Journal of Corporate Finance 98 (2026) 102973

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Corporate agility and monetary policy transmission☆

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ARTICLE INFO

Editor: K Hankins

JEL code:
C80
E52
E58
G01
G32
O16

Keywords:
Corporate agility
Machine learning
Monetary policy
Uncertainty
word2vec

ABSTRACT

Corporate agility – the ability to respond quickly and effectively to changing business conditions – is crucial for firms' success. While important, this concept is difficult to measure and use in quantitative research. By applying machine learning techniques, we develop reliable measures of agility and analyse how agile firms manage exposure to monetary policy uncertainty, a significant and frequently occurring form of threat. Agile firms' stocks are significantly less exposed to this uncertainty as they proactively apply risk management techniques to reduce their exposure. This has real consequences: agile firms' investments are less affected by monetary policy tightening episodes.

"Lack of agility is the kiss of death. Position your company to succeed in world of change."

–Michael J. Arena, Chief Talent Officer of General Motors

☆ We would like to thank Triwit Ariyathugun (discussant), Zhi Da, Isil Erel, Mengchuan Fu, Iftekhar Hasan, Karel Janda, Markku Kaustia, Henry Kye (discussant), Mikko Leppämäki, Anders Löflund, Ville Savolainen, Meng Wang (discussant), Eliza Wu, Abalfazl Zareei (discussant); and the participants at the 2021 Winter GSF Workshop (online); 2022 International PhD Colloquium on Machine Learning in Hanken School of Economics; 2022 PhD Nordic Finance Workshop in Stockholm School of Economics; 2022 FMA Annual Meetings in Atlanta; 2022 FMA Asia-Pacific Conference in Melbourne; Herriot-Watt University workshop, and the 12th Biennial Conference of the Czech Economic Society in Prague. Gonul Colak acknowledges financial support from the Czech Science Foundation (GACR grant number 24-10008S). Sinh Thoi Mai gratefully acknowledges financial support from The Foundation for Economic Education and from Hanken Support Foundation.

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https://doi.org/10.1016/j.jcorpfin.2026.102973
Received 24 September 2024; Received in revised form 27 January 2026; Accepted 29 January 2026
Available online 3 February 2026
0929-1199/

1. Introduction

Firms operate in an environment that is constantly changing and subject to various uncertainty shocks, such as economic policy uncertainty (Baker et al., 2016), monetary policy transmissions (Bernanke and Kuttner, 2005), and financial uncertainties (Jurado et al., 2015). To survive and succeed in such an environment, it is crucial for firms to be agile and prepared for such conditions (Lim et al., 2017; Omidvar et al., 2023). Corporate agility is an economic concept that describes the ability to adapt and respond quickly and effectively to rapidly changing business conditions (Goldman et al., 1995; Cho et al., 1996; Menor et al., 2001; Lehn, 2018, 2021). The theoretical importance of agility can be dated back to the seminal paper by Alchian (1950) on evolution and economic theory, which uses the concepts of biological evolution and natural selection to analyse economic systems. The theory predicts that in a changing environment, adaptation through imitation or trial and error becomes a matter of life or death (Li et al., 2023).

Despite the importance of the topic, very little is known about the real and financial consequences of corporate agility. A few studies conducted on this topic are mostly conceptual and are positioned within the context of corporate governance (Lehn, 2018, 2021) rather than corporate strategic management. Some studies in operations research (e.g., Kumar and Motwani, 1995; Cho et al., 1996; Menor et al., 2001; Ganguly et al., 2009) examine the implications of corporate agility to corporate operations. However, almost all of them are related to production management literature and rely on limited data involving only manufacturing firms. The main challenge facing financial economists is that it is difficult to quantify corporate agility systematically and accurately, as the concept is complex and multidimensional (Gunasekaran, 1999; Seethamraju, 2006). Some prior papers propose different methods to quantify corporate agility (see Kumar and Motwani, 1995; Metes et al., 1998; Dove, 2001; Datta, 2006). However, those methods have some drawbacks. First, they depend heavily on human judgment, which is subject to inconsistency and inaccuracy. Second, they require detailed data about each firm's technology, product, and human resources, which is often unavailable for a large set of firms. Third, those measures of agility may not be suitable to study financial research questions as they focus on how firms respond to technological changes and product competition, but not financial threats like monetary policy uncertainty (Bernanke and Kuttner, 2005; Husted et al., 2020).

The goals of this study are twofold. We construct a firm-level measure of corporate agility by applying a machine learning method, *word2vec,* to the Management Discussion and Analysis (MD&A) sections of firms' 10-K filings. Machine learning is a reliable technique to measure a multidimensional concept like corporate agility (Mullainathan and Spiess, 2017; Goldstein et al., 2021). Furthermore, the MD&A section of a firm's annual (or quarterly) financial report provides rich and detailed textual data to measure corporate agility. In this section of the 10-K reports, managers discuss which threats are affecting or can affect financial results in the future, and how they manage and respond to those threats. Using a topic modelling technique to analyse the content of MD&A sections, we find that the topic of "threat"—which covers issues such as financial crisis, economic uncertainty, and war— emerges as one of the most prominent concerns for managers. It ranks immediately after the well-known accounting concepts widely covered in 10-K reports, such as income, business plan, taxes, expenses, and compensation. With the focus on the financial aspect, we thus define corporate agility as the ability to respond quickly and effectively to financial threats. Our machine learning method requires much less subjective judgment and can be applied to compute an agility measure for all public firms due to the wide availability of 10-K reports.

The second goal of this study is to understand how agile firms manage their exposure to uncertainty, which can be perceived by managers as a form of threat to their personal well-being (Hogg, 2007). Some prior papers show evidence about the negative effect of monetary policy uncertainty on corporate performance. For example, Husted et al. (2020) find that a one standard deviation increase in monetary policy uncertainty leads to about a 10.34% decrease in investment in the next quarter. Indeed, we find that among 40 topics discussed in the MD&A section, the topic of "threat" has the strongest relationship with monetary policy. Specifically, the more firms are concerned about threats in their annual reports, the more sensitive they are to monetary policy uncertainty. This result implies that monetary policy uncertainty is a significant form of threat, and thus, agile firms are expected to manage this threat effectively.

Our machine learning approach to measuring corporate agility aims to capture how well a firm responds to financial threats. Specifically, in creating this measure, we apply the following procedures. First, we use MD&A sections to train the *word2vec* algorithm, and then we use the trained *word2vec* to create two dictionaries: *Threat* and *Response*. The *Threat* dictionary includes 574 words related to various threats like economic slowdown, political turmoil, and social instability. The *Response* dictionary includes 471 words, which are mainly synonyms of key words that define agility, such as adapt, react, respond, effectively, and quickly. Second, we generate *Threat* and *Response* scores for each firm-year observation based on a weighted frequency count of words in their dictionaries. A firm's *Threat* score represents quantitatively how many threats it faces, while its *Response* score represents quantitatively how intensely it responds to these threats. Third, we construct an *Agility* score for each firm-year observation as the *Response* score scaled by the *Threat* score. Thus, the *Agility* score quantitatively captures how much a firm responds to each unit of threat and allows for comparisons across firms, as it is measured on a consistent scale (i.e., independent of the length of the 10-K report).

Word2vec, an unsupervised machine learning and a deep learning model, is a state-of-the-art in Natural Language Processing, developed by Mikolov et al. (2013a) and Mikolov et al. (2013b). The model first uses textual data to learn the meaning of words, and then quantifies the meaning of words by mapping each word to a real-valued vector. We use all MD&A sections from 1997 to 2020 to train our *word2vec* model. After training this model, we compare the synonymity between two words by comparing the similarity between their corresponding vectors based on the cosine similarity measure. Two words are synonymous if their vectors have similar directions. Using this technique, we find top synonyms and form dictionaries for two concepts: "Threat" and "Response." Recent papers by Bhatia (2019), Hanley and Hoberg (2019), Li et al. (2020) have successfully applied *word2vec* to generate dictionaries related to difficult-to-measure abstract concepts like "risk perceptions," "emerging risks," or "corporate culture." Given its advantages, prior research (Gentzkow et al., 2019; Li et al., 2020; Guzman and Li, 2023) claims that *word2vec* is the most effective machine learning method for measuring abstract concepts like culture, founding strategy, and corporate agility.

To ensure that our measure generated by *word2vec* accurately captures corporate agility, we conduct different validation tests. First, we show that the *Threat* and *Response* scores and our agility measure change over time in a predictable manner. For example, the *Threat* score and Economic Policy Uncertainty (EPU) index by Baker et al. (2016) closely move together with a high correlation of 0.72, suggesting that the *Threat* score captures well the changes in the business environment. Second, the agility measure shows meaningful correlations to other firm characteristics. For example, agile firms are less likely to be financially constrained. Agile firms tend to have a strong corporate culture, characterized by innovation, quality, respect, and teamwork, suggesting that a strong culture supports firms in being more agile in response to environmental changes. Agile firms are also more likely to have a smaller board size and a lower proportion of independent directors. The relationship is consistent with predictions from Lehn (2018, 2021), who explains that smaller board size or a lower proportion of independent directors helps firms become nimbler in making decisions in response to a rapidly changing business environment. Third, we find that agile firms are more resilient during crises, including the Dotcom Bubble (2001), the Global Financial Crisis (2008), and the COVID-19 pandemic (2020). Their stock returns, sales, profits, investments, R&D, and employment are less affected compared to other firms. The results are consistent with the hypothesis that agile firms are prepared and can respond quickly and effectively to crisis conditions. Fourth, we show that agile firms respond to macroeconomic uncertainty in a manner that is broadly consistent with the Oi-Hartman-Abel framework (Oi, 1961; Hartman, 1972; Abel, 1983), as we find that they operate in industries characterized by more reversible capital and lower adjustment costs, which are features associated with lower asset specificity as documented in Kermani and Ma (2023). Fifth, consistent with the dynamic theory of organizational rigidity, proposed by Li et al. (2023), we find that the adoption of standardized processes reduces future agility. Finally, we verify that our method of measuring agility is robust to alternative machine learning methods or textual data (corpus). Overall, while these results do not necessarily imply causality, they suggest that our agility measure exhibits the key characteristics typically associated with agile firms.

In the second part of our study, we examine how agile firms manage their exposure to monetary policy uncertainty. Monetary policies can affect firms through different channels. Tightening polices can make firms more financially constrained and force them to forgo profitable investment opportunities. When facing higher monetary uncertainty, we expect agile firms to respond quickly. To reduce their exposure, some agile firms can even stay constantly prepared for unexpected uncertainty spikes, and hence, they are likely to show less sensitivity to monetary policy surprises. To test our hypothesis regarding the value of corporate agility during monetary policy transmission periods, we use two proxies to measure monetary policy uncertainty. The first proxy is monetary surprises, which is computed as a weighted average (the first principal component) of 30-min changes in money market futures rates around the FOMC announcements, following recent studies (e.g., Armstrong et al., 2019; Bauer and Swanson, 2023). Using the event study approach of Bernanke and Kuttner (2005), Ippolito et al. (2018), and Armstrong et al. (2019), we find that the stock returns of agile firms are less sensitive to monetary surprises on the FOMC announcement dates. On average, a one standard deviation increase in agility leads to around 7% lower exposure to monetary policy surprises.

The second proxy we use is the monetary policy uncertainty (MPU) index developed by Bauer et al. (2022). High MPU implies that the market is uncertain about the future monetary policy, which in turn leads to high stock volatility. Using a similar event study approach, we find that the stock volatility of agile firms is less affected by MPU around FOMC announcement dates. Thus, agile firms weather the monetary policy transmission periods with less turmoil. Overall, regardless of the monetary policy uncertainty measure, the agile firms' stocks are less exposed to this uncertainty. This corroborates our main hypothesis.

Next, we examine the actions agile firms take to reduce their exposure to monetary policy uncertainty. Because high MPU leads to high market risk (Savor and Wilson, 2013; Husted et al., 2020), we expect that agile firms are more likely to actively take measures to manage the potential market risk that arises from uncertainty spikes. Consistent with the hypothesis, we find that when MPU or market risk increases, agile firms are more likely to hedge, diversify their investments, use different sources of funding, or use risk quantification techniques such as sensitivity analysis, shock simulation, and value at risk (VAR). Finally, we test whether there are real effects of being agile during episodes of heightened uncertainty. We find that agile firms' investments (capital expenditures) are less sensitive to monetary policy tightening. On average, a one standard deviation increase in agility is associated with approximately a 17% reduction in investment exposure to interest rate changes. This suggests that corporate agility enables firms to better implement their desired corporate policies unencumbered by macroeconomic uncertainty.

Our paper makes two main contributions to the financial economics literature. First, to the best of our knowledge, it is one of the first in finance that applies machine learning techniques to measure corporate agility across a large set of firms and over time.[1] Our approach requires less subjective judgment and can be universally applied to all firms using their publicly available 10-K files, which increases the replicability of the measure. Using various validation tests, one can confirm the validity of our agility measure. By introducing a firm-level measure of agility, we enhance academic research about the implications of corporate agility on corporate governance, corporate finance, and asset pricing.

Our paper also contributes to the literature studying the cross-sectional variation in firms' reaction to monetary policy transmission (e.g., Ozdagli, 2018; Armstrong et al., 2019; Afzali et al., 2025). Existing studies provide evidence of the significant impact of monetary policy on firm performance (e.g., Chan et al., 1996; Bernanke and Kuttner, 2005; Rigobon and Sack, 2003). However, much is unknown about the cross-sectional variation in firms' reactions to monetary policy shocks. Janet Yellen, the former chair of the U.S. Federal Reserve Board, called for more research on how different firms react to and anticipate monetary policy news (Yellen, 2016). In

[1] A contemporaneous working paper by Bae (2020) applies textual analysis, but not machine learning methods, on business description section of 10-K filings to measure corporate agility. Furthermore, the paper focuses on corporate response to product competition, not financial threats like we do. Hence, the two papers differ from each other in terms of focus, data, and methodology.

response to the call, some prior papers document different factors, including accounting quality (Armstrong et al., 2019), financial frictions (Ozdagli, 2018), price stickiness (Gorodnichenko and Weber, 2016), and floating-rate borrowing (Ippolito et al., 2018). Our study adds to the literature by showing that corporate agility is another factor explaining the different reactions of firms to monetary policy. Lastly, we also demonstrate that agile firms actively employ hedging or other risk management techniques to mitigate their exposure to monetary policy uncertainty.

2. Data

2.1. 10-K sample formation

We measure corporate agility based on textual data from the Management Discussion and Analysis (MD&A) sections in 10-K filings. In this section, managers analyse the current and future threats they are facing, such as crisis, economic uncertainty, war, and energy crisis. They also discuss actions that have been taken or will be taken to address those threats. Hence, the section provides rich information about how well firms respond to threats. Furthermore, the section is legally required to be accurate (see Durnev and Mangen, 2020), and as such, the measurement error in the corporate agility variable should be small. Other researchers also use this section to build their empirical proxies for different economic concepts. For example, Loughran and McDonald (2011) use it to measure sentiment tone; Hoberg and Maksimovic (2015) use it to measure financial constraints; Lattanzio and Ma (2023) use it to measure cybersecurity risk.

We download 10-K and 10-K405 filings, excluding amended documents, from the SEC's EDGAR database from 1994 to 2020 via a web scraping technique. However, because the number of 10-K filings from 1994 to 1996 is not stable, we start our sampling period in 1997. A filing is collected if it has an available matching CIK from Compustat. Then, we use a regular expression to extract only text data in the MD&A section from each filing. To minimize errors and ensure that the extracted MD&A section indeed reflects the management's perspective, we set a minimum threshold of 450 words for each MD&A section. Following this selection procedure, we end up collecting 116,353 MD&A sections over the period from 1997 to 2020.[2]

2.2. Pre-processing, parsing, and learning phrases

Following Li et al. (2020), we implement certain steps to clean and process the MD&A sections extracted from 10-K filings. We break down MD&A sections into sentences. Then, we remove tables, numbers, special characters, and stop-words (these are the commonly used words but convey no or very little information, such as “a,” “an,” “the,” and “about”). We also remove words indicating time like “year,” “month,” “quarter,” and words about units like “millions,” “percent.” We keep only sentences with at least three words. After that, we lemmatize words, which is a process of changing words into their original forms, such as transforming the words “looked” and “looking” into “look.” Furthermore, we use the *Genism* package in Python to find two and three-word phrases such as “financial statement,” “property right,” and “look forward to.” We concatenate all the phrases using the underscore symbol “_” and treat them as a single word. This word-selection procedure helps reduce measurement error due to the features of textual data, which in turn, improves the quality of the trained *word2vec* model.

3. Measuring corporate agility using *word2vec*

Prior papers (e.g., Goldman et al., 1995; Cho et al., 1996; Yusuf et al., 1999; Ganguly et al., 2009; Lim et al., 2017; Lehn, 2018) define corporate agility as “the ability to adapt or respond quickly and effectively to business environment changes.” Dove (1999, 2002) further divides corporate agility into two components: reactive agility, which refers to a firm's responsiveness to threats that could disrupt business operations, and proactive agility, which reflects a firm's ability to innovate and influence the market through new technologies, services, or strategies.

Building on the terms and words utilized by these papers, we measure corporate agility by first exploring which threats managers are concerned about in the MD&A sections. Then, we measure corporate agility based on how well firms respond to those threats. As described below, we end up creating a word library that includes synonyms of agility, such as adapt, respond, react, expand, reorganize, reconfigure, improve, modify, shift, scalable, flexible, reactive, proactive, rapidly, quickly, effectively, efficiently, and dynamically.

3.1. Exploring the MD&A section: Which threats are firms concerned about?

Before applying *word2vec*, we first explore the key topics discussed in the MD&A sections using the Latent Dirichlet Allocation (LDA) topic modelling method. We then determine which threats firms are concerned about. LDA is an unsupervised machine learning technique that uncovers abstract topics within a collection of documents by assuming that each document is generated from a probability distribution over a fixed number of topics. Prior studies (e.g., Dyer et al., 2017; Hanley and Hoberg, 2019; Li et al., 2020; Jin, 2024) have applied this method for similar purposes.

[2] Please refer to Table IA1 in our Internet Appendix for more details about the sample selection procedure.

We train the LDA model on cleaned MD&A sections from 1997 to 2020 and identify 40 key topics that are frequently discussed in these sections, which are labelled based on their top keywords. Next, we measure the proportion of each MD&A section dedicated to each of these topics. Further details on the LDA procedure are provided in Section 2 of the Internet Appendix.

We find that most of the listed topics align with issues commonly discussed in the 10-K reports, such as "Income," "Business Plan," "Tax," "Compensation," "R&D," and "Expense."[3] Among these, "Threat" and "Risk" are the only two topics directly reflecting managerial concerns. However, we find that "Threat" is more relevant to corporate agility, as it ranks 12th in prominence, compared to "Risk," which ranks 18th and is primarily discussed in Subsection 7A – an optional section not included in all filings. The "Threat" topic relates to external business environment changes, such as economic uncertainty, political instability, and crises, which impact most firms.

In summary, LDA topic modelling reveals that firms are most concerned with threats related to business environment changes, aligning with the concept of agility as defined by Alchian (1950). In the following sections, we use *word2vec* to quantify the abstract concept of corporate agility.

3.2. Measuring corporate agility

We measure corporate agility by quantifying how much a firm responds to the threats it faces (Li et al., 2023); both threats and responses are measured systematically. We base our quantification procedure on the verbal definition of corporate agility provided by prior researchers (e.g., Alchian, 1950). Specifically, we apply the following steps to measure agility:

- First, we use MD&A sections to train *word2vec*, and then we use the trained *word2vec* to create two dictionaries: *Threat* and *Response.*[4]
- Second, based on these dictionaries, we generate *Threat* and *Response* scores for each 10-K in each firm-year observation.
- Third, we calculate the *Agility* score for each firm-year observation as the *Response* score scaled by the *Threat* score.

The *Threat* dictionary contains synonyms of the word "threat", such as crisis, war, and natural disaster. The *Threat* score measures quantitatively the threats faced by the focal firm. The *Response* dictionary contains words expressing firms' actions in reaction to threats, such as respond, adapt, address, quickly, and efficiently. It captures quantitatively the degree to which a firm responds to threats. Our final *Agility* score reflects how much a firm responds to each unit of threat (*Response* score / *Threat* score). The next few subsections explain our methodology in more detail.

3.3. Why word2vec?

Textual analysis is widely used in finance and accounting research to quantify abstract concepts. The most common approach relies on pre-specified dictionaries (e.g., Loughran and McDonald, 2011). For instance, sentiment analysis typically involves counting words associated with a predefined dictionary, such as Harvard's General Inquirer tag categories or Loughran and McDonald's (2011) dictionaries, and scaling by the total word count. However, as Loughran and McDonald (2011, 2016) note, the effectiveness of dictionary-based textual analysis heavily depends on the dictionary's suitability for the specific context of the text. For instance, the Harvard dictionary performs poorly in assessing the tone of financial documents, such as 10-Ks, due to its lack of alignment with financial terminology.

Traditional dictionary construction, as in Loughran and McDonald (2011) and Pennebaker et al. (2015), involves manual word classification, which presents several challenges, as highlighted in prior papers (e.g., Li et al., 2020; Loughran and McDonald, 2020). First, firms face diverse and evolving threats (e.g., political instability, economic shocks, and environmental disaster), making it difficult for experts to create a comprehensive and adaptable dictionary. Second, dictionary formation relies on subjective judgment, which can introduce inconsistencies and limit the replicability of results. Third, manually inspecting and categorizing over 100,000 words from MD&A sections is time-consuming and prone to human error.

To overcome these limitations, we use *word2vec*, a state-of-the-art machine learning method in natural language processing, to create dictionaries for *threat* and *response* (Mikolov et al., 2013a). *Word2vec* represents words as real-valued vectors based on their contextual usage in a large text corpus, allowing words used in similar contexts (synonyms) to have similar vector representations. This approach is rooted in the *distributional hypothesis* (Harris, 1954), which suggests that words appearing in similar contexts share related meanings, summarized by Firth (1957) as *"You shall know a word by the company it keeps."* Once trained, *word2vec* enables semantic comparisons between words (e.g., "threat" and "shock") by computing the cosine similarity between their vectors, capturing nuanced relationships more effectively than traditional dictionary-based methods. For more explanation of *word2vec,* please see Section 7 in the Internet Appendix.

Word2vec offers key advantages: (i) it constructs dictionaries dynamically by analyzing the full MD&A text, ensuring greater completeness and adaptability to emerging threats; (ii) it reduces subjectivity, enhancing consistency and replicability; and (iii) it

[3] See Table IA5 in the Internet Appendix for the full ranking of 40 topics based on its average discussion proportion in the MD&A sections.

[4] We use the word "response" to refer to all actions taken by firms to handle threats, including adaptation, hedging, etc. We find that "response" and "adaptation" are top synonyms of each other. The results are very similar if we generate "adaptation" dictionary instead of "response" dictionary. Hence, our methodology of measuring corporate agility is consistent with Alchian (1950) who uses the term "adaptation" to define agility.

requires significantly less manual effort. Gentzkow et al. (2019) highlight the advantages of word embedding techniques, such as *word2vec*, over traditional textual analysis methods, emphasizing their ability to provide a richer representation of text. Hanley and Hoberg (2019) apply *word2vec* to identify emerging risks in the banking sector, while Li et al. (2020) use it to develop corporate culture measures and advocate for its broader application in analyzing abstract concepts.

3.4. Training the model and generating dictionaries

We use the *Genism* package in Python and take the processed MD&A sections data from 1997 to 2020 as our input to train our *word2vec* model. We set the dimension of word vectors to 300; define two words as neighbours if they are no farther apart than five words in a sentence; omit words that appear fewer than 20 times in the corpus (totally 84,879 words satisfies the condition); and set the number of iterations over the corpus to 20.[5] After the training, the model maps each word to a 300-dimensional vector that represents its contextual meaning. For example, the word "threat" is represented as [0.602842, 0.162545, …, 1.37522]. Each word is represented by a point in a 300-dimensional space, and words with similar meanings are positioned close together in that space.

To illustrate this point, Fig. 1 presents a word visualization in a 3-dimensional space for 24 words coming from four topics: threat, income, director, and innovation. We first form a matrix with dimensions 24×300 (each row representing a vector of words), and then apply principal component analysis (PCA) to reduce the matrix dimension from 24×300 to 24×3. As a result, each word is represented by a 3-dimensional vector. Finally, we use each element of their vectors to visualize each word in a 3-dimensional space. Fig. 1 shows that words of each topic tend to stay close together, as they share similar meanings, but also remain separate from other topics. This implies that our trained *word2vec* model can understand the meanings of words well and compare any set of words. The high quality of our trained *word2vec* assures the creation of accurate and comprehensive dictionaries for our *Threat* and *Response* scores.

Based on the trained *word2vec* model, we generate two dictionaries: *Threat* and *Response*. As explained above, the trained *word2vec* model allows us to find and rank synonyms of any two words in our corpus based on their cosine similarity. To generate the *Threat* dictionary, we use the word "*threat*" as our seed word to find its top 1000 synonyms.[6] To generate the *Response* dictionary, we find its top 1000 synonyms for the combination of three seed words: "adapt," "respond," and "react."[7]

Panel A of Table IA11 in our Internet Appendix shows the top 50 words most frequently used in the same sentences with the word "threat" in the MD&A sections. We find that firms use "respond" or "response" most frequently to express their response actions to threats. For example, Pacificorp's 2013 10-K report contains the following sentence: "*PacifiCorp has identified critical assets, created an effective management structure to* ***respond*** *to* ***threats*** *and developed several approaches to security to meet the changed environment.*" For more examples, please refer to panel B of Table IA11 in the Internet Appendix. Therefore, we name our dictionary as *Response* and use "respond" as one of our key words to form the dictionary. We additionally use "adapt" and "react" as keywords to form the *Response* dictionary for three reasons. First, firms also use these words to express actions to threats, though less frequently than "respond." Second, our trained *word2vec* model shows that "adapt," "respond," and "react" are top synonyms of each other. Third, these words are key terms in defining corporate agility, as discussed in Section 2.

For the final step, following Li et al. (2020), we manually review the list of 1000 synonyms and exclude words that do not align with the intended concepts. To ensure accurate selection, we analyse 20 randomly selected sentences where each synonym appears, helping us assess its contextual meaning. Words are excluded for two main reasons:

- First, more than half of the excluded words are dropped due to overlap between the *Threat* and *Response* dictionaries. For example, words like "respond," "reaction," and "adapt" appear in both dictionaries, so we exclude them from the *Threat* dictionary.
- Second, we exclude words whose meanings are unclear or unrelated to threat or response. For instance, words like "communication," "industry," "economy," "nature," and "profitability" are not directly tied to threats or responses. Depending on neighbouring words, these terms could refer to both.

After this manual inspection, the *Threat* dictionary contains 574 words, and the *Response* dictionary includes 471 words, with no overlap between them. Table 1 lists the top 20 synonyms of the seed words "threat" and "response."[8] The *Threat* dictionary captures threats from various sources, such as economic slowdowns, political and social instability, and natural disasters. The *Response* dictionary primarily consists of synonyms for key words that define agility, such as "respond," "adapt," "address," "quickly," and "efficiently."

[5] We choose these hyperparameters, following Li et al. (2020). They are default hyperparameters of the *word2vec* model, suggesting that they are common choice of the model. We verified that our *word2vec* model is not sensitive to the choice of those hyperparameters like the number of iterations or the word window.

[6] Our results are quantitatively similar if we choose other thresholds other than 1000 (e.g., 500). The quality of synonyms decreases gradually from the top synonyms; thus, based on our judgment, 1000 is a reasonable choice.

[7] To find synonyms for the combination of those three words, the model computes the average vector of those words' corresponding vectors, then uses the vector to find synonyms.

[8] See Table IA2 for the full list of terms in the *Threat* and *Response* dictionaries and Table IA20 for thirty most frequently occurring words of these dictionaries in the Internet Appendix.

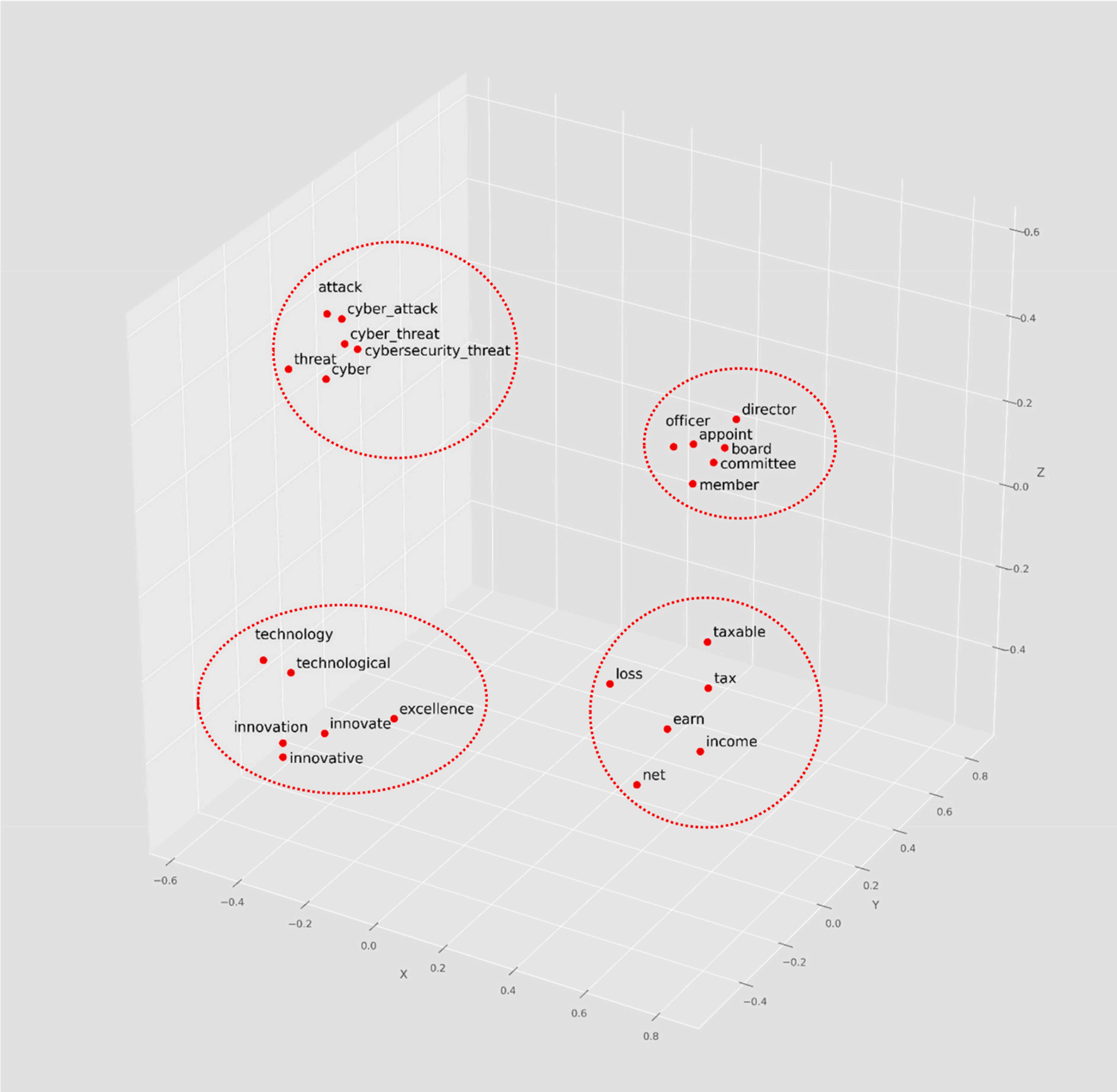


Fig. 1. Word visualization in a 3-dimensional space by *word2vec*.
The figure represents a 3-dimensional word visualization of 24 words belonging to four topics: "threat," "income," "director," and "innovation." After training the *word2vec* model, each word is represented by a 300-dimensional vector. Using these vectors, we form a 24 × 300 matrix, then use principal component analysis (PCA) to reduce the matrix's dimension to 24 × 3.

3.5. Constructing threat, response, and corporate agility scores

Based on the *Threat* and *Response* dictionaries, we generate the *Threat* and *Response* scores for each firm-year observation by using the weighting scheme TF.IDF, a widely used method in textual analysis research (e.g., Loughran and McDonald, 2011). The TF (term frequency) component measures how often a word appears in a document, while the IDF (inverse document frequency) component adjusts for the word's overall prevalence across all documents, ensuring that frequently used but uninformative words are given less weight. Specifically, the TF.IDF of the word *i,* in document *j,* is computed as follows:

$$TF.IDF_{i,j} = TF_{i,j}.IDF(i,j) = TF_{i,j}.Log\left(\frac{N}{DF_i}\right)$$

where N represents the total number of documents in the sample, DF_i is the number of documents containing at least one occurrence of word i, and $TF_{i,j}$ is the raw count of word i in document j. This method ensures that a word is considered more important if it appears

Table 1
The twenty most representative words in threat and response dictionaries.

Threat	Response
Threat	Respond
Terrorist	React
Attack	Adapt
Threaten	Alleviate
War	Response
Attack_war	Respond_quickly
Terrorist_attack	Address
War_terrorism	Quickly
Terrorist_threat	Responsive
Challenge	Withstand
Hostility_terrorist	Quickly_adapt
Cyber_attack	Efficiently
Bioterrorism	Respond_promptly
Terrorism	Compete_effectively
Act_war	Technological
Terrorism_threat	Lessen
Concern	Respond_technological
Threat_terrorist	Swiftly
Threat_pose	Adequately_address
Perceive_threat	React_quickly

This table lists the 20 most representative words in the *Threat* and *Response* dictionaries in descending order of similarity to threat and response seed words.

frequently in a document but is relatively rare across the entire corpus.[9,10]

The *Threat* score captures how much a firm is exposed to changes in its business environment, while the *Response* score captures how much a firm responds to these changes. The *Agility Score* is measured as the *Response* score divided by the *Threat* score. We do not directly use the *Response* score as our measure of agility because of the high correlation (0.80) between the *Threat* and *Response* scores, which is expected given that firms respond more when facing more threats. Following Li et al. (2020), the final *Agility* score for each firm-year observation is computed as a three-year moving average of the annual agility measure.[11] Among the two components of agility, reactive and proactive, our measure primarily captures the reactive aspect. By examining 1000 randomly selected sentences containing the word "response" and its variations, we find that firms primarily respond to current changes in the business environment rather than those they anticipate in the future.[12]

In addition to the aggregate corporate agility measure, we construct alternative agility measures tailored to specific types of threats, including economic shocks, climate-related disasters, and geopolitical disruptions. We then demonstrate that these measures can be used to analyse specific types of threats and exhibit similar elasticities in share price performance during crisis episodes. See Section 8 of the Internet Appendix for further details.

3.6. Descriptive statistics

Panel A of Fig. 2 presents the time series of the *Threat*, *Response*, and *Agility* scores from 1997 to 2020, with each score measured at the median level per year. The *Threat* score rises significantly during periods of major economic and geopolitical shocks, such as the Russian crisis, the 2008 Global Financial Crisis (GFC-2008), and the Iraq War. Notably, the *Threat* score reached an unprecedented level in 2020 due to the COVID-19 pandemic, highlighting the widespread impact of health-related threats. Furthermore, the *Response*

[9] We find that our results are qualitatively the same if we change our weighting scheme to the following formula: $TF.IDF_{i,j} = \left(1 + log\left(TF_{i,j}\right)\right).Log\left(\frac{N}{DF_i}\right)$.

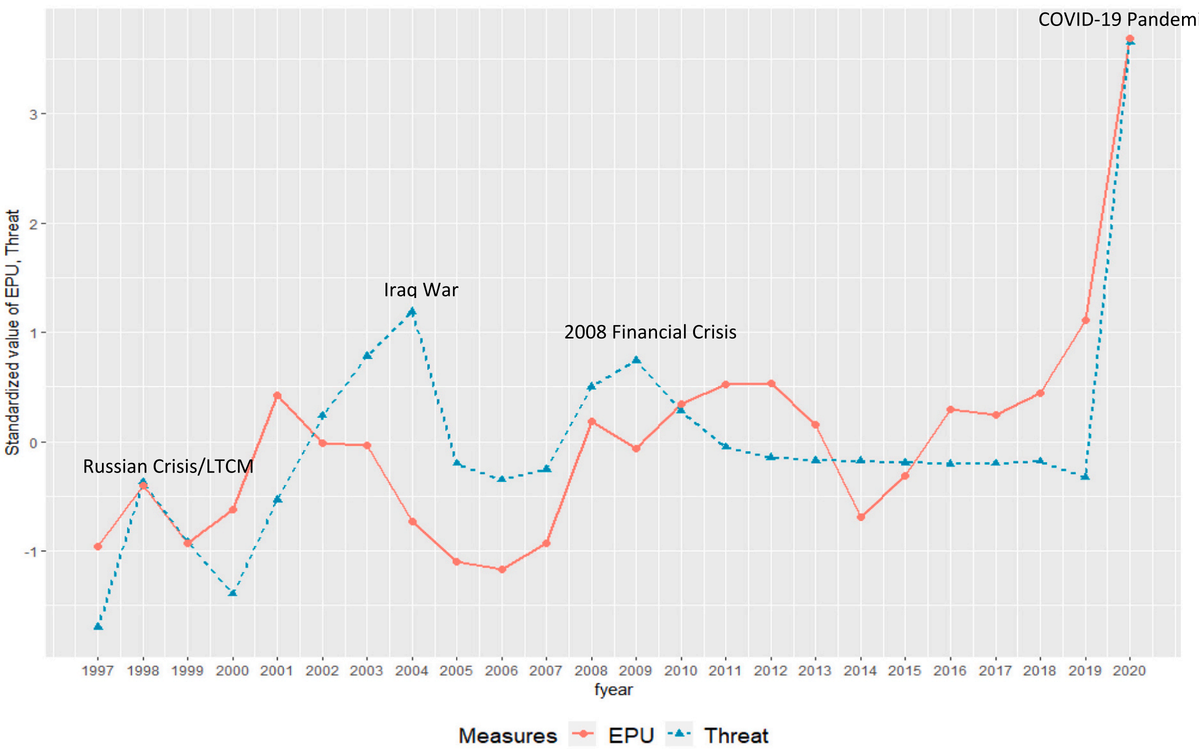
[10] We do not adjust for document length since we measure *Agility* score as the *Response* score scaled by the *Threat* score. Document length can affect these scores, but its effect is cancelled out when measuring corporate agility.

[11] Without taking a three-year moving average, our main results are similar. However, we find that taking a three-year moving average improves our measure of agility, since it helps reduce the effects of idiosyncratic spikes in a given year.

[12] We offer alternative ways to measure corporate agility. Specifically, we change the machine learning method from *word2vec* to the *Latent Dirichlet Allocation (LDA)* topic modelling method, and change the textual data from 10-K to 10-Q or to earnings call transcripts. We find high correlations between our main agility measure and alternative agility measures; see Section 5 in the Internet Appendix for more details.

A Changes in Agility, Threat, Response over time.

B Changes in Threat and Economic Policy Uncertainty (EPU) over time.



(caption on next page)

Fig. 2. Changes in agility, threat, response, and EPU from 1997 to 2020.
Each year, threat, response, and agility are measured at the median level during the year, and EPU is measured at the mean. EPU is the Economic Policy Uncertainty index by Baker et al. (2016). All variables are standardized. $\text{Corr}_{\text{response,threat}} = 0.80, \text{corr}_{\text{agility,threat}} = -0.09, \text{corr}_{\text{agility,response}} = -0.11, \text{corr}_{\text{threat,EPU}} = 0.72$.

and *Threat* scores move closely together in most periods, with a high correlation of 0.8, indicating that firms respond more drastically when faced with larger threats.[13] However, this pattern changes during the COVID-19 pandemic, where the *Threat* score surges while the *Response* score declines, suggesting that firms struggled to respond effectively to this unprecedented crisis. The *Agility* score tends to be negatively correlated with the *Threat* score, decreasing in periods of heightened uncertainty and increasing when external pressures ease. This pattern suggests that firms often struggle to respond promptly to unexpected shocks, such as the GFC-2008 or COVID-19, which temporarily reduce their agility.

In Panel B of Fig. 2, we compare the *Threat* score with the Economic Policy Uncertainty (EPU) Index developed by Baker et al. (2016). The two measures exhibit a strong co-movement with a correlation of 0.72, reinforcing that the *Threat* score effectively captures prevailing macroeconomic uncertainty.

To understand further the changes in corporate agility over time, we classify firms into 12 Fama-French industries and examine the *Agility* score at the median level in each industry. Fig. 3 plots this variable over time for the top three (Panel A) and the bottom three (Panel B) industries from 1997 to 2019. We exclude 2020 due to the small number of MD&A sections in our sample. We rank industries based on their median agility from 2010 to 2019.

The results reveal that business equipment, nondurables, and shops exhibit the highest agility, while chemicals, utilities, and telecommunications rank the lowest. This finding aligns with Lehn (2021), who argues that firms in dynamic industries—such as retail—must continuously adapt to frequent business environment changes, making agility essential for survival. In contrast, firms in more stable industries like utilities and telecommunications face fewer disruptions and tend to have larger and older corporate structures, making them less nimble and responsive to change. The plots in Fig. 3 also show a decline in agility across almost all industries in 2019, except for the utilities sector. This trend suggests that by the time firms prepared their 10-Ks (around February–March 2020), they were already experiencing disruptions from the COVID-19 crisis, resulting in a noticeable decline in reported agility.

Table 2 provides descriptive statistics for our sample from 1997 to 2020. Panel A reports the descriptive statistics of *Agility* score, monetary policy variables, and other variables, while Panel B shows the average autocorrelation of *Agility* score. To compute autocorrelation, we first compute it for each firm with at least 15 observations, and then we take the average autocorrelation coefficient across firms. The average autocorrelation between year *t* and *t*-1 is 0.683, and between year *t* and *t*-2 is 0.328. The average autocorrelation between year *t* and *t*-3 is 0.058, and the autocorrelation turns out to be negative when comparing year *t* with year *t*-4 or *t*-5. The pattern of autocorrelation suggests that the *Agility* score evolves slowly over time.

4. Validating our measure of corporate agility

4.1. *Testing for the dynamic theory of organizational rigidity*

First, we use our agility measure to test the dynamic theory of organizational rigidity proposed by Li et al. (2023). The theory posits that the adoption of standardized processes reduces a firm's future agility because it centralizes the decision-making process and curtails the autonomy of regional managers. Therefore, firms become less responsive to local information and adapt less effectively.

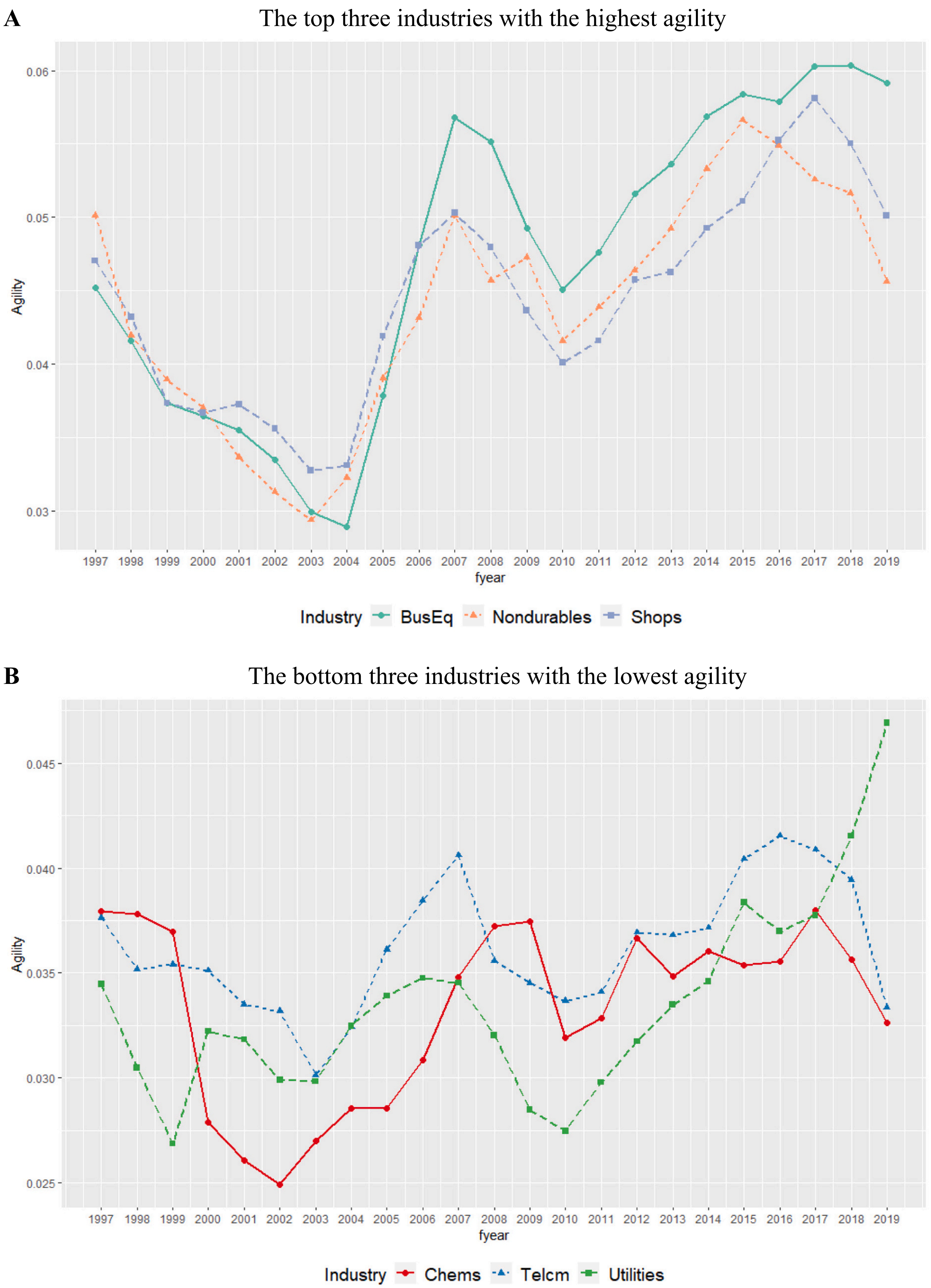
We measure a firm's adoption of standardized processes (*Standardization*) by using a textual analysis technique. Specifically, we use a list of words related to standardization and the TF.IDF weighting scheme to score each MD&A section.[14] Panel A of Table 3 presents the estimation results of regressing future agility, measured from one to three years, on *Standardization*. We control for firm characteristics, including firm size, leverage, sales growth, market share, book-to-market (BM) ratio, gross margin, investment, receivables, and depreciation, as well as industry and year fixed effects. The coefficients of *Standardization* are significantly negative across all columns, supporting the dynamic theory of organizational rigidity—higher adoption of standardized processes is associated with lower future agility.

4.2. *Corporate agility and corporate governance*

Next, we examine the relationship between corporate agility and corporate governance. Lehn (2018, 2021) suggests that firms with smaller boards tend to be more agile because they have lower coordination costs and fewer free-rider problems, enabling quicker responses to changes in the business environment. Additionally, these two papers predict that board independence may be negatively related to corporate agility, as outsider-dominated boards tend to be more deliberate and less nimble in decision-making.

[13] Despite the high correlation between the *Threat* and *Response* scores, our *Agility* score still exhibits substantial variation. For example, some firms—such as Intel Corp and Ametek Inc. in 2006—show high *Agility* scores due to their low *Threat* scores but high *Response* scores. In contrast, others—such as Titan International Inc. in 2014—show low *Agility* scores due to high *Threat* scores but low *Response* scores. See Table IA19 in the Internet Appendix for more examples. Additionally, our *Agility* score shows a big coefficient of variation (CV) (6.05).

[14] The list of words includes standardize, standardization, centralize, and centralization.



(caption on next page)

Fig. 3. The top and bottom three industries by Agility.
Firms are classified into 12 Fama-French industries. Industries are ranked based on the median value of agility during 2010–2019. For each industry-year, agility is measured at the median level. The top three (Panel A) and bottom three (Panel B) industries are plotted over the period from 1997 to 2019.

Table 2
Descriptive statistics.

Panel A: Descriptive statistics						
Statistic	Obs	Mean	St. Dev.	Min	Median	Max
Monetary policy variables						
Surprise (200 FOMC meetings)	313,066	−0.003	0.059	−0.283	0.006	0.152
MPU (200 FOMC meetings)	313,066	0.447	0.197	0.100	0.423	1.362
Firm variables						
Agility	313,066	0.152	0.967	0.009	0.04	10.446
Stock return	313,066	0.004	0.049	−0.867	0.000	8.250
Stock volatility [−1; +1]	313,066	0.03	0.029	0.001	0.021	0.167
Depreciation	313,066	0.086	0.164	0.003	0.041	1.285
Investment	313,066	0.105	0.276	0.001	0.034	2.246
Leverage	313,066	0.49	0.264	0.058	0.471	1.438
Firm Size	313,066	5.864	1.879	1.734	5.777	10.88
Gross margin	313,066	0.013	2.399	−19.912	0.359	0.923
Receivable	313,066	0.066	0.106	−0.234	0.057	0.420
ROA	313,066	−0.029	0.239	−1.534	0.032	0.381
Sale growth	313,066	0.15	0.509	−0.685	0.07	4.090
Sales volatility	313,066	0.265	0.232	0.018	0.198	1.454
Market share	313,066	0.001	0.003	0.000	0.0002	0.026
BM ratio	313,066	3.017	5.101	−16.053	2.032	33.27
sale volatility	313,066	0.148	0.092	0.033	0.123	0.555
MKT Beta	313,066	1.059	0.752	−0.843	1.006	3.366
SMB Beta	313,066	0.922	1.016	−1.482	0.806	4.201
HML Beta	313,066	0.025	1.143	−3.621	0.093	2.972
WML Beta	313,066	−0.196	0.734	−2.758	−0.127	1.803
LW_equity index	313,066	−0.176	0.683	−2.248	−0.272	4.766
LW_debt index	313,066	0.113	0.724	−2.917	0.096	3.300
Cash ratio	313,066	0.253	0.375	0.000	0.133	7.502
Short-term debt	313,066	0.038	0.108	0.000	0.006	6.837
Long-term debt	313,066	0.206	0.270	0.000	0.122	2.241
Panel B: Agility autocorrelation						
	lag 1 year	lag 2 year	lag 3 year	lag 4 year	lag 5 year	
Agility	0.683***	0.328***	0.058***	−0.053***	−0.101***	

The table reports the descriptive statistics for the sample from 1997 to 2020 at the firm-FOMC meeting level. Following convention (e.g., Armstrong et al., 2019; Husted et al., 2020), we exclude financial (SIC between 6000 and 6999) and utility (SIC between 4900 and 4999) firms. Panel A shows the descriptive statistics of monetary policy uncertainty measures, *Agility,* and other firm variables. Panel B shows the average autocorrelation of *Agility*. First, we compute autocorrelation at each lag level for each firm with at least 15 observations, then compute their average across firms. We winsorize all continuous variables at the 1% and 99% levels.

To test these predictions, Panel B of Table 3 presents the estimation results of regressing the *Agility* score on board size or on the percentage of independent directors, controlling for firm characteristics, industry, and year fixed effects. Board size and independent director data are sourced from the BoardEx database. In all columns, the coefficients of board size and percentage of independent directors are negative and significant at the 1% level, indicating a negative relationship between corporate agility and these governance characteristics. These findings support Lehn's (2018, 2021) predictions that smaller boards and a lower proportion of independent directors enhance firms' ability to respond quickly to threats and adapt to changing business environments.

4.3. Agile firms and the Oi-Hartman-Abel theoretical framework

In this subsection, we analyse whether agile firms operate with more reversible capital and face lower costs of adjusting the capital stock, making them more likely to exhibit behavior consistent with the Oi-Hartman-Abel framework. A key implication of the Oi-Hartman-Abel framework (Oi, 1961; Hartman, 1972; Abel, 1983) is that firms with more reversible capital and lower capital adjustment costs are better positioned to adjust investment asymmetrically in response to uncertainty. In contrast, firms facing greater investment irreversibility and higher adjustment costs are more constrained in their responses to changing economic conditions and therefore behave in a manner consistent with real options theory (Bernanke, 1983; Bloom, 2014). If our text-based agility measure

Table 3
Validation tests of our agility measure.

Panel A: Testing the dynamic theory of organizational rigidity

	Agility		
	1-year	2-year	3-year
	(1)	(2)	(3)
Standardization	−3.056***	−2.713**	−2.293**
	(1.146)	(1.054)	(1.091)
Controls	Yes	Yes	Yes
Industry and year fixed effects	Yes	Yes	Yes
Clustering at firm and industry × year	Yes	Yes	Yes
Num. obs.	79,552	68,807	59,735
Adjusted R^2	0.055	0.052	0.060

Panel B: The relationship between corporate governance and agility

	Agility			
	(1)	(2)	(3)	(4)
Board size	−0.295***	−0.209***		
	(0.054)	(0.067)		
% Independent directors			−1.388***	−1.061***
			(0.445)	(0.370)
Controls	No	Yes	No	Yes
Industry and year fixed effects	Yes	Yes	Yes	Yes
Clustering at firm and industry × year	Yes	Yes	Yes	Yes
Num. obs.	70,272	60,653	62,401	55,287
Adjusted R^2	0.013	0.014	0.012	0.016

Panel C: Agility and irreversible capital (liquidation recovery rate)

	Agility			
	Top and bottom five industries		Top and bottom ten industries	
	(1)	(2)	(3)	(4)
Intercept	0.172***	0.196***	0.172***	0.193***
	(0.007)	(0.009)	(0.007)	(0.009)
Top industry (liquidation recovery rate)	0.115***		0.107***	
	(0.043)		(0.042)	
Bottom industry (liquidation recovery rate)		−0.055***		−0.050***
		(0.016)		(0.017)
Controls	Yes	Yes	Yes	Yes
Clustering at firm level and industry × year	Yes	Yes	Yes	Yes
Num. obs.	73,387	73,387	73,387	73,387
Adj. R^2	0.003	0.004	0.003	0.003

Panel D: Agility and financial constraint

	LW equity index	LW debt index
	(1)	(2)
Agility	−0.010***	−0.007**
	(0.003)	(0.004)
Controls	Yes	Yes
Industry and year fixed effects	Yes	Yes
Clustering at firm and industry × year	Yes	Yes
Num. obs.	56,358	56,358
Adjusted R^2	0.303	0.303

Panel E: Agility and firm performance during crises

	Stock return	Asset turnover	ROA	Investment	R&D	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis	−0.042***	−0.034***	−0.019**	−0.010***	−0.002*	−0.741***

(*continued on next page*)

Table 3 (*continued*)

Panel E: Agility and firm performance during crises

	Stock return	Asset turnover	ROA	Investment	R&D	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.013)	(0.005)	(0.008)	(0.002)	(0.001)	(0.092)
Agility	−0.000	0.001	0.001	0.000	−0.000*	−0.059
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.041)
Crisis × Agility	0.004***	0.003**	0.002**	0.001**	0.001***	0.077***
	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Crisis × Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by firm	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by month	Yes	No	No	No	No	No
Clustered by industry × year	No	Yes	Yes	Yes	Yes	Yes
Num. obs.	459,957	226,869	226,869	226,869	226,869	68,830
Adjusted R^2	0.034	0.772	0.588	0.535	0.730	0.934

The table reports validation tests for our measure of corporate agility for a sample period from 1997 to 2020. Panel A reports the estimation results from regressing *Agility* on *standardization* for different horizons from one year to three years. *Standardization* is measured by counting the list of words related to standardization in the MD&A sections. Panel B reports the estimation results from regressing *Agility* on corporate governance measured by *board size* or *% independent directors*. *Board size* is measured as the total number of directors. *%Independent directors* variable is the number of independent directors scaled by board size and multiplied by 100. Panel C reports estimation results from regressing *Agility* on indicator variables for industries with high or low average liquidation recovery rates (proxy for capital reversibility). In columns (1) and (2), the *Top* (*Bottom*) *industry* equals one if a firm's industry is among the five industries with the highest (lowest) average liquidation recovery rates. In columns (3) and (4), the indicators are defined analogously based on the top (bottom) ten industries. In Panel D, we regress financial constraint proxies on *Agility*. We use two proxies for financial constraints: the *LW equity index* and the *LW debt index*, both developed by Linn and Weagley (2024). These indices are expanded text-based financial constraint measures developed by Hoberg and Maksimovic (2015). In Panel E, we assess how agile firms perform during crises by estimating Eq. (1). Our analysis focuses on three NBER-defined crises: the Dotcom Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020). The variable *Crisis* is a binary indicator for crisis periods. The dependent variables include *stock return* (column 1); *asset turnover*, measured as sales scaled by beginning-of-year total assets (column 2); *ROA*, calculated as income before extraordinary items scaled by beginning-of-year total assets (column 3); *investment*, defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-year total assets (column 4); *R&D*, computed as R&D expense scaled by beginning-of-year total assets (column 5); and *employment*, measured by the number of employees (column 6). We use monthly data in column (1), quarterly data in columns (2)–(5), and annual data in column (6). In all panels, controls include firm size, leverage, sales growth, market share, BM ratio, gross margin, investment, receivable, and depreciation. In Panel E, we additionally control for corporate culture measured by Li et al. (2020). *Agility* and Controls are measured at the end of the previous year. All continuous variables are winsorized at the 1% and 99% levels. Please refer to Table A1 in the Appendix for the source of data and construction of variables. Clustered SE is in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

captures firms' operational flexibility, it could be systematically related to reversible capital, a key condition in the Oi-Hartman-Abel mechanism.[15]

To examine this implication, we link our text-based agility measure to an external, theory-grounded measure of capital irreversibility developed by Kermani and Ma (2023). Specifically, Kermani and Ma construct industry-level liquidation recovery rates for different asset categories using Chapter 11 bankruptcy filings. These recovery rates are closely related to asset specificity: lower recovery rates imply more irreversible, relationship-specific capital and higher adjustment costs, while higher recovery rates indicate more generic and redeployable assets. Kermani and Ma (2023) show that investment responsiveness to uncertainty is stronger when assets are more irreversible, consistent with classic irreversibility models (Pindyck, 1991; Guiso and Parigi, 1999).

Using their two-digit SIC industry-level liquidation recovery rates for property, plant, and equipment (PPE), we classify industries based on the average recoverability of physical capital. We then estimate regressions of firm-level agility on indicator variables for industries with high versus low recovery rates, controlling for firm characteristics. Panel C of Table 3 reports the results. Across specifications, firms operating in industries with high liquidation recovery rates exhibit significantly higher agility scores. Conversely, firms in industries with low recovery rates exhibit significantly lower agility. These patterns hold whether we focus on the top and bottom five industries or the top and bottom ten industries ranked by recovery rates.

Taken together, these results provide validation that our agility measure captures firms' flexibility when facing uncertainty. Consistent with the Oi-Hartman-Abel framework, agile firms tend to operate in environments with lower irreversibility and lower adjustment costs, which can enable them to contract more readily during adverse states and expand more aggressively when conditions improve. While this analysis does not establish causality, it supports the interpretation of corporate agility as capturing economically meaningful differences in firms' ability to respond quickly and effectively to uncertainty shocks.

[15] Note that the Oi-Hartman-Abel framework is a very specific theoretical environment with strict assumptions such as risk neutrality, competitive markets, convex profits, and full reversibility of capital investment. Operating in reversible-capital industries is necessary but not sufficient conditon for classifying firms as behaving in a manner consistent with this framework. Thus, the descriptive analyses that we conduct in this subsection should not be interpreted as causal evidence that agile firms behave in this manner.

4.4. Corporate agility and financial constraints

Another validation test we conduct is to examine the relationship between agility and financial constraint. Financial constraints could pose a threat as they limit firms' ability to raise capital and invest in profitable projects. Because agile firms can respond quickly to threats, we predict that agile firms are less likely to be financially constrained. To test this, we regress financial constraint proxies on *Agility* score together with firm controls, and industry and year fixed effects. We use two proxies for financial constraints: the LW equity index and the LW debt index, both developed by Linn and Weagley (2024).[16] These indices capture financial constraints related to equity and debt and are extensions of the text-based financial constraint measures originally developed by Hoberg and Maksimovic (2015).[17]

We control for firm characteristics, industry, and year fixed effects. The *Agility* score and firm controls are measured as of the end of the previous year. We cluster standard errors at the firm and industry × year levels. Panel D of Table 3 reports our estimation results using annual data from 1997 to 2020. Consistent with our prediction, agile firms have a lower LW equity and LW debt indexes. Agile firms are less financially constrained than other firms. However, in this test, causality is difficult to establish, as there may be a reverse relationship in which lower financial constraints facilitate firms in becoming more agile.

4.5. Corporate agility during crises

Next, we examine how agile firms performed during periods of major financial crises. This serves as an additional validation test of our agility measure, as such crises are characterized by severe disruptions and heightened uncertainty. If agility reflects a firm's ability to prepare for and respond effectively to shocks, we would expect agile firms to outperform their peers during these periods. Following prior studies (e.g., Fama and French, 1989; Danielsson et al., 2023), we focus on three NBER-defined crises: the Dotcom Bubble (2001), the Global Financial Crisis (2007–2009), and the COVID-19 pandemic (2020). Consistent with Lins et al. (2017) and Carney et al. (2020), we estimate the following difference-in-differences specification:

$$\begin{aligned} \mathit{Firm\ performance}_{i,t} = & \beta_0 + \beta_1 \mathit{Agility}_{i,t-1} + \beta_2 \mathit{Crisis}_{i,t} + \beta_3 \mathit{Agility}_{i,t-1} \\ & \times \mathit{Crisis}_{i,t} + \beta_n \mathit{Controls}_{i,t-1} + \beta_m \mathit{Controls}_{i,t-1} \times \mathit{Crisis}_{i,t} \\ & + \mathit{Firm\ FE} + \mathit{Year\ FE} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where *Firm performance* is a generic term for various economic indicators of firm performance (or an economic outcome), including *stock return*; *asset turnover* – measured as sales scaled by beginning-of-year total assets; *ROA* - calculated as income before extraordinary items scaled by beginning-of-year total assets; *investment* - defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-year total assets; *R&D* - defined as R&D expenses scaled by beginning-of-year total assets; and *employment* - measured by the number of employees. We use monthly data for *stock return*, quarterly data for *asset turnover*, *ROA*, *investment*, *R&D*, and annual data for *employment*. The sample period is from 1997 to 2020. *Crisis* is a binary indicator equal to one during crisis periods and zero otherwise. For *stock returns*, crisis periods are defined as February 2001 to March 2001; January 2008 to March 2009; and January 2020 to May 2020—corresponding to major declines in the S&P 500 index. For *asset turnover*, *ROA*, *investment*, and *R&D*, the crisis periods are April 2001 to October 2001; December 2007 to June 2009; and February 2020 to May 2020. For *employment*, the crisis periods are defined at the annual level as 2001, 2002, 2009, and 2020.

We control for firm characteristics, as shown in Panel A of Table 3, and corporate culture, as measured by Li et al. (2020). We include firm fixed effects to control for time-invariant variables and year fixed effects to control for macroeconomic events. *Agility* and controls are measured at the last year-end. We cluster standard errors at the firm and month levels for *stock return* and at the firm and industry × year levels for all other dependent variables. Following convention (e.g., Lins et al., 2017; Armstrong et al., 2019; Husted et al., 2020), we exclude financial firms (SIC between 6000 and 6999) and utility firms (SIC between 4900 and 4999).

Panel E of Table 3 reports our estimation results. In column (1), while the coefficient of *Crisis* is negative and significant at 1% level, the coefficient of *Agility* × *Crisis* is positive and significant at 1% level, implying that agile firms' stocks outperform other firms' stocks during the crises. A one-standard-deviation increase in the *Agility* measure leads to approximately a 9% lower stock exposure to crises. The results are consistent across other columns when using alternative economic outcome measures that reflect firms' real (rather than financial) decisions; agile firms experience smaller declines in asset turnover, ROA, investment, and employment during financial crises. Overall, our agility measure captures well the firms that are nimble and tend to perform better during crisis periods.[18] These tests provide insight into the economic mechanisms that drive the behavior of agile firms.

[16] We are grateful to Linn and Weagley (2024) for making their data publicly available at https://www.danielweagley.com/data.

[17] Our results remain unchanged when we use other proxies for financial constraints, including short-term crediting rating, long-term credit rating, HP index developed by Hadlock and Pierce (2010), and the dividend payout ratio. Please see Table IA13 in the Internet Appendix.

[18] We additionally examine the relationship between corporate agility and corporate culture. Li et al. (2021) shows that firms with strong corporate culture outperform others during the COVID-19 pandemic because corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise (Kreps, 1990). We find that agility has significantly positive relationships with corporate culture, such as innovation, teamwork, quality, and respect, suggesting that strong culture supports firms to be more agile to business changes. See Section 4 in the Internet Appendix for more details.

4.6. The role of measurement error

In this sub-section, we discuss potential sources of measurement error in our *Response* and *Threat* scores. One potential source of measurement error in our *Response* and *Threat* scores is the managerial discretion in Management Discussion and Analysis (MD&A) disclosures. Managers may attempt to influence investor sentiment by understating threats and overstating responses, potentially leading to an overestimation of agility. While we do not rule out this concern, we expect it to have a minimal impact for several reasons. First, regulatory constraints limit managers' ability to manipulate disclosures. U.S. securities laws prohibit materially false or misleading statements in 10-K filings, and the Sarbanes-Oxley Act requires CEOs and CFOs to certify their accuracy (Securities and Exchange Commission (SEC), 2011). Concealing significant threats could expose managers to litigation risks, which they seek to avoid (e.g., Rogers and Buskirk, 2009). Moreover, to the best of our knowledge, no prior study has suggested that MD&A sections are excessively polished.

Second, we validate our *Threat* score by examining its association with firm-level risk or uncertainty measures. We find that higher *Threat* score is significantly associated with the risk or uncertainty measures, including i) the stock volatility in the next 6-, 12-, 18-, and 24-months after the 10-K release; ii) the implied volatility, which is derived from stock options (Alfaro et al., 2024); iii) LM uncertainty, which is measured by frequency of uncertainty-related words in MD&A sections (see Loughran and McDonald, 2011); iv) the firm-specific political risk developed by Hassan et al. (2019); and v) the economic uncertainty beta (as in Bali et al., 2017), which captures the firm's exposure to the economic uncertainty. For more details, see Table IA10 in the Internet Appendix. Additionally, as shown in the Descriptive Statistic Section, at the aggregate level, our *Threat* score exhibits a high correlation (0.72) with the Economic Policy Uncertainty (EPU) index, further supporting its validity.

Third, to mitigate potential measurement errors in the *Threat* score arising from firms overlooking various threats, we employ an instrumental variable (IV) approach. Following the Bartik-type instrument literature (e.g., Goldsmith-Pinkham et al., 2020; Breuer, 2022), we construct an industry-level threat measure and use it as an IV for the agility measure. The results remain consistent with our main findings. For further details, see Section 6 in our Internet Appendix.[19] Taken all together, these findings suggest that the measurement error, resulting from self-promotion or dismissive attitudes by the managers, should be minimal.

Measurement errors may also arise because some words in our dictionaries have multiple meanings (senses), and *word2vec* represents all senses with a single vector.[20] However, since our corpus consists of MD&A sections from 10-K filings—focused specifically on financial disclosures—the likelihood of ambiguity is lower than in a general corpus like Wikipedia (Henry and Leone, 2016). Furthermore, when selecting words for dictionaries, we carefully examine 20 randomly selected sentences for each word and remove words with ambiguous or multiple senses. To assess the impact of multiple-sense words, we examine 1000 randomly selected sentences containing the word "response" and its variations, finding that only 4% of cases involve ambiguity. Additionally, following Li et al. (2020), we apply the algorithm developed by Pelevina et al. (2016) to identify words with multiple meanings in our dictionaries. Approximately 8% of words have multiple senses; however, excluding these and recalculating our agility measure yields a high correlation (0.88) with the original measure, suggesting a minimal effect. Given this, we retain these words in our dictionaries.

Another source of measurement error could be negations, where firms describe their responses in negative sentences or positive sentences with negative meanings.[21] After manually reviewing 1000 randomly selected sentences containing the word "response" and its variations, we find that negation causes measurement errors in less than 5% of cases. To address this, we adjust our *Response* and *Agility* scores by identifying and excluding negative sentences containing words from the *Response* dictionary. The adjusted agility measure remains highly correlated (0.83) with the original measure, suggesting that negation has a minimal impact on our results.

5. The value of corporate agility during monetary policy transmission episodes

In this section, we examine how agile firms manage their exposure to monetary policy uncertainty. Hogg (2007) shows that uncertainty can be perceived by a manager as a significant form of threat to oneself. Prior papers provide evidence about the significantly negative effect of monetary policy uncertainty on corporate performance. For example, Husted et al. (2020) find that a one-standard-deviation increase in monetary policy uncertainty results in a decrease of approximately 10.34% in investment in the next quarter. Monetary policy shocks can affect firms through different transmission channels. Interest rate tightening by the Fed can make firms more financially constrained, forcing them to forgo profitable investment opportunities. We hypothesize that agile firms are less sensitive to such monetary policy shocks since they can respond quickly and effectively to this frequently occurring and forecastable threat that is observed in every business cycle. We use two proxies to measure monetary policy transmission episodes, including interest rate surprises (e.g., Bernanke and Kuttner, 2005, and Bauer and Swanson, 2023) and monetary policy uncertainty (MPU) by Bauer et al. (2022).

5.1. Corporate agility and FOMC announcements (interest rate surprises)

We use interest rate surprises as our first proxy for monetary policy uncertainty. Following recent studies (e.g., Gertler and Karadi,

[19] We appreciate this suggestion from an anonymous reviewer.
[20] For example, the word "response" can mean responding to an email, request, or questionnaire, which is unrelated to response to business environment changes.
[21] For example, firms may state that they "fail to respond to business environment changes."

2015; Gilchrist et al., 2015; Gorodnichenko and Weber, 2016; Armstrong et al., 2019), we use intraday data to measure monetary policy surprises and call that variable *Surprise*. This variable is computed as a weighted average (the first principal component) of 30-min changes in money market futures rates around the FOMC announcements (Bauer and Swanson, 2023).[22] Using this intraday setting allows for the isolation of monetary policy shocks from other confounding effects occurring on the announcement dates, which improves the identification quality of our tests. Following convention (e.g., Armstrong et al., 2019; Husted et al., 2020), we exclude financials (SIC between 6000 and 6999) and utilities (SIC between 4900 and 4999). To examine how agile firms' stocks perform on the FOMC announcement dates, we follow the approach of Bernanke and Kuttner (2005), Gorodnichenko and Weber (2016), Ippolito et al. (2018), and Armstrong et al. (2019), and estimate the following regression specification with a sample comprised of the announcement dates:

$$Return_{i,t} = \alpha + \beta_1 Agility_{i,t-1} + \beta_2 Agility_{i,t-1} \times Surprise_t + \beta_n Controls_{i,t-1} + \beta_m Controls_{i,t-1} \times Surprise_t + Firm\ FE + Date\ FE + \varepsilon_{i,t}, \quad (2)$$

where $Return_{i,t}$ is stock return for firm i on the announcement date t,[23] and $Suprise_t$ is the monetary policy surprise on the announcement date t. We control for 21 variables, including 12 different firm characteristic variables (firm size, market share, investment, sale growth, leverage, ROA, sale volatility, BM ratio, depreciation, gross margin, receivable, and stock volatility), four betas from Carhart four-factor model, financial constraint proxies (LW equity and debt indexes), and financial flexibility proxies (Cash ratio, Short-term debt, and Long-term debt). *Agility* and the controls are measured at the most recent fiscal-year end. Please refer to Table A1 for the source of data and construction of these variables. We interact all control variables with *Surprise* ($Controls_{i,t-1} \times Surprise_t$) to allow for the variation of slope coefficients. We also include firm and date fixed effects. Firm fixed effects control for time-invariant firm characteristics that can affect stock returns, such as industry membership and organizational capital, while date fixed effects control for macroeconomic conditions that can affect all firms' stock returns on the announcement dates. Date fixed effects also absorb the main effect of *Surprise*. We cluster standard errors by firm and date. Our main coefficient of interest is β_2. Since we hypothesize that agile firms are less sensitive to monetary policy surprises, we predict that β_2 is significantly positive.

Table 4 reports the results from estimating Eq. (2) for a sample period from 1997 to 2020. The coefficient of *Surprise* in column (1) is −7.104, and significant at the 1% level. This implies that a one basis point increase in monetary surprise results in a 7.104 basis points decrease in the stock returns, on average. Columns (2) shows that the coefficient of *Agility* × *Surprise* is 0.521 and significant at the 1% level. The inclusion of controls (shown under column (3)) yields qualitatively similar results. These results are consistent with our hypothesis that agile firms are less exposed to monetary policy uncertainty.[24] On average, a one standard deviation increase in *Agility* leads to around 7% less exposure to monetary policy uncertainty.[25,26] Furthermore, in Section 3 of the Internet Appendix, we perform robustness tests to control for zero-lower-bound periods and unconventional monetary policies. The results are qualitatively similar.

In addition, we analyse the cases when managers are indeed concerned about monetary policy uncertainty, and they discuss it extensively in the 10-K reports. Specifically, we examine which topic among the top 40 topics discussed in the MD&A sections has the strongest relationship with monetary policy uncertainty. By using the LDA topic modelling from Section 2.1, we can compute what proportion of a firm's 10-K report discusses each of the 40 topics. Then, for each topic, we estimate Eq. (2) with the replacement of *Agility* by the topic's standardized proportion while keeping other settings unchanged. The coefficient β_2 measures how much each topic is sensitive to monetary surprises. Table 5 lists and ranks the top 10 topics that are the most sensitive to monetary surprises, based on the magnitude of β_2. We find that, among all the β_2 coefficients, the one for the "threat" topic has the highest magnitude and statistical significance. This result implies that when a firm is exposed to monetary policy uncertainty, its managers' concerns about threats increase. In other words, monetary policy uncertainty is a highly significant form of threat, and being agile can help firms protect themselves against it.

5.2. *Corporate agility, stock volatility, and monetary policy uncertainty (MPU)*

Together with the interest rate surprises, we use the *MPU* measure of Bauer et al. (2022) as a second proxy for monetary policy uncertainty. This uncertainty measure is calculated as the square root of the "model-free variance" obtained from interest rate

[22] We are grateful to Bauer and Swanson (2023) for sharing the data about monetary policy surprises, which is available at https://www.frbsf.org/research-and-insights/data-and-indicators/monetary-policy-surprises/.

[23] Our results are unchanged if we define return as cumulative return from announcement date until up to four days after that. We do not use this method, as returns can be confounded by other events happening after announcement dates.

[24] We find that the effect of agility on firms' reactions to monetary surprises is more pronounced for small, young, growth-oriented, and low-leverage firms. Please see Table IA15 in the Internet Appendix for more details. These results suggest that such firms, being smaller in scale, nimbler, and financially flexible, are better positioned to respond swiftly to shocks.

[25] We find similar results if we take the log of *Agility* or log of (*Agility* + 1), or if we replace the main measure of *Agility* by alternative measures of agility that are measured by the topic modelling method (LDA) or using 10-Q data. Please refer to Table IA8 in the Internet Appendix for more details.

[26] Examining the relationship between *Threat* score and *Surprises*, we find that a firm with a high *Threat* score is more sensitive to monetary surprises. The result confirms that monetary surprises are a significant form of threat. Please refer to Table IA6 in the Internet Appendix for more details.

Table 4
Agility and monetary policy transmission.

	Stock return		
	(1)	(2)	(3)
Surprise	−7.104***		
	(1.698)		
Agility		−0.006	−0.006
		(0.013)	(0.013)
Agility × Surprise		0.521***	0.382**
		(0.171)	(0.158)
surprise × Depreciation			−0.800
			(2.670)
surprise × Investment			−0.229
			(1.144)
surprise × Leverage			−0.153
			(0.197)
surprise × Firm size			−0.137
			(2.256)
surprise × Gross Margin			2.393
			(2.249)
surprise × Receivable			−1.207***
			(0.434)
surprise × ROA			1.637
			(1.908)
surprise × Sale growth			−1.488**
			(0.572)
surprise × Sales volatility			−3.727***
			(1.050)
surprise × Market share			299.218**
			(136.559)
surprise × BM ratio			−0.133**
			(0.059)
surprise × Stock volatility			−19.810**
			(9.132)
surprise × MKT beta			−0.580
			(0.487)
surprise × HML_beta			0.986
			(0.637)
surprise × SMB_beta			−0.222
			(0.338)
surprise × WML_beta			0.056
			(0.427)
surprise × LW_equity index			0.355
			(0.414)
surprise × LW_debt index			−0.381
			(0.392)
surprise × Cash ratio			−0.449
			(1.014)
surprise × Short-term debt			0.435
			(2.327)
surprise × Long-term debt			1.696
			(1.157)
Controls	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	No	Yes	Yes
Clustering at firm and date	Yes	Yes	Yes
Num. obs.	313,066	313,066	313,066
Adjusted R^2	0.041	0.107	0.110

The table reports the estimation results of Eq. (2) for the sample period from 1997 to 2020. The dependent variable is the stock returns on the FOMC announcement dates. Following Bauer and Swanson (2023), *Surprise* is computed as a weighted average (the first principal component) of 30-min changes in money market futures rates around the FOMC announcements. *Agility* and controls are measured at the end of the previous year. We winsorize all continuous variables at 1% and 99%. Please refer to Table A1 for the source of data and measurement of variables. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Clustered standard errors at the firm and date levels are shown in the parentheses.

Table 5
The sensitivity of the top 10 topics in the MD&A sections to monetary surprises.

Topics	Proportion	Sensitivity to monetary surprises (Coefficient β_2)	Statistical significance (t_statistics of β_2)
(1)	(2)	(3)	(4)
Threat	0.033	−0.927	5.665***
Product selling	0.029	−0.901	2.099**
Software product	0.036	−0.683	2.986**
Retail sale	0.024	−0.497	1.267
Pension	0.029	−0.417	1.297
Wireless communication	0.017	−0.401	1.698
Asset	0.034	−0.218	0.708
Common share	0.034	−0.130	0.825
Real estate	0.011	−0.114	0.519
Expense	0.035	−0.113	0.809

The table shows the top 10 topics discussed in the MD&A sections that are the most sensitive to monetary surprises. The topics are ranked based on their sensitivity to monetary surprises (β_2). For each topic, we estimate the Eq. (2) with the replacement of agility by a standardized proportion of that topic. Sensitivity to monetary surprises and its statistical significance are the coefficient and *t*-statistics of the interaction variable proportion × *Surprise*. Proportion in column (2) is the mean proportion of discussing a topic in MD&A sections, computed based on the topic modelling method. ***p < 0.01; ***p* < 0.05; *p < 0.1.

derivatives (futures and options) on FOMC dates.[27] High *MPU* implies that the market is uncertain about monetary policy, which in turn leads to high stock volatility. We examine whether agility helps firms mitigate stock volatility problems during the high *MPU* periods. We estimate the following modified version of Eq. (2) on the FOMC announcement dates:

$$Stock\ volatility_{i,t} = \alpha + \beta_1 Agility_{i,t-1} + \beta_2 Agility_{i,t-1} \times MPU_t + \beta_n Controls_{i,t-1} + \beta_m Controls_{i,t-1} \times MPU_t + Firm\ FE + Date\ FE + \varepsilon_{i,t}, \tag{3}$$

Where stock volatility is measured as the standard deviation of the daily stock returns during the window [−1; +1] around the announcement dates. We use the same control variables, fixed effects, and clustering as in Eq. (2). Table 6 reports our estimation results. In column (1), the coefficient of *MPU* is 2.456 (significant at the 1% level), implying that higher *MPU* leads to higher market uncertainty and stock volatility. In column (3), the coefficient of *MPU* × *Agility* is −0.097 (significant at the 5% level), implying that agile firms' stocks are less volatile due to MPU. *Agility* seems to help in minimizing the effect of *MPU* on stock volatility, which confirms our hypothesis that agile firms are less exposed to monetary policy uncertainty.[28]

5.3. How do agile firms protect themselves?

Next, we analyse how exactly the agile firms protect themselves against monetary policy uncertainty and against the overall risks.

5.3.1. Monetary policy uncertainty (MPU)

In Sections 5.1 and 5.2 above, we show that agile firms are less sensitive to monetary policy uncertainty. As shown in Table 6, high *MPU* leads to high market risk. In this section, we examine how agile firms manage (or hedge) their exposure to monetary policy uncertainty. We expect agile firms to be proactive and more likely to take measures to manage their exposure. Prior papers show that firms apply different techniques to manage risk, such as hedging (Friberg and Seiler, 2017). Specifically, we look at the following two risk management techniques: risk hedging and risk quantification. To examine our hypothesis, we use annual data from 1997 to 2020 to estimate the following equation:

$$\begin{aligned} Risk\ management_{i,t} = {} & \alpha + \beta_1 Agility_{i,t-1} + \beta_2 MPU_{i,t} + \beta_3 Agility_{i,t-1} \\ & \times MPU_t + \beta_n\ Macroeconomic\ variable_{i,t} + \beta_m Firm\ controls_{i,t-1} + Firm\ FE + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where *Risk management* is measured by *hedging* or *risk quantification,* both of which are binary indicators capturing the extensive margin of these activities. *Hedging* is an indicator of whether a firm applies derivatives to hedge risk, following the method of Ippolito et al. (2018). To construct this measure, we first search for hedging-related words, such as "hedge" or "hedging," in the MD&A sections. We then adjust for false positives, ensuring that firms explicitly stating they do not engage in hedging are not misclassified. *Risk Quantification* is a binary variable indicating whether a firm applies risk assessment techniques such as shock simulation, sensitivity analysis, or value-at-risk (VaR). To identify firms that engage in risk quantification, we use *word2vec* to generate synonyms of "risk

[27] We are grateful to Bauer et al. (2022) for sharing the data, which is available at https://www.frbsf.org/research-and-insights/data-and-indicators/market-based-monetary-policy-uncertainty/.

[28] A potential concern is that the correlation between monetary surprise and the monetary uncertainty measure can affect our regression results (Bauer et al., 2022). To address this, we re-estimate equation (2), including both variables and their interactions with agility. While the effect of monetary surprise is somewhat smaller, our main results remain qualitatively unchanged. See Table IA16 in the Internet Appendix for details.

Table 6
Agility and the effect of monetary policy uncertainty (MPU) on stock volatility.

	Stock volatility [−1; +1]		
	(1)	(2)	(3)
MPU	2.456***		
	(0.305)		
Agility		0.065**	0.054*
		(0.030)	(0.029)
MPU × Agility		−0.131**	−0.097**
		(0.053)	(0.040)
MPU × Depreciation			−0.010
			(0.007)
MPU × Investment			0.002
			(0.003)
MPU × Leverage			0.000
			(0.000)
MPU × Firm size			−0.008*
			(0.004)
MPU × Gross Margin			−0.014***
			(0.003)
MPU × Receivable			−0.000
			(0.001)
MPU × ROA			0.000
			(0.003)
MPU × Sale growth			0.001
			(0.001)
MPU × Sales volatility			0.003
			(0.002)
MPU × Market share			−0.329*
			(0.193)
MPU × BM ratio			−0.000
			(0.000)
MPU × Stock volatility			0.035***
			(0.013)
MPU × MKT beta			0.005***
			(0.001)
MPU × HML beta			−0.000
			(0.001)
MPU × SMB beta			−0.000
			(0.001)
MPU × WML beta			−0.000
			(0.001)
MPU × LW_equity index			0.000
			(0.001)
MPU × LW_debt index			0.002***
			(0.001)
MPU × Cash ratio			−0.002
			(0.002)
MPU × Short-term debt			0.010
			(0.007)
MPU × Long-term debt			−0.001
			(0.002)
Control	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes
Date fixed effects	No	Yes	Yes
Clustering at firm and date	Yes	Yes	Yes
Num. obs.	313,066	313,066	313,066
Adjusted R^2	0.237	0.297	0.307

The table reports the estimation results of Eq. (3) for the sample period from 1997 to 2020. The dependent variable is stock volatility measured as the standard deviation of daily stock return during the window [−1; +1] around the FOMC announcement dates. *MPU* is the market-based monetary policy uncertainty measure developed by Bauer et al. (2022), derived from 6-month Eurodollar futures and options. *Agility* and controls are measured at the end of the previous year. We winsorize all continuous variables at 1% and 99%. Please refer to Table A1 for the source of data and construction of variables. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Clustered standard errors (SE) at the firm and date are shown in the parentheses.

quantification" and compile a list of 49 related terms. We verify that these terms do not overlap with response-related words and then search for them in the MD&A sections. A firm is classified as engaging in risk quantification (indicator = 1) if at least one of these terms appears in its MD&A section; otherwise, the indicator is set to 0. For further methodological details, see Section 1 of our Internet Appendix.

In Eq. (4), *MPU* is measured as the sum of monetary policy uncertainty on FOMC meeting dates during a year, following the approach developed by Bauer et al. (2022). We control for various macroeconomic variables during the year, including *EPU*, GDP growth, CPI growth, and consumer confidence, following Husted et al. (2020). Those variables are measured as the average of the

Table 7
Why agile firms fare better during high MPU: corporate responses.

Panel A: Corporate responses to MPU: Hedging and risk quantification		
Dependent variable	Hedging	Risk Quantification
	(1)	(2)
MPU	1.462***	0.392***
	(0.131)	(0.059)
Agility	−0.028***	−0.027***
	(0.009)	(0.004)
MPU × Agility	0.294**	0.309***
	(0.115)	(0.052)
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Clustering at firm and industry × year	Yes	Yes
Num. obs.	50,284	50,284
Adjusted R^2	0.620	0.416

Panel B: Corporate responses to risk: Hedging			
Dependent variable	Hedging		
Risk proxies	Realized risk	Implied risk	Textual_analysis_risk
	(1)	(2)	(3)
Risk	−0.013	−0.063*	0.195***
	(0.020)	(0.033)	(0.000)
Agility	−3.687***	−5.100***	−0.710*
	(1.393)	(1.711)	(0.431)
Risk × Agility	6.173***	9.768***	3.147*
	(2.193)	(3.065)	(1.841)
Controls	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes
Clustered at firm and industry × year	Yes	Yes	Yes
Num. obs.	22,353	22,353	49,597
Adjusted R^2	0.652	0.652	0.635

Panel C: Corporate responses to risk: Diversifying financially			
Dependent variable	Diversifying financially		
Risk proxies	Realized risk	Implied risk	Textual_analysis_risk
	(1)	(2)	(3)
Risk	−0.026	−0.030	0.183***
	(0.016)	(0.027)	(0.000)
Agility	−1.141	−1.448*	−0.167
	(0.719)	(0.744)	(0.305)
Risk × Agility	2.035*	2.835**	2.712**
	(1.197)	(1.273)	(1.198)
Controls	Yes	Yes	Yes
Firm and year fixed effects	Yes	Yes	Yes
Clustered at firm and industry × year	Yes	Yes	Yes
Num. obs.	22,736	22,736	49,597
Adjusted R^2	0.123	0.122	0.564

Panel A reports the estimation results of Eq. (4) for the sample period 1997–2020. The dependent variable is an indicator capturing whether a firm engages in *Hedging* or *Risk Quantification*, thus reflecting the extensive margin of these activities. *Hedging* is a binary variable indicating whether a firm uses derivatives to hedge risk. *Risk Quantification* is a binary variable indicating whether a firm applies risk assessment techniques such as sensitivity analysis and value-at-risk (VaR). *MPU* is the sum of monetary policy uncertainty on FOMC dates during a given year. Panels B and C report the estimation results of Eq. (5), where the dependent variable is *Hedging* (Panel B) and *Diversifying Financially* (Panel C). *Diversifying Financially* is a binary variable indicating whether a firm diversifies its financial strategy in terms of funding or investment, again capturing the extensive margin of financial diversification. *Risk* is proxied by *Realized Risk*, *Implied Risk*, and *Textual Analysis Risk*. *Realized Risk* and *Implied Risk* are measured based on stock volatility and option volatility, respectively. *Textual Analysis Risk* is measured by counting the frequency of risk-related words in the MD&A sections. In all panels, we use the same controls as in Eq. (3). In Panel A, we additionally control for macroeconomic variables, including EPU, GDP Growth, CPI Growth, and Consumer Confidence. ***$p < 0.01$; $p < 0.05$; $p < 0.1$. Clustered standard errors are in parentheses.

corresponding macroeconomic variable during the year. We also control for the same firm characteristic variables as in Eq. (3). *Agility* and firm controls are measured at the end of the previous year. We include firm fixed effects and cluster standard errors at the firm and industry × year levels.

Panel A of Table 7 shows the estimation results from Eq. (4). The coefficient of *MPU* × *Agility* in column (1) is 0.294 and statistically significant at the 5% level, which suggests that agile firms are more likely to hedge risk when *MPU* increases. In column (2), the coefficient of *MPU* × *Agility* is 0.309 and significant at the 1% level, meaning that agile firms are more likely to apply risk quantification techniques, such as sensitivity analysis, shock simulation, and value at risk (VAR), when *MPU* increases. Overall, those results are consistent with our hypothesis that agile firms are more likely to apply risk management techniques to reduce their exposure to *MPU*. Hedging and risk quantification can explain why the agile firms are less sensitive to monetary policy uncertainty.

5.3.2. Hedging overall risk

To provide further evidence, we examine how agile firms manage their exposure to the overall risk in the economy. We focus on two risk management techniques: hedging and diversifying financially. Specifically, we estimate the following equation:

$$Risk\ management_{i,t} = \beta_0 + \beta_1 Agility_{i,t-1} + \beta_2 Risk_{i,t} + \beta_3 Agility_{i,t-1} \times Risk_{i,t} + \beta_n Controls_{i,t-1} + Firm\ FE + Date\ FE + \varepsilon_{i,t}, \tag{5}$$

where *Risk management* is measured by *hedging* or *diversifying financially*, both of which are binary indicators capturing the extensive margin of these activities. *Hedging* is measured as explained above. *Diversifying financially* is a binary variable equal to 1 if a firm engages in financial diversification through external funding or investment, and 0 otherwise. To identify such firms, we first search for sentences containing diversification-related terms (e.g., "diversification," "diversify," "diversifying"). We exclude negative sentences to correct for false positives. Next, we analyse the surrounding words of the diversification-related terms in each sentence to determine whether the diversification pertains to financial activities. A firm is classified as diversifying financially if the sentence includes terms related to funding or investment (e.g., "loan," "interest rate," "securities," "investment") and does not include terms related to customers, suppliers, or production. We measure risk using three proxies: *realized risk*, *implied risk*, and *textual_analysis_risk*. *Realized risk* is based on stock volatility, while *implied risk* is derived from stock option prices (Alfaro et al., 2024).[29] *Textual_analysis_risk* is measured by counting the frequency of risk-related words in the MD&A sections using a risk dictionary, following Friberg and Seiler (2017). We use the same firm-level control variables as in Eq. (3).

Panels B and C of Table 7 report the estimation results from Eq. (5). In Panel B, where the dependent variable is *Hedging*, we find that the coefficient of *Risk* × *Agility* is significantly positive regardless of the risk proxy. This implies that agile firms are more likely to use hedging when facing higher overall risk. Similarly, in Panel C, where the dependent variable is *Diversifying financially*, we find that agile firms are more likely to diversify in terms of funding sources and investment when the overall risk increases.

5.4. The real consequences of being agile

In this subsection, we examine the real consequences of being an agile firm. We analyse how corporate investment reacts to interest rate increases (monetary policy transmission) and whether corporate agility helps mitigate the negative real effects of monetary policy uncertainty. Tighter monetary policy by the Fed can make firms become more financially constrained, which in turn forces firms to reduce their investment. By contrast, looser monetary policy can increase corporate investment. We conjecture that agile firms' investments are less sensitive to monetary policy, as they can actively manage their exposure. Following the method of Chava and Hsu (2020), we use quarterly data from 1997 to 2020 to estimate the following equation:

$$Investment_{i,t} = \alpha + \beta_1 Agility_{i,t-1} + \sum_{j=0}^{12} \delta_j \Delta FFR_{t-j} + \sum_{j=0}^{12} \gamma_j\, Agility_{i,t-1} \times \Delta FFR_{t-j} + \beta_n Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}, \tag{6}$$

where *Investment* is the sum of capital expenditure and R&D expenses during the quarter scaled by the firm's total assets. ΔFFR_{t-j} is the sum of changes in federal fund rates during a quarter lagged j quarters from the investment quarter.[30] We use the same firm controls as in Eq. (3). We include industry and year fixed effects, and cluster standard errors at the firm and industry × year levels. Table 8 reports the estimation results from Eq. (6). For lag 1-year effect, the coefficient of ΔFFR, computed as the sum of δ_1 *to* δ_4, is -0.803 and significant at the 1% level. This implies that interest rate increases in the past 1-year lead to lower investment, on average. The coefficient of $Agility_{i,t-1} \times \Delta FFR_{t-j}$, computed as the sum of γ_1 *to* γ_4, is 0.104 and also significant at the 1% level, implying that the investment of agile firms is less affected by the interest rate increases. We find similar results for the lag 2- and 3-year effects of interest rate changes. On average, a one-standard-deviation increase in *Agility* leads to approximately 17% less exposure to interest rate changes.[31] These results suggest that agile firms, through active risk management, are better able to sustain their investment plans and

[29] We are grateful to Alfaro et al. (2024) for sharing their data that is available through https://www.policyuncertainty.com/firm_uncertainty.html

[30] We find similar results if we use the sum of interest rate surprises instead of the sum of real interest rate changes. However, we believe that the sum of real interest rate changes is more appropriate, as corporate investment is likely to respond directly to real interest rate levels, unlike stock returns, which are more sensitive to the unanticipated components of interest rate changes.

[31] Additional analyses reported in Table IA21 of the Internet Appendix show that agile firms' capital investment is less affected by monetary policy uncertainty (Bauer et al., 2022) compared to other firms.

Table 8
Real consequence of being agile towards monetary policy changes.

Dependent variable	Investment	
Independent variable	*ΔFFR*	*Agility*ΔFFR*
	(1)	(2)
Sum of Lag 1-year effect	−0.803***	0.104***
	(0.000)	(0.009)
Sum of Lag 2-year effect	−0.971***	0.149***
	(0.003)	(0.001)
Sum of Lag 3-year effect	−0.840**	0.153***
	(0.016)	(0.042)
Controls	Yes	
Industry and year fixed effects	Yes	
Clustered at firm and industry × year	Yes	
Numb obs.	138,343	
Adjusted R^2	0.269	

The table reports the estimation results of Eq. (6) for the sample period from 1997 to 2020, following Chava and Hsu (2020). Dependent variable is measured by investment scaled by total asset. *ΔFFR* is the sum of changes in Federal Fund Rate during the quarter. For *ΔFFR* column, *Sum of lag 1-year effect* is the sum of δ_1 *to* δ_4, *Sum of lag 2-year effect* is the sum of δ_1 *to* δ_8, and *Sum of lag 3-year effect* is the sum of δ_1 *to* δ_{12}. For *Agility*ΔFFR* column, *Sum of lag 1-year effect* is the sum of γ_1 *to* γ_4, *Sum of lag 2-year effect* is the sum of γ_1 *to* γ_8, *Sum of lag 3-year effect* is the sum of γ_1 *to* γ_{12}. Standard errors are clustered at the firm and industry × year. Controls include firm size, market share, investment, sale growth, leverage, ROA, sale volatility, BM ratio, depreciation, gross margin, receivable, stock volatility, four betas from Carhart four-factor model, LW_equity index, LW_debt index, cash ratio, short-term debt, and long-term debt. *P*-values from the tests of the null hypothesis that the sum of coefficients is equal to zero are in the parenthesis.

mitigate the impact of monetary policy changes on their operations.

6. Conclusion

Corporate agility is an important strategic management tool for firms operating in a dynamic business environment characterized by various external threats and uncertainties (Alchian, 1950). While important, this concept is difficult to measure, which makes quantitative analysis on the topic difficult. As a result, little is known about why and under which circumstances corporate agility is beneficial to firms. To analyse such issues, we apply an advanced machine learning method (*word2vec*) to build a reliable measure of agility. After constructing this measure, we demonstrate that it effectively captures the firms' responsiveness to financial threats. For example, agile firms are less likely to be financially constrained and tend to outperform other firms during crises, including the global financial crisis of 2008 and the COVID-19 pandemic.

In the second part of our study, we examine how well agile firms fare during monetary policy transmission events, which tend to occur frequently enough for the firms to anticipate and plan for them. Such events are accompanied by high monetary policy uncertainty, which negatively affects corporate performance (Baker et al., 2016; Husted et al., 2020). Thus, agile firms are expected to be particularly cognizant of risks and threats that may arise during such uncertainty-ridden periods. We hypothesize that agile firms are less sensitive to monetary policy uncertainty since they are better prepared and more capable of responding effectively to such challenges.

We employ two proxies to measure monetary policy uncertainty, including monetary surprises (Bauer and Swanson, 2023) and the Monetary Policy Uncertainty (*MPU*) index (Bauer et al., 2022). Regardless of proxies for monetary policy uncertainty, we find results consistent with our hypothesis. A one-standard-deviation increase in agility is associated with approximately a 7% lower exposure of the firm's stock return to monetary policy uncertainty. We further find that, in anticipation of such uncertainties, the agile firms are more likely to actively apply risk management techniques to reduce their exposure. These hedging techniques include financial hedging, diversifying investments, utilizing different sources of funding, and employing risk quantification techniques such as sensitivity analysis, shock simulation, and value at risk (VaR). Finally, we demonstrate that being agile during monetary policy transmission episodes has real consequences: the capital spending (corporate investment) of agile firms is less sensitive to monetary policy tightening.

Our paper is one of the first in finance to apply machine learning techniques to measure and quantify the concept of corporate agility. The approach requires little to no subjective judgment and can be applied to any publicly traded firm with available 10-K filings. By introducing a replicable and quantifiable firm-level measure of agility, we enhance academic research on the value of corporate agility during periods of high uncertainty. We also contribute to the literature on the cross-sectional variation in firms' reaction to monetary policy transmission (Yellen, 2016; Gallo and Kothari, 2019). We show that corporate agility is a factor that can explain the different reactions of firms to monetary policy shocks. Agile firms actively apply hedging or other risk management techniques to manage their exposure to monetary policy uncertainty. Our agility measure can be easily applied in other quantitative analyses related to corporate agility and various economic outcomes.

CRediT authorship contribution statement

Gonul Colak: Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Sinh Thoi Mai:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation.

Appendix A. Appendix

Table A1
Variable definitions.

Variables	Source of data	Definition
A. Macroeconomic variables		
Surprise	Bauer and Swanson (2023)	Following Bauer and Swanson (2023), Surprise is computed as a weighted average (the first principal component) of 30-min changes in money market futures rates around the FOMC announcements.
MPU	Bauer et al. (2022)	The square root of the "model-free variance" obtained from interest rate derivatives (futures and options) on FOMC dates.
EPU	Baker et al. (2016)	Average of monthly Economic policy uncertainty index from Baker et al. (2016).
GDP growth	FRED	Average of quarterly GDP growth.
CPI growth	FRED	Average of monthly CPI growth.
Consumer confidence	FRED	Average of the monthly consumer sentiment index constructed by the University of Michigan.
B. Agility variables		
Agility	SEC's EDGAR	3-year moving average of *Response* score scaled by *Threat* score.
Threat	SEC's EDGAR	Measuring *Threat* score by applying the *Threat* dictionary and TF.IDF method on the MD&A sections.
Response	SEC's EDGAR	Measuring *Response* score by applying the *Response* dictionary and TF.IDF method on the MD&A sections.
C. Firm variables		
Stock return	CRSP	Daily on announcement dates or monthly stock returns.
Stock volatility	CRSP	Standard deviation of daily stock return during the window [-1; $+1$] around announcement dates, or standard deviation of monthly stock returns during the twelve-month period prior to fiscal year-end.
BM Ratio	Compustat	Book value of equity scaled by market value of equity, measured at fiscal yearend.
Depreciation	Compustat	Depreciation expense scaled by sales during the current fiscal year.
Market share	Compustat	The proportional share of sales of firms in their industries during the current year, based on 2-digit SIC code.
Investment	Compustat	The ratio of sum of capital expenditures and R&D expense to total assets at the beginning year.
Leverage	Compustat	Total liabilities scaled by total assets at fiscal yearend.
Firm size	Compustat	Natural logarithm of total assets at fiscal yearend.
Gross Margin	Compustat	Sales minus cost of goods sold, scaled by sales during the current fiscal year.
Receivable	Compustat	Accounts receivable minus accounts payable, scaled by total assets, measured at fiscal yearend.
ROA	Compustat	Income before extraordinary items scaled by beginning of the year total assets.
Sales Growth	Compustat	Percentage growth in current fiscal year sales over the prior year.
Sales volatility	Compustat	Standard deviation of sales scaled by total assets over the previous ten years with at least 2 observations.
MKT Beta	CRSP	Factor loading on the market factor from the Carhart four-factor model using monthly return over the past 5 years from the month prior to announcement dates with at least 30 observations, based on Dimson (1979) approach.
SMB Beta	CRSP	Factor loading on the SMB factor from the Carhart four-factor model using monthly return over the past 5 years from the month prior to announcement dates with at least 30 observations, based on Dimson (1979) Dimson (1979) approach.
HML Beta	CRSP	Factor loading on the HML factor from the Carhart four-factor model using monthly return over the past 5 years from the month prior to announcement dates with at least 30 observations, based on Dimson (1979) Dimson (1979) approach.
WML Beta	CRSP	Factor loading on the WML factor from the Carhart four-factor model using monthly return over the past 5 years from the month prior to announcement dates with at least 30 observations, based on Dimson (1979) Dimson (1979) approach.
Realized risk	Alfaro et al. (2024)	Standard deviation of 12-month fiscal-year daily CRSP returns.
Implied risk	Alfaro et al. (2024)	365-day implied volatility of at-the-money-forward call options.
Textual_analysis_risk	SEC's EDGAR	Following the method of Friberg and Seiler (2017), textual_analysis_risk is measured by counting the frequency of risk-related words on MD&A sections based on a risk dictionary.
Corporate culture measures	Earnings call conference	Following the method of Li et al. (2020), corporate culture is measured by counting culture-related words on Q&A sections of earnings call transcripts.
D. Firm response variables		

(*continued on next page*)

Table A1 (*continued*)

Variables	Source of data	Definition
Hedging	SEC's EDGAR	A dummy variable, equal 1 if a firm applies derivative to hedge risk, following the method of Ippolito et al. (2018). First, we search for the word related to hedging such as "hedge", "hedging". Then, we adjust for the case of false positive. For example, firms may say that they do not hedge risk.
Diversifying financially	SEC's EDGAR	A dummy variable, equal 1 if a firm apply diversifying financially in terms of funding and investment. First, we search for words related to diversify and its other forms such as diversification, diversifying. Then, we examine the surrounding words of the word "diversify" in the same sentence. We classify as diversifying financially if the sentence contains words related to funding or investment like loan, interest rate, securities, invest and do not contain words related to customers, suppliers, production.
Risk quantification	SEC's EDGAR	A dummy variable, equal 1 if a firm applies technique to quantify risks like sensitivity analysis, shock simulation, value at risk (VAR), based on a list of 49 words, please refer to table IA3 on internet appendix for the list of words.
E. Corporate governance variables		
Board size	BoardEx	The total number of directors.
% Independent directors	BoardEx	The number of independent directors scaled by board size and multiplied with 100.
F. Financial constraint variables		
LW equity index	Linn and Weagley (2024)	Financial constraints related to equity, an extension of the text-based financial constraint measures originally developed by Hoberg and Maksimovic (2015).
LW debt index	Linn and Weagley (2024)	Financial constraints related to debt, an extension of the text-based financial constraint measures originally developed by Hoberg and Maksimovic (2015).
G. Financial flexibility variables		
Cash ratio	Compustat	Cash/assets
Short-term debt	Compustat	Short-term debt/assets
Long-term debt	Compustat	Long-term debt/assets

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2026.102973.

Data availability

The authors do not have permission to share data.

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