.5001)***	−4.3492 (0.5028)***
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	163.42***	164.36***	164.17***	162.21***	160.45***	159.96***	159.49***	159.43***
N	668	668	668	668	668	668	668	668

Table 10: Panel regression results for firm value with fixed effects for country, industry, and year and robust standards errors. The largest VIF for variables of interest and control variables is 4.57 across all models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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

5.3. Robustness Tests

We carried out some further tests to assure robustness of our results against alternative research design decisions. First, companies might behave differently during years in which they report negative earnings (i.e., loss years). Also investors might react differently to the rather negative content of risk disclosure during loss years. Therefore, we added a dummy variable, which equals one for firm-years with negative income and is zero otherwise. We also interacted the loss-variable with the risk disclosure variables. The results are provided in Table A.3. We find qualitatively very similar results as reported in our main analyses for 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-years investor are more uncertain about the future prospects of a firm. The interaction of loss and risk disclosure does not attain significance for total risk disclosure or any risk disclosure category, which further shows that the relation 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, which does not considerably vary 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 results for H1 are still supported, meaning that total risk disclosure is still significantly and negatively related to idiosyncratic volatility.

Third, most of the variables in our models build on logarithmic values or, in the case of the ESG score, only occur 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 applied winsorizing at the lowest and highest percentile. In robustness tests, we also analyze models, where all variables and where no variables were winsorized. The results are provided in Table A.5 in Panel 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 signalling hypothesis of risk disclosure due to a significantly negative relation between risk disclosure and idiosyncratic volatility and a significantly positive relation between risk disclosure and firm value. More detailed analyses show that the relations are not observable for all risk categories, but they are observable for total risk disclosure and the majority of risk categories. In additional analyses, we ruled out that reverse causality drives our results—meaning that firm's lower or higher volatility are 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 after all 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 regulation and might aim to further increase the specificity of such disclosures. Companies should take our findings as an encouragement to voluntarily disclose more information regarding their risk exposure and management.
2. On another note, we are quite surprised that even in the light of the Paris Agreement on Climate Change, the probably most influenced and influencing industry in this regard is not reporting on climate change related risk at a detectable level. We can neither 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 evidences that all the stakeholders are bearing great risks. 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 & Sakhel (2019) show that some forms of climate related risk disclosure are associated with lower information asymmetry. While the awareness of climate-related risk for energy utilities appears to be increasing, it is still not spread over all of Europe.[12] Of course, an increasing 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 & Krzus, 2018). This means that

[12] 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/).

policy makers are interested in companies' disclosures of climate-related risks, in order to assess the industry's vulnerability to climate change. While firms may choose to report their exposure in their voluntary sustainability reports, it appears that the energy companies perceived the financial implications of climate-related risks to be rather low—at least until 2017, the end of our sample period.[13]

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). While this allows the analysis of many reports and a thematic interpretation of risk disclosure, we do not aim to analyse further aspects of such disclosures (e.g. quantitative vs. qualitative disclosure, use of boilerplate statements, or the tone of the statements). Therefore, our results are only applicable to the extensiveness of the risk disclosure. If other aspects of risk disclosure are of interest, other methods must be employed.[14]

Our study contributes to the literature by its focus on risk disclosure, as one building stone of corporate governance. Thereby, we not only support the findings of Srivastava & Kathuria (2020), who show that high quality corporate governance systems are related to better firm performance. We also extend Srivastava & Kathuria (2020) through our focus

[13] 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).

[14] 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 insights 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.

on risk disclosure and its perception on the capital market. Furthermore, we complement literature on risk management in the energy sector (e.g., Kim & Choi, 2019, Nguyen et al., 2021, Sadorsky, 2001) by focusing on the consequences of companies' actual reporting behavior. More specifically, we contribute to the literature focusing on the usefulness of risk disclosure. While the literature reports some critical issues connected to risk disclosure, such as an indication of more boilerplate disclosures (Kravet & Muslu, 2013), higher audit fees related to more extensive risk disclosure (Yang et al., 2018), or negative short-term market reactions to considerable increases of a company's risk disclosure (Campbell et al., 2014), we find support for risk disclosures' being useful for (potential) investors and being generally regarded as a signal of a high quality of company's risk management—at least in the energy sector.

It remains for future research to examine whether the increasing focus on sustainablity 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.

References

Abraham, S., & Cox, P. (2007). Analysing the determinants of narrative risk information in UK FTSE 100 annual reports. *British Accounting Review*, *39*, 227–248. doi: 10.1016/j.bar.2007.06.002.

Amran, A., Bin, A. M. R., & Hassan, B. C. H. M. (2009). Risk reporting: An exploratory study on risk management disclosure in Malaysian annual reports. *Managerial Auditing Journal*, *24*, 39–57. doi: 10.1108/02686900910919893.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics*, *131*, 1593–1636. doi: 10.1093/qje/qjw024.

Bao, Y., & Datta, A. (2014). Simultaneously Discovering and Quantifying Risk Types from Textual Risk Disclosures. *Management Science*, *60*, 1371–1391. doi: 10.1287/mnsc.2014.1930.

Barakat, A., & Hussainey, K. (2013). Bank governance, regulation, supervision, and risk reporting: Evidence from operational risk disclosures in European banks. *International Review of Financial Analysis*, *30*, 254–273. doi: 10.1016/j.irfa.2013.07.002.

Barth, M. E., & McNichols, M. F. (1994). Estimation and market valuation of environmental liabilities relating to superfund sites. *Journal of Accounting Research*, *32*, 177–209. doi: 10.2307/2491446.

Bekaert, G., Hodrick, R. J., & Zhang, X. (2012). Aggregate idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, *47*, 1155–1185. doi: 10.1017/S0022109012000543.

Benlemlih, M., Shaukat, A., Qiu, Y., & Trojanowski, G. (2018). Environmental and Social Disclosures and Firm Risk. *Journal of Business Ethics*, *152*, 613–626. doi: 10.1007/s10551-016-3285-5.

Beretta, S., & Bozzolan, S. (2004). A framework for the analysis of firm risk communication. *The International Journal of Accounting*, *39*, 265–288. doi: 10.1016/j.intacc.2004.06.006.

Berkman, H., Jona, J., & Soderstrom, N. S. (2021). Firm-specific climate risk and market valuation. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2775552.

Blei, D. M. (2012). Probabilistic Topic Models. *Communications of the ACM*, *55*, 70–84. doi: 10.1145/2133806.2133826.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Boussanni, A., Desrochers, J., & Préfontaine, J. (2011). Liquidity Risk Financial Disclosure: The Case Of Large European Financial Groups. *International Business & Economics Research Journal (IBER)*, *7*, 47–56. doi: 10.19030/iber.v7i7.3269.

Breitenstein, M., Anke, C.-P., Nguyen, D. K., & Walther, T. (2022). Stranded Asset Risk and Political Uncertainty: The Impact of the Coal Phase-out on the German Coal Industry. *The Energy Journal*, *43*. doi: 10.5547/01956574.43.5.mbre.

Brown, N. C., Crowley, R. M., & Elliott, W. B. (2019). What are You Saying? Using Topic to Detect Financial Misreporting. URL: https://ssrn.com/abstract=2803733. doi: 10.2139/ssrn.2803733.

Brown, S. V., (Shaolee) Tian, X., & Wu Tucker, J. (2018). The Spillover Effect of SEC Comment Letters on Qualitative Corporate Disclosure: Evidence from the Risk Factor Disclosure. *Contemporary Accounting Research*, *35*, 622–656. doi: 10.1111/1911-3846.12414.

Bybee, L., Kelly, B. T., Manela, A., & Xiu, D. (2021). Business News and Business Cycles. *SSRN Electronic Journal*, . doi: 10.2139/ssrn.3940030.

Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H. m., & Steele, L. B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, *19*, 396–455. doi: 10.1007/s11142-013-9258-3.

Campbell, K., Sefcik, S. E., & Soderstrom, N. S. (2003). Disclosure of private information and reduction of uncertainty: environmental liabilities in the chemical industry. *Review of Quantitative Finance and Accounting*, *21*, 349–378. doi: 10.1023/B:REQU.0000004783.24513.ea.

Chalmers, K., & Godfrey, J. (2004). Reputation costs: The impetus for voluntary derivative financial instrument reporting. *Accounting, Organizations and Society*, *29*, 95–125. doi: 10.1016/S0361-3682(02)00034-X.

Chuang, J., Manning, C. D., & Heer, J. (2012). Termite: Visualization techniques for assessing textual topic models. In *Proceedings of the international working conference on advanced visual interfaces* (pp. 74–77). doi: 10.1145/2254556.2254572.

Cooke, T. E. (1989). Voluntary corporate disclosure by Swedish companies. *Journal of International Financial Management & Accounting*, *1*, 171–195. doi: 10.1111/j.1467-646X.1989.tb00009.x.

Deumes, R. (2008). Corporate Risk Reporting: A Content Analysis of Narrative Risk Disclosures in Prospectuses. *Journal of Business Communication*, *45*, 120–157. doi: 10.1177/0021943607313992.

Dobler, M. (2008). Incentives for risk reporting — A discretionary disclosure and cheap talk approach. *The International Journal of Accounting*, *43*, 184–206. doi: 10.1016/j.intacc.2008.04.005.

Dobler, M., Lajili, K., & Zéghal, D. (2011). Attributes of Corporate Risk Disclosure: An International Investigation in the Manufacturing Sector. *Journal of International Accounting Research*, *10*, 1–22. doi: 10.2308/jiar-10081.

Dobler, M., Lajili, K., & Zéghal, D. (2014). Environmental Performance, Environmental Risk and Risk Management. *Business Strategy and the Environment*, *23*, 1–17. doi: 10.1002/bse.1754.

Dyer, T., Lang, M., & Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, *64*, 221–245. doi: https://doi.org/10.1016/j.jacceco.2017.07.002.

Eccles, R. G., & Krzus, M. (2018). Why Companies Should Report Financial Risks from Climate Change. *MITSloan Management Review*, *59*.

Elshandidy, T., Fraser, I., & Hussainey, K. (2013). Aggregated, voluntary, and mandatory risk disclosure incentives: Evidence from UK FTSE all-share companies. *International Review of Financial Analysis*, *30*, 320–333. doi: 10.1016/j.irfa.2013.07.010.

Elshandidy, T., Fraser, I., & Hussainey, K. (2015). What drives mandatory and voluntary risk reporting variations across Germany, UK and US? *British Accounting Review*, *47*, 376–394. doi: 10.1016/j.bar.2014.06.001.

Elshandidy, T., & Shrives, P. J. (2016). Environmental Incentives for and Usefulness of Textual Risk Reporting: Evidence from Germany. *International Journal of Accounting*, *51*, 464–486. doi: 10.1016/j.intacc.2016.10.001.

Elshandidy, T., Shrives, P. J., Bamber, M., & Abraham, S. (2018). Risk reporting: A review of the literature and implications for future research. *Journal of Accounting Literature*, *40*, 54–82. doi: 10.1016/j.acclit.2017.12.001.

Elzahar, H., & Hussainey, K. (2012). Determinants of narrative risk disclosures in UK interim reports. *The Journal of Risk Finance*, *13*, 133–147. doi: 10.1108/15265941211203189.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, *51*, 55–84. doi: 10.1111/j.1540-6261.1996.tb05202.x.

Filzen, J. J. (2015). The information content of risk factor disclosures in quarterly reports. *Accounting Horizons*, *29*, 887–916. doi: 10.2308/acch-51175.

Finon, D., & Locatelli, C. (2008). Russian and European gas interdependence: Could contractual trade channel geopolitics? *Energy Policy*, *36*, 423–442. doi: 10.1016/j.enpol.2007.08.038.

Frankel, R., Jennings, J., & Lee, J. (2022). Disclosure sentiment: machine learning vs. dictionary methods. *Management Science*, *68*, 5514–5532.

Friederich, D., Kaack, L. H., Luccioni, A., & Steffen, B. (2021). Automated Identification of Climate Risk Disclosures in Annual Corporate Reports. URL: https://arxiv.org/abs/2108.01415.

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

Griffiths, T. L., Jordan, M. I., Tennebaum, J. B., & Blei, D. M. (2004). Hierarchical Topic Models and the Nested Chinese Restaurant Process David. *Advances in Neural Information Processing Systems*, *16*, 106.

Hannigan, T. R., Haans, R. F., Vakili, K., Tchalian, H., Glaser, V. L., Wang, M. S., Kaplan, S., & Jennings, P. D. (2019). Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals*, *13*, 586–632.

Hansen, S., McMahon, M., & Prat, A. (2018). Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach. *The Quarterly Journal of Economics*, *133*, 801–870. doi: 10.1093/qje/qjx045.

Hassan, M. K. (2009). UAE corporations-specific characteristics and level of risk disclosure. *Managerial Auditing Journal*, *24*, 668–687. doi: 10.1108/02686900910975378.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*, 405–440. doi: 10.1016/S0165-4101(01)00018-0.

Hope, O.-K., Hu, D., & Lu, H. (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies*, *21*, 1005–1045. doi: 10.1007/s11142-016-9371-1.

Huang, A. H., Lehavy, A. Y., & Zang, R. Z. (2017). Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. *Management Science*, *64*, 1–23. doi: https://doi.org/10.1287/mnsc.2017.2751.

Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, *49*, 633–656. doi: 10.1057/s41267-017-0125-5.

Jones, M., Melis, A., Gaia, S., & Aresu, S. (2018). Does graphical reporting improve risk disclosure? Evidence from European banks. *Journal of Applied Accounting Research*, *19*, 161–180. doi: 10.1108/JAAR-07-2016-0068.

Kim, H., & Yasuda, Y. (2018). Business risk disclosure and firm risk: Evidence from Japan. *Research in International Business and Finance*, *45*, 413–426. doi: 10.1016/j.ribaf.2017.07.172.

Kim, S. T., & Choi, B. (2019). Price risk management and capital structure of oil and gas project companies: Difference between upstream and downstream industries. *Energy Economics*, *83*, 361–374. doi: 10.1016/j.eneco.2019.07.008.

Kölbel, J. F., Leippold, M., Rillaerts, J., & Wang, Q. (2022). Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks Affects the CDS Term Structure. *Journal of Financial Econometrics*, . doi: 10.1093/jjfinec/nbac027.

Kothari, S. P., Li, X., & Short, J. E. (2009). The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *Accounting Review*, *84*, 1639–1670. doi: 10.2308/accr.2009.84.5.1639.

Kravet, T., & Muslu, V. (2013). Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies*, *18*, 1088–1122. doi: 10.1007/s11142-013-9228-9.

Lajili, K., Dobler, M., & Zéghal, D. (2012). An Empirical Investigation of Business and Operational Risk Disclosures. *The International Journal of Management and Business*, *3*, 53–71.

Lajili, K., & Zéghal, D. (2005). A Content Analysis of Risk Management Disclosures in Canadian Annual Reports. *Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de l'Administration*, *22*, 125–142. doi: 10.1111/j.1936-4490.2005.tb00714.x.

Leuz, C., & Wysocki, P. D. (2016). The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, *54*, 525–622. doi: 10.1111/1475-679X.12115.

Lin, C., Schmid, T., & Weisbach, M. S. (2020). Product Price Risk and Liquidity Management: Evidence from the Electricity Industry. *Management Science*, . doi: 10.1287/mnsc.2020.3579.

Linsley, P. M., & Shrives, P. J. (2005). Examining risk reporting in UK public companies. *The Journal of Risk Finance*, *6*, 292–305. doi: 10.1108/15265940510613633.

Linsley, P. M., & Shrives, P. J. (2006). Risk reporting: A study of risk disclosures in the annual reports of UK companies. *The British Accounting Review*, *38*, 387–404. doi: 10.1016/j.bar.2006.05.002.

Linsley, P. M., Shrives, P. J., & Crumpton, M. (2006). Risk disclosure: An exploratory study of UK and Canadian banks. *Journal of Banking Regulation*, *7*, 268–282. doi: 10.1057/palgrave.jbr.2350032.

Lopes, P. T., & Rodrigues, L. L. (2007). Accounting for financial instruments: An analysis of the determinants of disclosure in the Portuguese stock exchange. *International Journal of Accounting*, *42*, 25–56. doi: 10.1016/j.intacc.2006.12.002.

Loughran, T., & McDonald, B. (2020). Textual analysis in finance. *Annual Review of Financial Economics*, *12*, 357–375.

Lyocsa, S., & Todorova, N. (2021). What drives volatility of the U.S. oil and gas firms? *Energy Economics*, *100*, 105367. doi: 10.1016/j.eneco.2021.105367.

Marston, C. L., & Shrives, P. J. (1991). The use of disclosure indices in accounting research: A review article. *The British Accounting Review*, *23*, 195–210. doi: 10.1016/0890-8389(91)90080-L.

Miihkinen, A. (2012). What Drives Quality of Firm Risk Disclosure? *The International Journal of Accounting*, *47*, 437–468. doi: 10.1016/j.intacc.2012.10.005.

Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing* (pp. 262–272). Edinburgh, Scotland, UK.: Association for Computational Linguistics. URL: https://www.aclweb.org/anthology/D11-1024.

Mohanty, S. K., & Nandha, M. (2011). Oil risk exposure: The case of the U.S. oil and gas sector. *Financial Review*, *46*, 165–191. doi: 10.1111/j.1540-6288.2010.00295.x.

Mokhtar, E. S., & Mellett, H. (2013). Competition, corporate governance, ownership structure and risk reporting. *Managerial Auditing Journal*, *28*, 838–865. doi: 10.1108/MAJ-11-2012-0776.

Nagel, D. Y., Fuhrmann, S., Tietmeyer, R., & Guenther, T. W. (2021). The perception of risk disclosure characteristics on the credit default swap market-an automated analysisrisk disclosure characteristics. *Accounting Horizons*, . doi: 10.2308/HORIZONS-19-058.

Nelson, M. W., & Rupar, K. K. (2015). Numerical formats within risk disclosures and the moderating effect of investors' concerns about management discretion. *Accounting Review*, *90*, 1149–1168. doi: 10.2308/accr-50916.

Ng, J., Verrecchia, R. E., & Weber, J. (2009). Firm performance measures and adverse selection. doi: 10.2139/ssrn.1324874.

Nguyen, Q., Diaz-Rainey, I., & Kuruppuarachchi, D. (2021). Predicting corporate carbon footprints for climate finance risk analyses: A machine learning approach. *Energy Economics*, *95*, 105129. doi: 10.1016/j.eneco.2021.105129.

Oliveira, J., Rodrigues, L. L., & Craig, R. (2011a). Risk-related disclosure practices in the annual reports of Portuguese credit institutions: An exploratory study. *Journal of Banking Regulation*, *12*, 100–118. doi: 10.1057/jbr.2010.20.

Oliveira, J., Rodrigues, L. L., & Craig, R. (2011b). Risk-related disclosures by non-finance companies: Portuguese practices and disclosure characteristics. *Managerial Auditing Journal*, *26*, 817–839. doi: 10.1108/02686901111171466.

Oliveira, J., Rodrigues, L. L., & Craig, R. (2011c). Voluntary risk reporting to enhance institutional and organizational legitimacy: Evidence from Portuguese banks. *Journal of Financial Regulation and Compliance*, *19*, 271–289. doi: 10.1108/13581981111147892.

Pérez-González, F., & Yun, H. (2013). Risk Management and Firm Value: Evidence from Weather Derivatives. *The Journal of Finance*, *68*, 2143–2176. doi: 10.1111/jofi.12061.

Polyzos, E., & Wang, F. (2022). Twitter and market efficiency in energy markets: Evidence using LDA clustered topic extraction. *Energy Economics*, *114*, 106264. doi: 10.1016/j.eneco.2022.106264.

Rajab, B., & Schachler, M. H. (2009). Corporate risk disclosure by UK firms: trends and determinants. doi: 10.1504/WREMSD.2009.026801.

Rajgopal, S. (1999). Early evidence on the informativeness of the SEC's market risk disclosures: The case of commodity price risk exposure of oil and gas producers. *Accounting Review*, *74*, 251–280. doi: 10.2308/accr.1999.74.3.251.

Sadorsky, P. (2001). Risk factors in stock returns of canadian oil and gas companies. *Energy Economics*, *23*, 17–28. doi: 10.1016/S0140-9883(00)00072-4.

Sadorsky, P. (2012). Modeling renewable energy company risk. *Energy Policy*, *40*, 39–48. doi: 10.1016/j.enpol.2010.06.064.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2021). Pricing Climate Change Exposure. *SSRN Electronic Journal*, . doi: 10.2139/ssrn.3792366.

Schiemann, F., & Sakhel, A. (2019). Carbon disclosure, contextual factors, and information asymmetry: The case of physical risk reporting. *European Accounting Review*, *28*, 791–818. doi: 10.1080/09638180.2018.1534600.

Sievert, C., & Shirley, K. (2014). Ldavis: A method for visualizing and interpreting topics. In *Proceedings of the workshop on interactive language learning, visualization, and interfaces* (pp. 63–70). doi: 10.3115/v1/W14-3110.

Srivastava, G., & Kathuria, V. (2020). Impact of corporate governance norms on the performance of indian utilities. *Energy Policy*, *140*, 111414. doi: 10.1016/j.enpol.2020.111414.

Srnka, K. J., & Koeszegi, S. T. (2007). From Words to Numbers: How to Transform Qualitative Data into Meaningful Quantitative Results. *Schmalenbach Business Review*, *59*, 29–57. doi: 10.1007/BF03396741.

Tulloch, D. J., Diaz-Rainey, I., & Premachandra, I. (2017). The Impact of Liberalization and Environmental Policy on the Financial Returns of European Energy Utilities. *The Energy Journal*, *38*, 77–106. doi: 10.5547/01956574.38.2.dtul.

Wei, L., Li, G., Zhu, X., & Li, J. (2019a). Discovering bank risk factors from financial statements based on a new semi-supervised text mining algorithm. *Accounting & Finance*, *59*, 1519–1552.

Wei, L., Li, G., Zhu, X., Sun, X., & Li, J. (2019b). Developing a hierarchical system for energy corporate risk factors based on textual risk disclosures. *Energy Economics*, *80*, 452–460. doi: 10.1016/j.eneco.2019.01.020.

Wei, S. X., & Zhang, C. (2006). Why did individual stocks become more volatile? *Journal of Business*, *79*, 259–292. doi: 10.1086/497411.

Xu, Y., & Malkiel, B. G. (2003). Investigating the Behavior of Idiosyncratic Volatility. *Journal of Business*, *76*, 613–644. doi: 10.1086/377033.

Yang, R., Yu, Y., Liu, M., & Wu, K. (2018). Corporate Risk Disclosure and Audit Fee: A Text Mining Approach. *European Accounting Review*, *27*, 583–594. doi: 10.1080/09638180.2017.1329660.

Ye, J., & Xue, M. (2021). Influences of sentiment from news articles on EU carbon prices. *Energy Economics*, *101*, 105393. doi: 10.1016/j.eneco.2021.105393.

Zhang, H. G., CAO, T., Li, H., & Xu, T. (2021). Dynamic measurement of news-driven information friction in China's carbon market: Theory and evidence. *Energy Economics*, *95*, 104994. doi: 10.1016/j.eneco.2020.104994.

A. Appendix

A.1. Feature Selection

To reduce the vocabulary, we rank 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 based on tf-idf. We use the 5000 most informative words to obtain the vocabulary for our topic model.

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

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

The LDA assumes the following generative process for a document $w = (w1, \ldots, wN)$ of a corpus D containing N words from a vocabulary consisting of V different terms, $w_i \in \{1, \ldots, V\} \quad \forall i = 1, \ldots, N$. 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 for 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 the terms in a topic contains the probability that each word occurs in the given topic.

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

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

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 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 summation over this index is performed. d_i indicates the document in the corpus to which w_i belongs. In the Bayesian model formulation, 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 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 $j = 1, \ldots, V$ and $d = 1, \ldots, D$.

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	interst_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

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

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 the subjective assignment of a label to each of the 30 topics, we pooled the topics into 6 categories, namely Market Risk, Credit Risk, Risk Management, Country Risk, Economic Risk, and Accounting Risk. Topics for which we could not find appropriate labels are grouped into Other Risks. The pooling of topics into categories may lead to some generalization of specific risks, e.g. Economic Risk includes the risk of a change in interest rates (as displayed 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

To not only use subjective judgement 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 models from $K = 10$ to $K = 60$ in steps of 5. The coherence score was found to be highest (and therefore best) with $K = 10$.

The number of topics strongly differs from the model used in the main analysis, being more coarse-grained. We interpreted the topics and linked these to the topics of the main analysis.

A.5. Data Heatmap

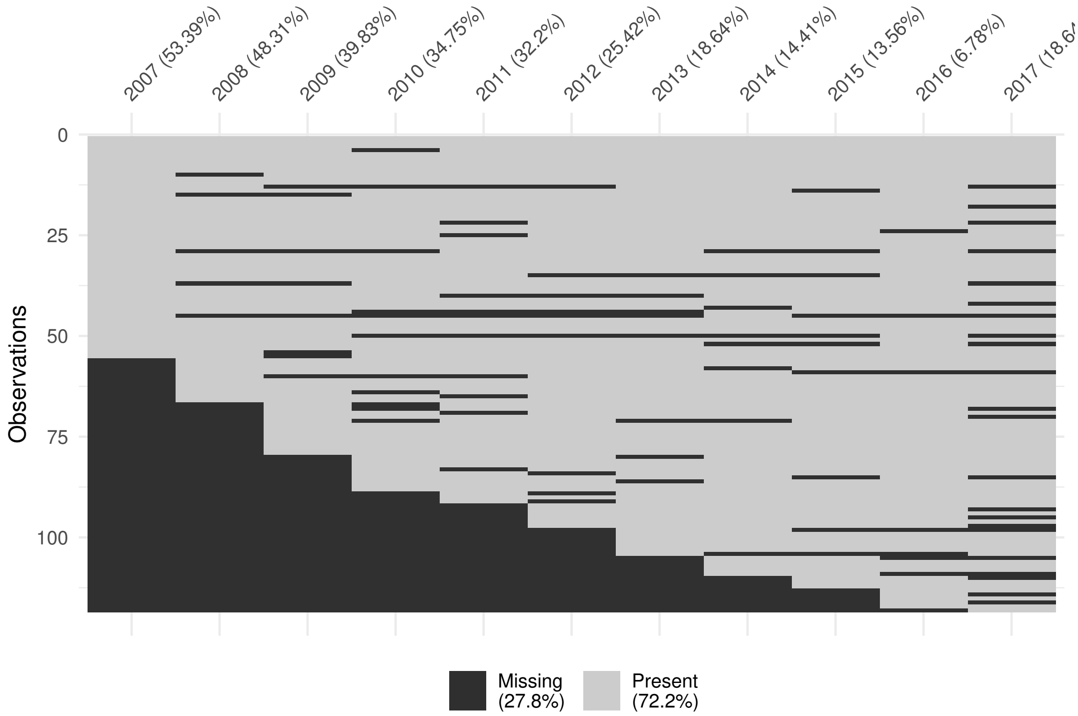

Figure A.3: Data Heatmap - Data availability of risk disclosures across the sample period

Vol_t^I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD_{t-1}	−0.0092							
	(0.0038)**							
RD_{t-1} * Loss	−0.0049							
	(0.0076)							
$RDmarket_{t-1}$		−0.0129						
		(0.0190)						
$RDmarket_{t-1}$ * Loss		−0.0196						
		(0.0448)						
$RDcredit_{t-1}$			−0.0428					
			(0.0135)***					
$RDcredit_{t-1}$ * Loss			−0.0203					
			(0.0252)					
$RDmgmt_{t-1}$				−0.0458				
				(0.0151)***				
$RDmgmt_{t-1}$ * Loss				0.0019				
				(0.0414)				
$RDcountry_{t-1}$					−0.0073			
					(0.0243)			
$RDcountry_{t-1}$ * Loss					0.0278			
					(0.0587)			
$RDecon_{t-1}$						−0.0104		
						(0.0128)		
$RDecon_{t-1}$ * Loss						−0.0108		
						(0.0161)		
$RDaccount_{t-1}$							−0.0749	
							(0.0231)***	
$RDaccount_{t-1}$ * Loss							0.0448	
							(0.0347)	
$Rdmisc_{t-1}$								0.0204
								(0.0084)**
$Rdmisc_{t-1}$ * Loss								0.0236
								(0.0260)
Loss	0.1406	0.1178	0.1456	0.1009	0.0922	0.1168	0.0761	0.0863
	(0.0688)**	(0.0539)**	(0.0605)**	(0.0645)	(0.0533)*	(0.0488)**	(0.0525)	(0.0477)*
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}	0.65	0.65	0.66	0.66	0.65	0.65	0.66	0.65
F	26.93***	26.52***	27.45***	27.09***	26.49***	26.58***	27.14***	26.66***
N	674	674	674	674	674	674	674	674

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 6.11 across all models (for *Loss*). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

	Vol_t^T	Vol_t^S	Vol_t^I
RD_{t-1}	-0.0046	-0.0018	-0.0083
	(0.0034)	(0.0059)	(0.0032)**
Vol_{t-1}^T	0.4015	0.4406	0.4200
	(0.0440)***	(0.0626)***	(0.0412)***
$Readability_{t-1}$	0.0002	-0.0047	0.0010
	(0.0017)	(0.0029)	(0.0016)
MTB_{t-1}	-0.0013	0.0377	-0.0092
	(0.0082)	(0.0120)***	(0.0077)
$Growth_{t-1}$	0.0737	0.1317	0.0708
	(0.0467)	(0.0762)*	(0.0410)*
$Size_{t-1}$	-0.0359	0.0971	-0.0766
	(0.0123)***	(0.0174)***	(0.0121)***
Lev_{t-1}	0.0130	-0.3647	0.1300
	(0.0733)	(0.1170)***	(0.0705)
$Profit_{t-1}$	-0.7996	-0.8437	-0.8522
	(0.2463)***	(0.3547)**	(0.2434)***
ESG_{t-1}	0.0044	0.0111	0.0051
	(0.0093)	(0.0155)	(0.0094)
Constant	2.1643	-0.4556	2.4923
	(0.2285)***	(0.3478)	(0.2246)***
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R^2_{adj}	0.66	0.64	0.70
F	28.15***	25.81***	33.82***
N	666	666	666

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 4.36 across all models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Vol_t^I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All variables winsorized								
RD_{t-1}	−0.0092 (0.0037)**							
$RDmarket_{t-1}$		−0.0062 (0.0195)						
$RDcredit_{t-1}$			−0.0431 (0.0120)***					
$RDmgmt_{t-1}$				−0.0413 (0.0152)***				
$RDcountry_{t-1}$					0.0017 (0.0263)			
$RDecon_{t-1}$						−0.0244 (0.0149)		
$RDaccount_{t-1}$							−0.0753 (0.0209)***	
$RDmisc_{t-1}$								0.0252 (0.0102)**
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	0.65	0.64
F	26.98***	26.62***	27.43***	27.08***	26.61***	26.74***	27.36***	26.80***
N	674	674	674	674	674	674	674	674
Panel B: No variables winsorized								
RD_{t-1}	−0.0091 (0.0036)**							
$RDmarket_{t-1}$		−0.0134 (0.0186)						
$RDcredit_{t-1}$			−0.0443 (0.0121)***					
$RDmgmt_{t-1}$				−0.0462 (0.0148)***				
$RDcountry_{t-1}$					0.0011 (0.0248)			
$RDecon_{t-1}$						−0.0131 (0.0080)		
$RDaccount_{t-1}$							−0.0598 (0.0200)***	
$RDmisc_{t-1}$								0.0223 (0.0082)***
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}	0.65	0.64	0.65	0.65	0.64	0.64	0.65	0.65
F	27.30***	26.95***	27.81***	27.57***	26.93***	27.00***	27.47***	27.11***
N	674	674	674	674	674	674	674	674

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 4.48 across all models (for $Size_{t-1}$). Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$