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Shared exposures or management fashions? Antecedents of convergence in the insurance and banking industries

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Abstract

We study convergence in the attention of decision-makers across the insurance and banking industries. Our analysis is based on textual risk disclosures (10-K reports, 2006–2018), providing a snapshot of corporate priorities and contexts. We theoretically link convergence with decision-making contexts via the Attention-Based View. Leveraging strategic management theory, we identify antecedents of convergence in attention and, therefore, potentially, risk contagion. These include common trends in the macro-environment, substitution threats, and management fashions. We combine this theoretical framework with machine learning tools to create quantitative measures of convergence in attention and its antecedents. We find that the proposed measure of convergence is predictive of inter- and intra-industry stock correlations. Finally, based on regression and sensitivity analyses, we identify the relative importance of different antecedents, showing that shared risk management fashions largely drive Inter-industry convergence in attention. This highlights challenges when interpreting regulatory text data in the context of predicting contagion risk.

KEYWORDS
contagion, industry convergence, management attention, risk disclosure, systemic risk, text analysis

1 | INTRODUCTION

While it is well understood that risks within a system can be interlinked, their systemic nature arising from such linkages has attracted increasing attention. *Systemic risks* are characterized by complexity, uncertainty, ambiguity, and wide ripple effects (Renn et al., 2022), with examples ranging from the 2007–2008 Financial Crisis (Earle, 2009; Ivashina & Scharfstein, 2010) and the COVID-19 pandemic (Botzen et al., 2022), to the current and accelerating climate crisis, which interconnects risks in complex ways on a global and trans-generational scale (Aglietta & Espagne, 2016).

In this study, we focus more narrowly on *contagion risk*, which relates to connectedness and risk transmission across the financial system, while the stronger notion of systemic risk additionally requires significant financial impacts to the economy. As laid out by Harrington (2009), contagion risk can be a harbinger of systemic risks, and arises via mechanisms that include asset fire sales following a shock, counterpart defaults in an interconnected system, informational effects (e.g., uncertainty/opaqueness impacting behavior), as well as irrational effects, such as panic-driven withdrawals that do not reflect institutions' actual risk.

Within the context of contagion risk, the convergence of the insurance and banking industries is an important area of study. These industries have distinct business models, but are at the same time subject to common pressures from their economic and broader environment, while their adjacency as parts of the financial system means that they are often able to enter each other's markets (Cummins & Weiss, 2009; Elyasiani et al., 2016; Harrington, 2009). For example, the near-collapse of the insurance giant AIG in 2008 demonstrated interconnectedness across industry boundaries, with insurers investing in mortgage-backed securities, which generated shared vulnerabilities and, ultimately, extreme downside risks (Billio et al., 2012; Bushman et al., 2017). Furthermore, the cultural commonalities of the financial services industries make issues such as groupthink and herding behavior a concern (Haldane & May, 2011; Trueman, 1994).

Consequently, important challenges arise for the risk management and governance responses to contagion risk. First, how can contagion risk be measured? Quantitative measures have extensively focused on econometric analyses, for example, by reflecting observed statistical associations and/or signals from credit markets; see indicatively Acharya et al. (2012, 2017); Billio et al. (2012); Brownlees and Engle (2017); Chen et al. (2014); Jourde (2022); Kaserer and Klein (2019). Furthermore, a fundamental element of contagion risk is the structural connectedness of affected institutions. Addressing this point is the burgeoning literature that combines econometric study with network analysis (Chen & Sun, 2020; Chen et al., 2020; Lin et al., 2015; Tang et al., 2022). A second and rather different challenge revolves around the identification of signals that can serve in the construction of early warning systems (Renn et al., 2022). Since the response to contagion risks—and consequently, their amplification or attenuation—is contingent on their perception by stakeholders, it matters how "signals get filtered and modulated, transmitted, and interpreted" (Schweizer et al., 2022). The importance of informational and institutional aspects of insurance contagion risk has been established in the studies of Ma and Ren (2021); Seog (2008).

In this paper, we take a different (in some sense a "sideways") perspective on these challenges and aim to contribute a set of quantitative tools helpful for the understanding of industry convergence and its antecedents. In the design of those tools, we mobilize the Attention-Based View (ABV) of the firm (Ocasio, 1997), thus associating a literature strand of management research with problems studied within the insurance literature. The ABV offers a conceptual framework for examining the focused attention of stakeholders, which is itself an antecedent of the risk perceptions that they form. We apply these ideas to the study of convergence in the attention of risk managers in the insurance and banking industries. For this, we use text data from risk disclosures as empirical manifestations of decision-makers' attention. The data are companies' 10-K reports, spanning the 2006–2018 period, which allows alignment between our theoretical framework and empirical strategy. The theory conceptualizes convergence in risk managers' attention as shaped by institutional forces, macro trends, and management fashions. This time frame captures the build-up to the financial crisis and over a decade of postcrisis managerial adaptation, avoiding contamination from exogenous shocks. We analyze these textual data quantitatively using machine learning techniques.

At this point, we need to anticipate a potential criticism of our use of text data from regulatory returns. In simple terms: how do we know that what risk managers *say* in these documents has any bearing on what they *do*? We counter such a criticism in three ways. First, we will provide empirical validation of our measure of convergence in attention, showing that it is predictive of a correlation-based measure of contagion risk. Second, we note that in the management literature, text data such as 10-K submissions have been long viewed as providing a reasonable reflection of managers' attention in different areas and functions of the organization, not least because of the legitimacy drawn from their status as formal documents (e.g., Dutt and Joseph [2019]; Eklund et al. [2024]; Flammer and Bansal [2017]; Guo et al. [2017]; McKenny et al. [2018]; Philippe and Durand [2011]).

Third, our approach is rooted in management theory and an institutional understanding of industry convergence. Over the last 50 years, management and finance scholars have established through empirical studies that company behavior is influenced by institutional forces. These forces include bandwagon effects (Abrahamson, 1991), the quest for legitimacy (Meyer & Rowan, 1977), and adherence to management trends (Filatotchev et al., 2025; Gompers et al., 2003). A key tenet of this body of research is that these institutional forces form external signals that companies adapt to and, for that reason, they become antecedents of management action. Within that context, firms' 10-K reports include a record of managers' considered response to those signals and thus give an empirical trace of the impact of institutional forces. At the same time, 10-Ks are public regulatory documents that influence the perception of shareholders and broader stakeholders. As such, 10-K reports are both influenced by and influence management bandwagons. We note that these institutional dynamics have a material reflection in resource allocation, as evidenced in the research stream spurred by the Carnegie School, for example, March and Simon (1958); Simon and March (2015). Therefore, noting that management attention and industry convergence are in an intricate two-way relationship, we advocate using text-based covariates as a proxy to capture salient forces that drive behavior and the potential for correlated actions.

The organization of the rest of the paper is as follows. In Section 2 we provide a discussion of the ABV of the firm and the use of the 10-K data in the management and finance literature.

In Section 3, we construct measures of convergence in the attention of risk managers, across- and within industries. For this, we employ machine learning techniques. We vectorize the risk disclosure documents using Doc2vec embeddings (Mikolov et al., 2013a, 2013b), and then use silhouette values (Rousseeuw, 1987) to quantify the semantic similarity between reports from individual companies and whole industries. We call this (firm-year specific) measure of semantic similarity *convergence in attention*. Furthermore, we show by regression analysis that convergence in attention is a significant predictor of contagion risk, as manifested through stock return correlations. This finding also provides a validation of the methodology pursued.

In Section 4, we turn to the antecedents of Inter-industry convergence in attention, between insurers and banks. We draw on the strategic management literature to formulate three contextual antecedents: *common trends* in the macro environment, managers' attention to an adjacent industry because of the threat of *substitution*, and management *fashions*. We argue that the dominance of any of those antecedents in explaining convergence in attention, brings different risk management implications. Subsequently, we construct quantitative measures of the context in which decision-makers' attention is situated, through topic analysis (Blei et al., 2003) of the Business section of 10-K reports.

In Section 5, we associate convergence in attention with its contextual antecedents, via Random Forest (Breiman, 2001) regression analysis. Thus, in contrast to Section 3, convergence now becomes the response variable. We use extensive sensitivity analysis to gain insights on the modeled response of convergence in attention measure to its antecedents, namely Accumulated Local Effects (ALE) (Apley & Zhu, 2020), feature importance (Breiman, 2001), and Shapley values (Lundberg & Lee, 2017a). The analysis leads to four key findings. First, the measure of convergence tends to be higher for insurers compared to banks, meaning that insurance risk managers' attention is to a larger extent directed towards banking, compared to bank risk managers' attention towards insurance. This finding is broadly consistent with econometric studies in insurance and banking (Bégin et al., 2019; Chen et al., 2014; Elyasiani et al., 2016; Kaserer & Klein, 2019). Second, the regression analysis shows that our measure of convergence has a positive time trend, consistently with the big-picture study of Jourde (2022). Furthermore, convergence increases in all three postulated antecedents (common trends, substitution, and fashions), which validates our theoretical framing. Third, the variable importance and sensitivity analyses consistently find that management fashions have a dominant impact on convergence in attention. This underlines the need for inclusive governance approaches (Eling & Marek, 2014; Renn et al., 2022; Schweizer et al., 2022). Finally, we find that management fashions, despite dominating convergence, are themselves not predictive of contagion risk (at least not at the time horizon considered), indicating the need for care in interpreting regulatory text data.

2 | ABV OF THE FIRM AND 10-K DATA

The ABV of the firm (Ocasio, 1997; Ocasio & Joseph, 2005) is an established theoretical perspective in management research on firm strategic behavior. The ABV theorizes firm strategic behavior as an outcome of the focusing and channeling of decision-makers' attention. Here, attention is understood as "the noticing, encoding, interpreting, and focusing of time and effort by organizational decision makers on both problems and solutions" (Ocasio, 1997). The theoretical tenet that the focus of decision-makers' attention leads to firm strategic behavior is supported by empirical evidence in a variety of contexts and for several strategic behaviors including: responses to institutional change (Ocasio & Radoynovska, 2016); multinational strategy (Bouquet & Birkinshaw, 2008); technology strategy (Eggers & Kaplan, 2009); strategic adaptation (Joseph & Ocasio, 2012), and corporate governance (Tuggle et al., 2010).

Furthermore, the focus of managers' attention is situated in the firm's context, which includes the environmental stimuli for decision-making, the interactions among participants in the context, and the embodiment of issues and answers in cultural symbols, artifacts, and narratives (Ocasio, 1997). It follows that, if decision makers are subject to a context that shares similarities, they are also likely to focus their attention towards similar issues, hence their firms are likely to exhibit similar strategic behaviors. Therefore, the ABV provides a theoretical framework to understand and anticipate strategic co-behaviors across firms and industries, through the lens of the convergence, or divergence, of the constituent elements of the contexts in which management attention is situated.

In the context of risk management, the role of risk perception (Slovic, 1992) is crucial, not least as perception itself influences human behavior and can thus be a driver of contagion risk (Renn et al., 2022; Schweizer et al., 2022). Furthermore, risk perception operates through information systems and channels of communication, based on which interpretations are formed, leading to different behavioral responses, ripple effects, and finally social impacts (Pidgeon et al., 2003). While these processes are multifaceted and complex, it is empirically more tractable to study their result: the limited set of issues that decision-makers focus their attention on (Ocasio, 1997). Furthermore, as decision-makers' attention is contextually situated, the strategy literature offers insights for identifying salient features of the decision context (Drucker, 1995; Grant, 2021; Porter, 1985; Porter, 1986)—we will return to this issue in Section 4.1.

A first challenge, then, is the identification of empirical traces of the context in which risk managers' attention is situated, which are also available and comparable for individual firms and across time. We suggest that a firm's 10-K report—the document that all listed companies have to submit yearly to the US Securities and Exchange Commission (SEC)—can play such a role. 10-Ks have been extensively used as data sources for describing managers' and firms' behaviors, in areas including management (Dutt & Joseph, 2019; Guo et al., 2017), accounting and valuation (Cazier et al., 2021; Fritzsch et al., 2021), risk management (Bao & Datta, 2014), and systemic risk measurement (Bushman et al., 2017). Existing literature on text analysis that evaluates contagion risk focuses on within-industry effects. For example, Bushman et al. (2017) measure a bank's connectedness within the banking sector based on the 10-K business section. They construct groups of connected peer banks and find that banks exhibit significantly stronger tail co-movements with their most similar peers Gupta et al. (2021) use 13-F filings, another type of financial report submitted to the SEC, to examine the interconnectedness within the banking system. Their findings indicate that contingent convertible debt significantly mitigates contagion risk in the banking industry.

The 10-K reports are structured in several sections, describing a company's business, the risks it faces, and the operating and financial results for the fiscal year. To capture the context of risk managers' situated attention, we focus on the 10-K's Risk Factors section, which includes information about the most significant risks that apply to the company or to its assets. The data have limitations, stemming from their formal regulatory purpose. Still, we choose 10-K filings for our research because: (a) every US-listed company has it in each year, (b) the format is consistent, and (c) there is a section specific on Risk Factors, which is pertinent to our paper. We focus on firms traded on the NYSE and do not include firms on, for example, NASDAQ, primarily due to data availability and consistency, as well as the need to minimize variability introduced by exchange-specific factors. Firms listed on the NYSE are typically larger and more established, which aligns more closely with the focus of our study.

Building on these premises, we argue that the textual closeness of different companies' 10-K Risk Factor sections with each other is a proxy for convergence in the focus of risk managers' attention, hence a potential driver of more similar firm strategic behaviors in response to the risk environment. In that sense, convergence among the content of companies' 10-K Risk Factor reports can be thought of as an potential indicator of contagion risk. In Section 3, we offer a methodology to operationalize these theoretical insights, by introducing text-based metrics of convergence, applied within and across industries.

3 | MEASURING CONVERGENCE IN ATTENTION

3.1 | Data

Our dataset contains 10-K submissions to the SEC of all 214 banks and 94 insurers listed on the New York Stock Exchange from 2006 to 2018. These are the industries across which we aim to measure convergence in attention. We focus on the two most substantial sections of those reports: the Business and Risk Factors sections. We collected all the 10-K reports manually from Filings Expert and classified the companies as Insurers or Banks based on the North American Industry Classification System (NAICS) codes. In addition, we use text data from 223 pharmaceuticals' 10-K reports over the same period—data from pharmaceuticals will be used in Section 3.4 for constructing a measure of management fashions.

Thus, the text data cover $T = 13$ years and $I = 531$ companies. Define the sets $\mathscr{T} = \{1, ..., T\}$ and $\mathscr{I} = \{1, ..., I\} = \mathscr{I}_{IN} \cup \mathscr{I}_{BK} \cup \mathscr{I}_{PH}$, where $i \in \mathscr{I}_{IN}$ if the ith company is an insurer, $i \in \mathscr{I}_{BK}$ if it is a bank, and $i \in \mathscr{I}_{PH}$ if it is a pharmaceutical. Thus, each 10-K report in the data corresponds to a pair (i, t), $i \in \mathscr{I}, t \in \mathscr{T}$. Let J_{it} be equal to one if there is a document for firm i in year t and zero otherwise. The numbers of documents in year t for each industry are then denoted as

$$n_{A,t} = \sum_{j \in \mathscr{I}_A} J_{j,t}, \quad A \in \{IN, BK, PH\}.$$

The total number of firms in each industry and year can be found in Table 1. The variation in the number of companies across insurers, banks, and pharmaceuticals over the years can be attributed to several factors, including IPOs, delistings, and broader economic events. We note that are no reinsurance firms in the first 3 years of the sample. This is because our analysis focuses exclusively on companies listed on the NYSE that are large enough to be required by regulations to disclose Section 1A: Risk Factors; smaller companies, which are not subject to this disclosure requirement, are excluded from the analysis.

Before any text analysis is carried out, some standard pre-processing steps are applied: (a) Stop words are those words most likely to appear in all documents in the corpus (e.g., "a" "the," "of", etc.), and they carry little semantic meaning (Bengfort et al., 2018, p. 65). Stop words are removed, which improves the performance of algorithms, as there are fewer and more meaningful tokens left (Bengfort et al., 2018, pp. 72–74). (b) Bigrams, possible contiguous subsequences of two words, are constructed. For example, "real estate" is understood as a one term when the two words appear together (Bengfort et al., 2018, pp. 132–145). (c) All the words and bigrams are lemmatized, that is, we remove inflectional endings and return the base or dictionary form of a word (Stanford & Group, 2009).

TABLE 1 Total number of firms for each industry and year in the dataset. The last four columns refer to insurance sub-industries.

Year	Banks	Pharmaceuticals	Insurers	Life	PC	Full Line	Reinsurance
2006	173	94	53	16	32	5	0
2007	171	99	55	17	33	5	0
2008	177	105	54	18	31	5	0
2009	182	113	54	15	33	5	1
2010	191	116	76	18	39	9	10
2011	194	118	82	21	42	10	9
2012	193	110	61	21	32	7	1
2013	202	103	84	20	43	11	10
2014	204	102	90	22	45	12	11
2015	200	94	89	23	45	11	10
2016	189	100	84	20	44	11	9
2017	171	92	60	16	34	8	2
2018	131	91	74	17	39	10	8

3.2 | Construction of the cross-industry convergence metric

Here, we construct a measure of convergence, which reflects the similarity of an individual bank's (resp. insurer's) Risk Factors section in their 10-K report, to the insurance (resp. banking) industry as a whole. This measure is meant to represent managers' cross-industry convergence of attention. Constructing such a measure entails two distinct steps. First, each individual document (Risk Factor sections of 10-K reports), needs to be converted to a vector representation. Second, a measure of similarity is employed to calculate inter-industry convergence, based on those vectors.

To convert each document into a vector, we use word embeddings constructed by Doc2vec, which is an unsupervised algorithm that learns fixed-length feature representations from documents of varying length (Le & Mikolov, 2014). Word embeddings are well-suited for mapping documents' semantic content onto a vector space, by explicitly considering the context in which individual words occur. Such context is not captured in standard approaches that are based purely on word frequencies, for example, frequency, one-hot, and TFIDF encoding (Bengfort et al., 2018; Kusner et al., 2015, pp. 65–66).

To derive word embeddings from our data, we use Gensim's Doc2vec class in Python. The Doc2vec algorithm represents each document by a dense vector, using a neural network. We choose Doc2vec over alternatives such as Word2Vec embeddings (Mikolov et al., 2013b) (which are word- rather than document- specific), because Doc2vec has been found to outperform, for example, simple averaging of Word2Vec vectors, in terms of the error rates of an information retrieval task (Le & Mikolov, 2014).

Given the representation of each document by a vector, we measure the convergence in management attention across organizations in distinct industries using silhouette values (Rousseeuw, 1987). The silhouette value is a measure, used in unsupervised learning, of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). It is calculated using the mean intra-cluster (here: intra-industry) distance and the mean nearest-cluster (here: inter-industry) distance for each observation. A low value indicates that the object is poorly matched to its own cluster and well matched to neighboring clusters, indicating, in our context, high convergence.

We define the vector representing each Risk Factors document for insurers and banks by D_{it}, $i \in \mathscr{I}_{IN} \cup \mathscr{I}_{BK}$, $t \in \mathscr{T}$. To calculate convergence for insurers, for each document with $i \in \mathscr{I}_{IN}$ and $J_{it} = 1$, we define the quantities:

$$a_{it} = \frac{1}{n_{IN,t} - 1} \sum_{j \in \{\mathscr{I}_{IN} \setminus i\}} J_{jt} \cdot d(D_{it}, D_{jt}),$$

$$b_{it} = \frac{1}{n_{BK,t}} \sum_{j \in \mathscr{I}_{BK}} J_{jt} \cdot d(D_{it}, D_{jt}),$$

where d represents the Euclidean distance between document vectors. Here, a_{it} represents the average dissimilarity of an insurer's Risk Factors section to other insurers' reports (across years) while b_{it} reflects the average dissimilarity to banks' reports. For $i \in \mathscr{I}_{BK}$, we define the quantities a_{it}, b_{it} analogously. Then, our measure of inter-industry convergence is given by the *negative silhouette value* defined as

$$Convergence\_interit = -\frac{b_{it} - a_{it}}{\max\{a_{it}, b_{it}\}}, \quad i \in \mathscr{I}_{IN} \cup I_{BK}. \tag{1}$$

The denominator, $\max\{a_{it}, b_{it}\}$, ensures scale invariance and constrains the measure to lie within the range $[-1, 1]$. This measure reflects the extent to which a document is close to documents from a different industry, compared to the baseline of the document's closeness to other documents from its own industry.

In Figure 1, we show boxplots of the $Convergence\_inter_{it}$ variable by year and by industry. It can be seen that the level of convergence varies widely across firms, with many outliers present. For banks, a slight positive trend towards higher convergence in attention may be observed, though this is clearly dominated by intra-year variability. For insurers, there is no clear trend. We will use regression analysis in the sequel to provide further insight in view of this variability: in Section 3.4 considering convergence as a predictor of a contagion risk measure, and in Section 5.2.1 relating the convergence measure to its theorized antecedents.

3.3 | Construction of a within-industry convergence measure

Here, we use the tools of the last section to produce, additionally, a measure of intra-industry convergence. This measure is defined as:

$$Convergence\_intra_{it} = -a_{it}, \quad i \in \mathscr{I}_{IN} \cup I_{BK}. \tag{2}$$

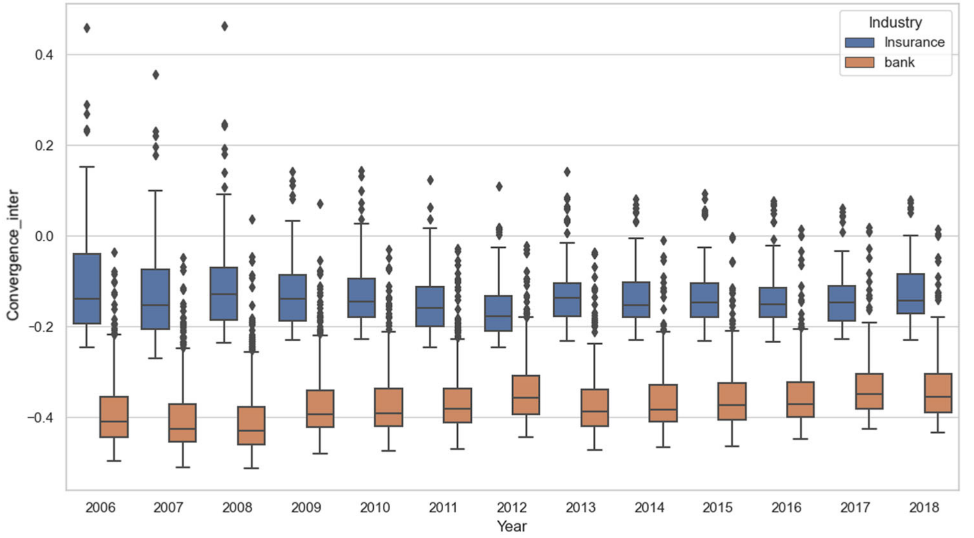

FIGURE 1 Boxplot of the *Convergence_inter*$_{it}$ variable by year and industry.

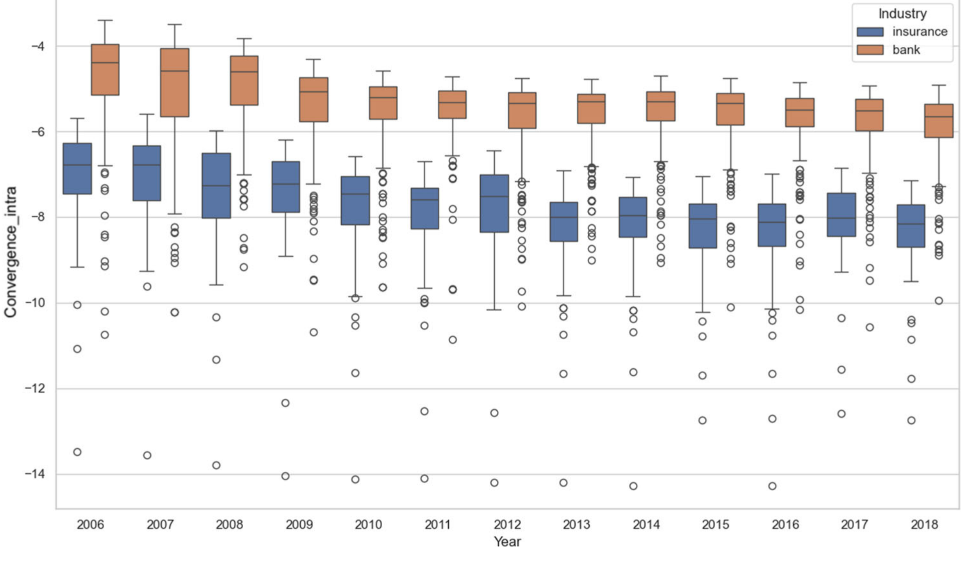

FIGURE 2 Boxplot of the *Convergence_intra*$_{it}$ variable by year and industry.

where a_{it} is defined in Section 3.2. The quantity $-a_{it}$ measures the degree of cohesion in management attention within an industry. Since a_{it} represents the average intra-cluster distance, its negative can serve as a measure of within-industry convergence.

In Figure 2, we show boxplots of the *Convergence_intra*$_{it}$ variable by year and by industry. Once again, it is seen that the level of intra-industry convergence varies considerably across firms, with a substantial number of outliers. There are no significant trends, but a slight decline in convergence over the postcrisis years may be observed.

3.4 | Convergence measures as predictors of contagion risk

Here, we use regression modeling to evaluate whether the inter- and intra-industry convergence measures developed can be effective predictors of contagion risk. This also serves the purpose of validating the convergence measures for subsequent use in Section 5.

3.4.1 | Variable definitions

The **dependent variables** in this analysis will be measures of inter- and intra-industry contagion risk. Specifically:

- Inter-industry stock return correlation, denoted as $StockCorr\_inter_{it}$ is Kendall's rank correlation between an individual insurer's (resp. bank's) daily stock return and the return on the S&P 500 Bank Index (resp. Insurance Index).
- Intra-industry stock return correlation, denoted as $StockCorr\_intra_{it}$, is Kendall's rank correlation between an individual insurer's (resp. bank's) daily stock return and the return on the S&P 500 Insurance Index (resp. Bank Index).

For each (i, t), the values of $StockCorr\_inter_{it}$ and $StockCorr\_intra_{it}$ are calculated on stock market data over the 1-year time period *after* the disclosure date of the corresponding 10-K report. Data on the stock price of each company come from the Quandl database. Data for the industry indices are downloaded from S&P Global Market Intelligence.

These correlation-based measures are closely related to the well-known ΔCoVaR measure (Adrian & Brunnermeier, 2016) of systemic risk. In particular, in a multivariate Gaussian (and more broadly, elliptical) setting, ΔCoVaR becomes exactly proportional to the correlation coefficient between the returns of a firm and the index (Adrian & Brunnermeier, 2016, p. 1713). (As we are focusing here on contagion risk rather than systemic risk impacts, we do not reflect the volatility component of ΔCoVaR, which in the Gaussian model acts as a multiplier of correlation.) We focus directly on correlation rather than tail risk measures, as we are not specifically focused on extreme levels of stock co-movement—our convergence measure reflects broad convergence in management attention rather than extreme cases. Furthermore, we do not want to make the signal we are trying to measure noisier, by, for example, ignoring non-extreme data and/or employing quantile regressions. Finally, we use Kendall's rank correlation, rather than product-moment correlation, because it has been shown to yield lower measurement error in the context of heavy tails (Lindskog et al., 2003).

The **independent variable** is $Convergence\_inter_{it}$ when predicting $StockCorr\_inter_{it}$, and $Convergence\_intra_{it}$, when predicting $StockCorr\_intra_{it}$. The measurement of convergence precedes observations on which stock correlations are calculated. We **control** for year and industry fixed effects.

3.4.2 | Model selection and results

For each of the two regressions, of inter- and intra-industry contagion risk (stock correlation), we select a model from within three classes of machine-leaning models commonly used for regression tasks: a regularized linear model (Elastic Net Regression) and two nonlinear models

(Random Forests and Gradient Boosting Trees). All three classes of models are widely used and have distinct characteristics. Elastic Net Regression combines L_1 and L_2 regularization, making it effective for handling multi-collinearity and feature selection, though it assumes linear relationships (Zou & Hastie, 2005). Random Forests are ensemble models that aggregate predictions from multiple decision trees, offering robustness to overfitting and capturing nonlinear interactions (Breiman, 2001). Gradient Boosting Trees sequentially build trees to minimize errors, providing high predictive accuracy for complex data, though they are more prone to overfitting and require careful hyperparameter tuning (Friedman, 2001).

All regressions are carried out in Python, using the scikit-learn package (Pedregosa et al., 2011). To evaluate the models, we use cross-validation with 10 folds. As we have far more banks than insurers in our sample, we make sure all folds are stratified and balanced, to have the same proportion of insurers and banks in each fold. We run each model for different hyperparameter settings and report the mean squared error (MSE), averaged over all folds. These prediction errors are reported in Table 3 in the Appendix 1, for different hyperparameter choices, in an approach similar to Agarwal et al. (2019). All other hyperparameter values are set at their default values, reported in Table 4 in the Appendix 1. For both inter- and intra-industry contagion risk, the selected models are Gradient Boosted Trees, based on the cross-validation results, while also checking the learning curves to avoid overfitting.

We visualize the results of the selected regression model via ALE plots. ALE plots, proposed by Apley and Zhu (2020), describe how features influence the prediction of a machine learning model on average, showing how predictions change in a small window of the feature, around a certain grid value for data instances in that window. ALEs can be efficiently calculated and are not distorted by correlation between features (Molnar, 2020), which affects alternatives such as Partial Dependence Plots.

The ALE plots for the chosen Gradient Boosting regression model are displayed in Figure 3 for the inter-industry case and Figure 4 for the intra-industry case. We observe the following for both cases. Year effects are substantial: there is a peak for the Year effect between 2008 and 2012, corresponding to the global financial crisis, followed by an increasing trend after 2016. This shows that the correlation-based measures used capture contagion risk effects consistently with expectations. Furthermore, the convergence measure positively impacts contagion risk in the coming 1 year at a scale broadly comparable to the Year effects. This finding supports the

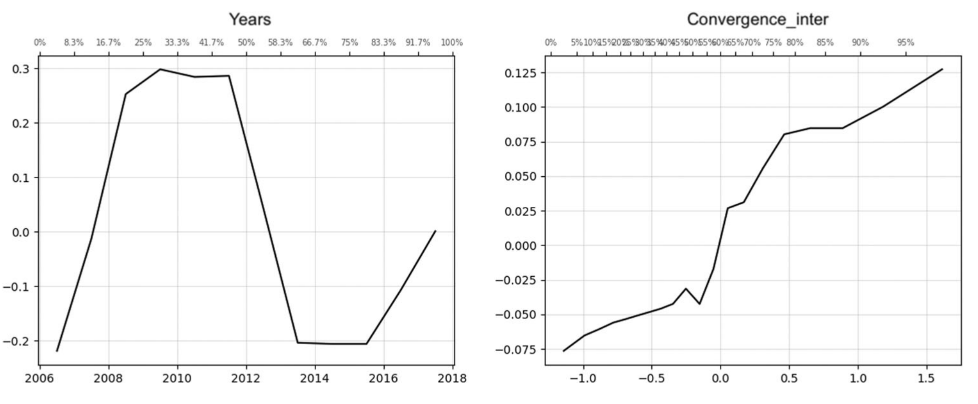

FIGURE 3 ALE plots for the prediction of inter-industry contagion risk from convergence in attention. ALE, Accumulated Local Effects.

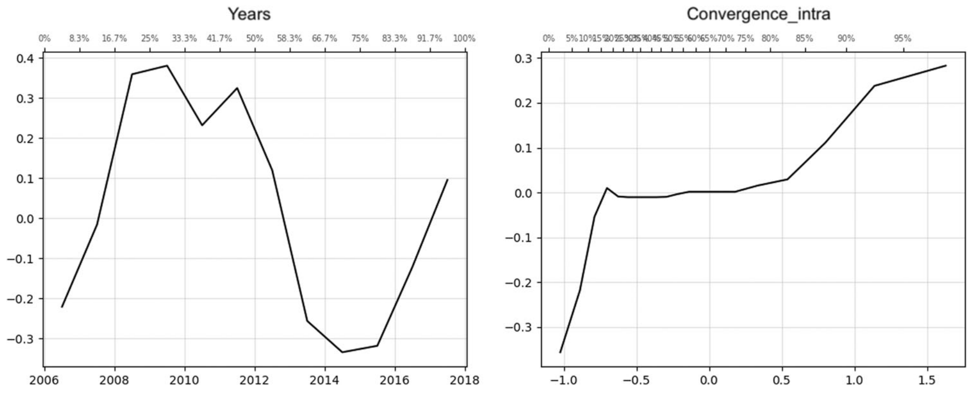

FIGURE 4 ALE plots for the prediction of intra-industry contagion risk from convergence in attention. ALE, Accumulated Local Effects.

idea that convergence can serve as a practically significant predictor of contagion risk. In particular, the ability of text-based measures of intra-industry convergence to predict contagion risk aligns with findings in the existing literature (e.g., Bushman et al., 2017).

For robustness, we also examined the results of Random Forest regression, which showed the same effects seen in Figures 3 and 4. In addition, we conducted standard linear panel data regression with random effects, demonstrating statistically significant results that are again consistent with the selected model; this finding is presented in Table 5 in the Appendix 1.

4 | ANTECEDENTS OF CONVERGENCE IN RISK MANAGERS' ATTENTION

Having established that our proposed measures for convergence of management attention are associated to a real-world manifestation of contagion risk, we proceed by studying the antecedents of such convergence. From this point onward, we focus on *inter-industry convergence* only.

4.1 | Antecedents of inter-industry convergence in risk managers' attention

The extent of convergence among companies' 10-K Risk Factors reports may signal an increase or decrease in contagion risk, but does not in itself specify the drivers of such a change. Hence, the convergence of attention, without reference to its drivers, does not give a clear signal to risk professionals and policymakers as to what might be suitable prevention or mitigation responses. To address this issue, we note that risk managers are exposed to considerations around a company's overall strategy. Then, the broader management literature can help us identify some specific dimensions of the context in which risk managers' attention is situated.

First, the strategic management literature has highlighted that, in developing their strategy, firms should look at the trends in their macro environment (Drucker, 1995; Grant, 2021) and describe scenarios that a firm is likely to face (Cornelius et al., 2005). These *common trends* are not limited to specific industries, and apply to the whole economy, for example, increased attention to customer services, operation of firms, products, asset management, gains and loss of investment, etc. In the context of risk management, we argue that a firm's business narrative around common trends is an important dimension that risk managers consider.

Second, (Porter, 1985, 1986) and the literature spurred from his seminal books on competitive strategy and competitive advantage have identified some factors—often referred as Porter's Five forces—that affect an industry's profitability, namely, suppliers' bargaining power, clients' bargaining power; intensity of competition, threat of new entrants, and threat of substitution. *Substitution* occurs when companies of one industry have to compete with those in other industries producing substitute products or services (e.g., insurers selling financial derivatives that are traditionally sold by banks). While narratives around, for example, competition and buyers/clients' bargaining power are related to dynamics within a firm's legacy industry, narratives around substitutes are more likely to be related to cross-industry dynamics and hence, pertinent to our analysis.

Finally, the management literature has also revealed that strategic choices often find their antecedents in management *fashions* (Abrahamson, 1996) and institutional legitimacy considerations (Suchman, 1995). Management fashions bear relevance for studying the antecedents of industry convergence: for example, it has been argued that the adoption of (risk) management systems can simply follow fashion rather than address real need, which reduces the usefulness of such systems and may even render them sources of risk (Power, 2009).

Hence, we identify common trends, threat of substitution, and management fashions as salient aspects of risk managers' context of attention. In Section 4.3, we present in detail the construction of quantitative measures of those antecedents based on the 10-K reports.

4.2 | Implications for risk management

Our theoretical framework has direct implications for risk professionals and policy makers. If different antecedents of attention are dominant as drivers of convergence, different types of systemic threats will prevail, which in turn would necessitate alternative risk management responses.

If the first antecedent—attention on common trends—prevails, there will be both cross-industry and economy-wide risk. Decision-makers' attention to common issues in the environment, for example, stock market performance, supply chain operation, or customer service, will be the main cause of convergence. Contagion risk caused by this antecedent is difficult to fully control because it is related to system-wide challenges; nonetheless, it can be to an extent mitigated (Hopkin, 2018). At individual firm level, risk can be diversified (e.g., the risk supply chain failure is managed by diversifying suppliers [Gornall & Strebulaev, 2018]) or partially transferred (e.g., by reinsurance). Even though reinsurance connectivity provides an additional route of transmitting financial shocks, the U.S. property and casualty insurance market, for example, has been shown to be resilient to risk contagion from reinsurance transactions (Chen et al., 2020). Regulators can help individual firms control the risk by setting risk limits, and guiding them to prepare for emerging system-wide risks.

If the second antecedent—attention on the adjacent industry and threat of substitution—is the main driver of the convergence, there will be a risk of cross-industry contagion. In that case, managers in insurers and banks are preoccupied by firms' selling products or adopting strategies traditionally associated with the other industry. As a consequence, shocks in one industry may spill over to the other. For instance, in the wake of the 2007–2008 financial crisis insurers' involvement in banking business, for example, selling structured credit products, was seen as a key cause of systemic risk (Cummins & Weiss, 2009). Hence, regulatory responses are called for that mitigate the risk of contagion, focusing on the type of activity as well as specific (e.g., systemically important) entities (Elyasiani et al., 2016; Kaserer & Klein, 2019). Furthermore, given the empirically observed asymmetry between the systemic effects of banks and insurance companies (Chen et al., 2014; Elyasiani et al., 2016), differential regulatory approaches are called in the two industries, reflecting both the type of exposure and the degree of connectedness (Jourde, 2022; Kaserer & Klein, 2019).

If the third antecedent—risk managers' exposure to similar (risk) management fashion—prevails, then both idiosyncratic and economy-wide risks arise. Managers' attention may be led to “fashionable” topics, for example, implementing enterprise risk management (ERM) frameworks without sufficiently reflecting on nonquantifiable uncertainties (Power, 2009). Attention and thus risk perception can become biased (Schweizer et al., 2022), possibly away from crucial risks (idiosyncratic or otherwise) towards less material ones. Furthermore, groupthink (Janis, 2008) may also lead to similar actions adopted when facing the same event, which further exacerbates contagion risk. A compounding issue is that then risk disclosure itself, by reflecting the biases of risk perception, becomes less informative in reflecting and anticipating the risks that firms are exposed to. Such problems invite a risk governance response. Previous studies show that corporate governance, especially the role of risk professionals, has a big impact on the performance of firms during crises (Aebi et al., 2012; Hunjra et al., 2021), and the need for inclusive governance (Renn et al., 2022; Schweizer et al., 2022) is well established, given the complexities and ambiguities of systemic risk management. In particular, lower levels of risk-taking in the insurance industry have been associated with factors including higher levels of board independence and increased monitoring (Eling & Marek, 2014).

4.3 | Measures for the antecedents of convergence

The calculation of the negative silhouette value defined in (1), based on vector representations of firms' Risk Factor sections, enabled us to construct a measure of convergence in management attention, as reflected in textual risk disclosures. Now we turn our attention to constructing firm/year-specific measures for the antecedents of attention. We first perform a topic modeling analysis, to identify general themes from the analyzed text documents. This helps us to derive interpretable descriptors of the composition of individual documents, which in turn will be used to construct the required measures.

4.3.1 | Topic modeling of 10-K business sections

A topic model is a type of statistical model for discovering a set of topics that are shared by a collection of documents. A well-established topic modeling approach is the Latent Dirichlet Allocation (LDA) introduced by Blei et al. (2003). Examples of application of LDA in risk analysis and management science include Bao and Datta (2014); Bellstam et al. (2021); Taeuscher et al. (2021). LDA generates summaries of topics in terms of a discrete probability distribution over words for each topic, and further infers, for each document, the distribution of its word content over topics.

LDA is a generative model, with the following underlying assumptions. A fixed number of topics, K, exists. Each document is assumed to be randomly constructed by choosing its composition by topic according to a Multinomial distribution with Dirichlet prior. Furthermore, for each topic, a Multinomial distribution over the vocabulary of size N is assumed, again with a Dirichlet prior, giving the probability of any word in the vocabulary belonging to this topic. LDA estimates (a) for each document (i, t), $i \in \mathscr{I}, t \in \mathscr{T}, k = 1, \ldots, K$, the proportion p_{itk} of the topic k in that document, and (b) for each word $n = 1, \ldots, N$ in the vocabulary, the relative frequency q_{nk} by which the word will appear as part of of topic k.

We run the LDA model on all the Business section from 10-K reports of all the three industries in all years. We use Business section rather than Risk Factors section (which was used to measure overall convergence) to (a) reflect the broader strategic focus of the firms, giving the context within risk managers' attention is situated, and (b) avoid endogeneity, since the variables constructed based on LDA will be used later as regression covariates. The number of topics K is a parameter set by the user of LDA. Since we use the topic distribution later to construct measures for the antecedents of convergence in attention, we selected K based on the interpretability and thematic clarity of the generated topics. Specifically, we chose the largest number of topics that produced distinct and interpretable thematic groupings, while avoiding excessive overlap across topics. Appendix 2 presents results for $K = 5$ and $K = 7$, where topics show overlapping themes across word clouds. In contrast, $K = 6$ produces clearer separation, with each topic aligning more closely with a primary theme. We therefore adopt $K = 6$ in our main analysis.

In Figure 5, we show word clouds generated for each topic, representing the estimates q_{nk}. We interpret these word clouds as distinct themes:

- Topics 1 and 3 are insurance-specific, referring to insurance liabilities and life policies, respectively.
- Topics 2 and 4 are idiosyncratic to banking, discussing loans and deposits, and bank regulation and capital.
- Finally, Topics 5 and 6 do not appear to be particular to any single industry, the first referring to operations, products and customer service, the latter to investments and assets.

In Table 2, we present the mean distribution of topics, for documents within each industry; that is, we show the average of p_{itk} over $t \in \mathscr{T}$ and over i in each of $\mathscr{I}_{IN}$, $\mathscr{I}_{BK}$. We see that the highest frequencies in each row of Table 2 are consistent with the way that we have interpreted Figure 5.

4.3.2 | Antecedent 1: Common trends

The first contextual antecedent of firm strategy relates to the challenges and opportunities in the industry environment. To quantify this antecedent, we introduce the variable $CommonTrend_{it}$. From the LDA analysis of Section 4.3.1, Figure 5, we identify two topics that reflect aspects of the environment that cut across industries, specifically Topics 5 ("Products, operations, and customers") and 6 ("Investment"). Hence we define:

$$CommonTrend_{it} = p_{it5} + p_{it6}, \quad i \in \mathscr{I}_{IN} \cup \mathscr{I}_{BK}.$$

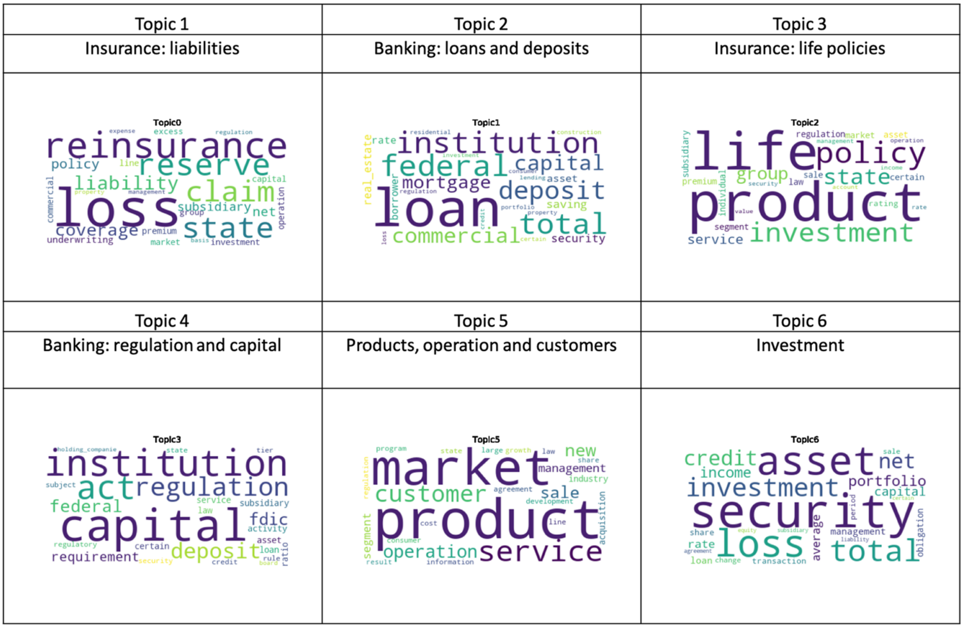

FIGURE 5 LDA-generated word clouds, representing the distribution of words within each topic. LDA, Latent Dirichlet Allocation

TABLE 2 Average percentage distribution of topics, for documents in each industry, including insurance sub-industries.

Topic	Banks	Insurers	Life	PC	Full line	Reinsurer
Topic 1: Insurance: liabilities	0.34	**51.04**	**11.91**	**69.83**	**54.64**	**59.13**
Topic 2: Banking: loans and deposits	**33.33**	1.90	3.48	1.22	1.19	2.59
Topic 3: Insurance: life policies	1.27	**25.21**	**66.22**	**6.56**	**33.59**	**9.96**
Topic 4: Banking: regulation and capital	**53.59**	3.34	2.57	0.78	0.60	3.63
Topic 5: Products, operation, and customers	4.54	0.14	0.28	0.19	0.04	0.15
Topic 6: Investment	**6.82**	**10.29**	**7.08**	**12.35**	4.44	**0.04**

4.3.3 | Antecedent 2: Threat of substitution

The second contextual antecedent of firm strategy relates to the potential for substitution and new industry entry. We measure the relevance of this antecedent for specific firms, via the variable $Substitution_{it}$, defined as follows. From the LDA analysis of Section 4.3.1, we have seen that there are insurance-specific and bank-specific topics. The variable $Substitution_{it}$ reflects the extent to which a firm (e.g., an insurer) places attention on topics specific to the industry it does not belong to (e.g., banking), measured by the percentage of the firm's 10-K Business section spent on those topics. Hence we have that:

$$Substitution_{it} = \begin{cases} p_{it2} + p_{it4}, & i \in \mathcal{I}_{IN}, \\ p_{it1} + p_{it3}, & i \in \mathcal{I}_{BK}. \end{cases}$$

4.3.4 | Antecedent 3: Management fashions

Finally, we identified as the third contextual antecedent of firm strategy, related to industry convergence, the level of attention to management fashions, generated by legitimacy concerns. To construct a relevant variable, we proceed in two steps. First, we evaluate the convergence of each firm to a third, not directly related industry. In this way, we control for the extent to which the 10-K submissions of an individual bank or insurer reflect themes that go beyond the issues specific to the banking and insurance industry. We measure the negative silhouette value between the Risk Factors sections of 10-K reports, but now with clusters formed by financial firms (insurers and banks combined) on the one hand and pharmaceuticals (which serve as the third reference industry) on the other. Specifically, we let

$$SVFP_{it} = -\frac{\tilde{b}_{it} - \tilde{a}_{it}}{\max\{\tilde{a}_{it}, \tilde{b}_{it}\}}, \quad i \in \mathcal{I}_{IN} \cup I_{BK},$$

where,

$$\tilde{a}_{it} = \frac{1}{n_{IN,t} + n_{BK,t} - 1} \sum_{j \in \{\mathcal{I}_{IN} \cup I_{BK} \setminus i\}} J_{jt} \cdot d(D_{it}, D_{jt}),$$

$$\tilde{b}_{it} = \tfrac{1}{n_{PH,t}} \textstyle\sum_{j \in \mathcal{I}} J_{jt} \cdot d(D_{it}, D_{jt}).$$

The variable $SVFP_{it}$ reflects the extent to which attention is placed on more general narratives about risk, which cut across the boundaries of industries that (even if not fully orthogonal) are not closely related.

Second, we note that the variable $SVFP_{it}$ will still contain aspects of the context of attention of risk managers, which reflect substantive concerns that happen to cut across industries, beyond insurance and banking. For that reason, the variables $SVFP_{it}$ and $CommonTrend_{it}$ are intertwined. In order to isolate effects mostly driven by legitimacy concerns, we regress $SVFP_{it}$ on $CommonTrend_{it}$ using Ordinary Least Squares, and generate a new measure, called $Fashion_{it}$, as the residual of this regression. In this way, $Fashion_{it}$ reflects elements of the (convergence in) attention of risk managers that (a) go beyond issues specific to insurance and banking and (b) cannot be attributed to shared concerns around the topics of "Products", operations and customers', and "Investment."

Finally, while different choices of a third industry would be plausible, we consider pharmaceuticals for two reasons. First, the pharmaceutical industry operates with fundamentally different business models and operational strategies compared to insurers and banks (Downs & Velamuri, 2016). The primary risks faced by pharmaceutical firms (e.g., R&D, clinical trials, patent expiration) differ significantly from the financial and operational risks faced by insurers and banks (Li, 2022). Unlike insurers and banks, which are interconnected within the broader financial system, the pharmaceutical industry participates much less in financial contagion risk dynamics. Second, similar to the insurance and banking sectors, the pharmaceutical industry is subject to extensive regulatory scrutiny (Cohen et al., 2012). This makes it suitable for comparison, as all industries in the analysis face similar pressures to disclose comprehensive risk factors. Naturally, it would be unrealistic to assume that the risk exposures pharmaceuticals are completely orthogonal to the financial system. However, we believe that being at some relative distance to insurance and banking suffices for the construction of the covariate in this section.

4.3.5 | Control variables

In Section 5, we will present nonlinear regressions of $Convergence\_inter_{it}$ on the metrics we just introduced to represent the theoretically derived antecedents of convergence. For this, we introduce a number of statistical controls. All control variables are defined for $i \in \mathscr{I}_{IN} \cup \mathscr{I}_{BK},\ t \in \mathscr{T}$.

In addition to **year fixed effects**, we control for **industry fixed effects**. (As a robustness check, we replaced the industry dummy variable with more granular subindustry classifications. For insurance firms, we distinguished between life, nonlife, and reinsurance companies; for banks, we separated commercial banks, investment banks, and universal banks. The results we obtained are consistent with the ones obtained in Section 5—despite the diversity of business models within insurance—and will not be reported. Our analysis seeks to assess the impact of different antecedents on industry convergence. It appears that the commonalities in the insurance market, in terms of, for example, regulatory frameworks, risk culture and management practices, are such that no complex interaction effects arise between the antecedents of convergence and sub-industries, which would produce a different response of convergence at a more granular level of analysis.

We also control **inter-industry stock return correlation.** This time, we use the 1-year-lagged stock return correlation as a control variable to predict convergence, reflecting the shift in research focus to address a different question. We use $StockCorr\_inter_{it}$ as defined in Section 3.4.1, but for each (i, t), the value of $StockCorr\_inter_{it}$ is calculated on stock market data over the 1-year time period *before* the disclosure date of the corresponding 10-K report. This variable is meant to control for 10-K reports responding to external shocks that affect both industries and are already reflected in stock movements. In regressions, $StockCorr\_inter_{it}$ is standardized by industry.

Boilerplate language. It may be plausible that the 10-K reports of a firms ar similar to reports in different industries, because of its use of non-informative language in risk disclosures, which is heavy with cliches, that is, standardized expressions carrying little meaning. To control for this effect, we quantify language non-informativeness, by slightly adapting the "boilerplate" language metric of Lang and Stice-Lawrence (2015). The resulting variable, $Boiler_{it}$, is calculated by the following process. We count all tetragrams contained in each document in the sample, where a tetragram is an ordered group of four words within a single sentence. We aggregate these counts by year of issue. We identify tetragrams that occur in at least 30% of the documents or on average at least five times per document across all the three industries in a year. The identified tetragrams are considered to reflect non-informative ("boilerplate") language. Then the percentage of the common boilerplate tetragrams out of all the tetragrams in each document is calculated, and set equal to $Boiler_{it}$. In regressions, $Boiler_{it}$ is standardized by industry. A limitation of this approach is that there could exist tetragrams that reflect standard risk management practices and thus occur multiple times in the text.

The relationship between *Convergence_inter* and all covariates (excluding industry fixed effects) is depicted in the scatter plot matrix of Figure 6. Time trends can be glanced in the first

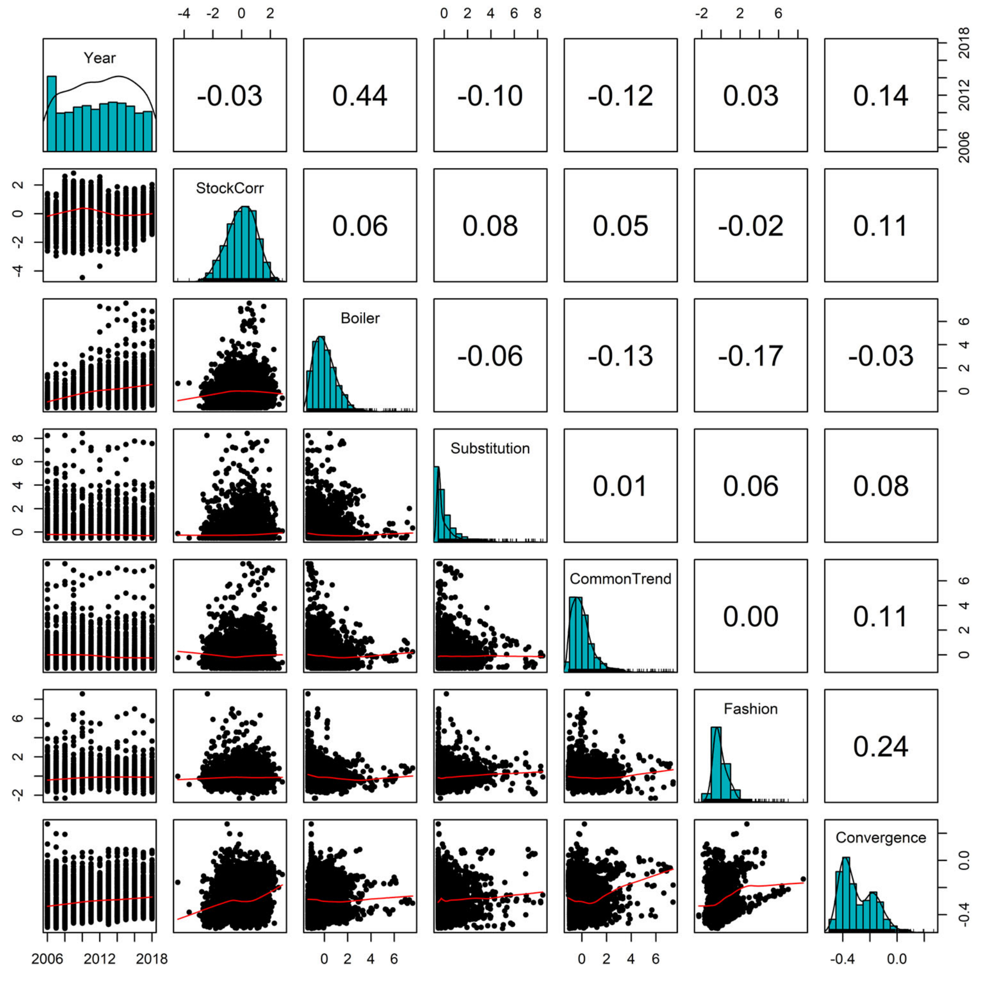

FIGURE 6 Scatter plot matrix of *Convergence_inter*$_{it}$, control variables and antecedents. The lower half-matrix displays pairwise scatter plots and nonlinear regression lines; the upper half-matrix shows Pearson correlation coefficients; the diagonal presents covariate histograms with non-parametrically fitted densities.

column; there are noticeable positive trends in the *Boiler* and *Convergence_inter* variables. Bivariate relationships between *Convergence_inter* and all covariates are seen in the last row. It is clear that *Convergence_inter* increases in the measures of its three postulated antecedents: *Substitution*, *CommonTrend* and *Fashion*.

5 | EXPLAINING CONVERGENCE OF RISK DISCLOSURES IN TERMS OF CONTEXTUAL ANTECEDENTS

5.1 | Regression model

In this section, we empirically investigate the extent to which the contextual antecedents of firm strategy drive convergence of attention. Empirically, we carry out regression models of the form $\mathbb{E}[Convergence\_inter_{it} \mid \mathbf{X}_{it}] = g(\mathbf{X}_{it})$, where g is a (nonlinear) regression function and $\mathbf{X}_{it}$ includes the covariates and controls developed in Section 4.3.

We select a regression model out of the same classes of models as in Section 3.4.2, using the same selection criteria. A comparison of the different models considered is given in Table 6 in the Appendix 1. In this case, we select a Random Forest regression model with 550 trees due to its lowest reported MSE. The superior predictive performance on nonlinear compared to linear models indicates the presence of important nonlinear effects and variable interactions. To disentangle these relationships, we carry out a detailed discussion of variable importance and sensitivity analysis in Section 5.2.

5.2 | Variable importance and sensitivity

5.2.1 | Accumulated local effects

The ALE plots for the chosen regression model are displayed in Figure 7. We observe the following:

- For all three the covariates, *CommonTrend*, *Substitution* and *Fashion*, we see a clear positive impact on the response variable *Convergence_inter*, which confirms our theoretical argument of Section 2.
- From observing the scale of the respective ALEs, we note that *Fashion* is the most impactful variable.
- We also see that the control *StockCorr_inter* is positively associated with the response, which reflects our assumption that co-movements of stock prices would have a positive impact on convergence of attention, which is a factor we control for.
- The ALE for *Year* also shows an increasing pattern, reflecting an underlying positive trend in convergence in general.
- Finally, there is no clear pattern for *BoilerPlate*. Hence, lack of informativeness in the language used does not appear to be a driver of text similarity between 10-K reports.

5.2.2 | Feature importance

We quantify the relative importance of the different covariates in our regression model. For that purpose, we use two standard variable importance measures in machine learning: the impurity-based feature importance and the variance permutation importance (Breiman, 2001). For each of the two methods, the higher the measure's value, the more important the feature. Impurity-based feature importance is specific to tree-based methods and is computed as the (normalized) total reduction of the error criterion (e.g., Gini or MSE) brought by that feature. A split (i.e., the separation of data into different nodes in a particular tree of the Random Forest) with a large decrease of impurity is considered important, and therefore, variables used for splitting at important splits are also considered important. The impurity is usually measured by the Gini impurity (Ishwaran, 2015). Permutation importance is defined to be the difference between the baseline prediction error of the fitted model and the error arising after randomly permuting a given feature column (Breiman, 2001). Impurity-based feature importance can be misleading for high cardinality

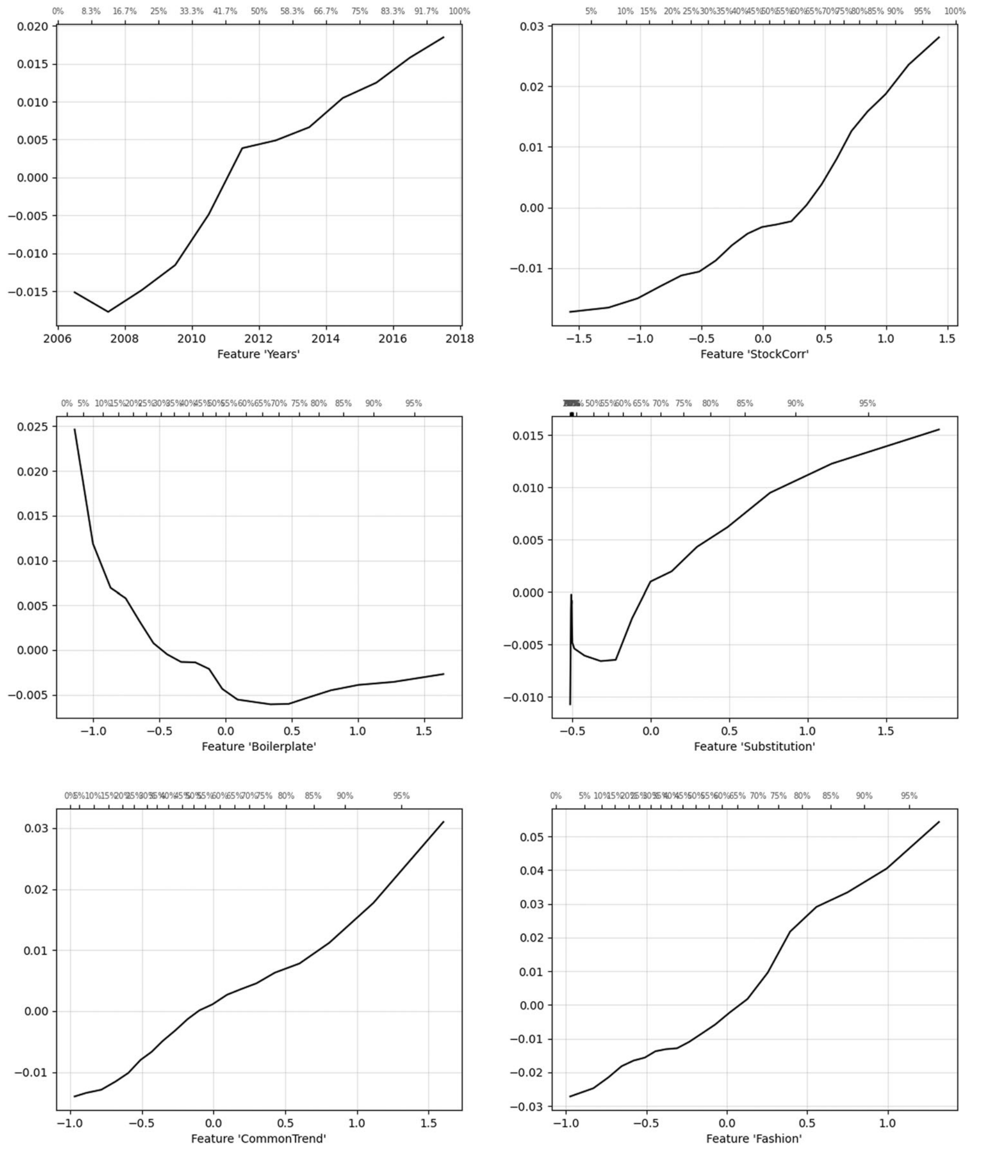

FIGURE 7 ALE plots for the Random Forest regression model, reflecting the effects of antecedents on Inter-industry convergence in attention. ALE, Accumulated Local Effects.

features, and permutation importance has been shown as an appropriate alternative to solve this problem (Breiman, 2001).

The feature importance and permutation importance of all the drivers of the Random Forest regression model can be found in Figure 8. According to both importance measures, among the three antecedents of convergence, the most important feature *Fashion*, followed by *CommonTrend*. The is consistent with the picture provided by ALEs and establishes *Fashion* as the most important driver of convergence. Of the various controls used, the industry effect is clearly dominant.

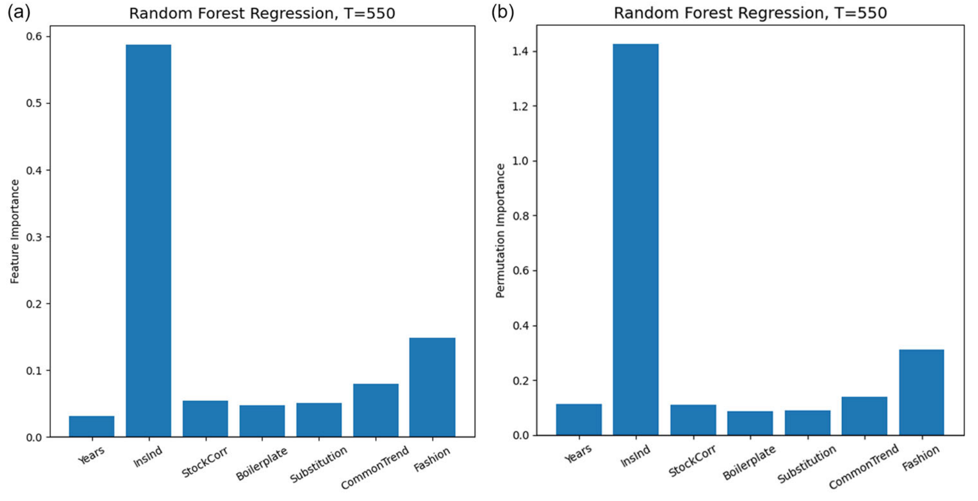

FIGURE 8 Variable importance of each antecedent: (a) impurity-based feature importance; (b) permutation importance.

5.2.3 | Shapley values and quantile contributions

Finally, we evaluate the contribution of individual antecedents to predictions at different—in particular, high-levels of convergence. We follow the Marginal Attribution by Conditioning on Quantiles framework of Merz et al. (2022). For this, we require an additive decomposition of individual predictions, such that for the ith observation in the sample, with features $\mathbf{x}_i$ and predictions $\hat{g}(\mathbf{x}_i)$, we have

$$\hat{g}(\mathbf{x}_i) = \textstyle\sum_j \phi_j(\mathbf{x}_i), \tag{3}$$

where $\phi_j(\mathbf{x}_i)$ represents the contribution of the jth covariate to the prediction of the ith observation. In Merz et al. (2022), such a decomposition was derived by a quadratic approximation to smooth prediction functions of deep learning models. Here, given the non-smoothness of the fitted Random Forest's prediction function, we instead carry out the decomposition in Equation (3) via Shapley values.

The Shapley value for a feature-observation combination is derived from the marginal contribution of the feature to individual predictions. Such marginal contributions are averaged across "coalitions" of features to which the one under focus is added. Thus, differently to feature importance measures, Shapley values quantify the contribution of each covariate at the individual observation level. Shapley values were originally defined in the context of co-operative game theory and have become popular for interpreting the predictions of machine learning algorithms following the SHAP framework of Lundberg and Lee (2017a, 2017b).

We plot in Figure 9 for each of the features *CommonTrend*, *Substitution*, and *Fashion*, the attributions $\phi_j(\mathbf{x}_i)$ on the vertical axis, against the quantile level u_i of the prediction $\hat{g}(\mathbf{x}_i)$, that is, $u_i = \hat{F}(\hat{g}(\mathbf{x}_i))$, where $\hat{F}$ is the empirical distribution of predictions $\hat{g}(\mathbf{X})$. We carry out the analysis separately for insurers (top row) and banks (bottom row). The red curves show non-parametric estimates of the function $u \mapsto \mathbb{E}[\phi_j(\mathbf{X}) \mid \hat{g}(\mathbf{X}_i) = \hat{F}^{-1}(u)]$, with the expectation taken over the

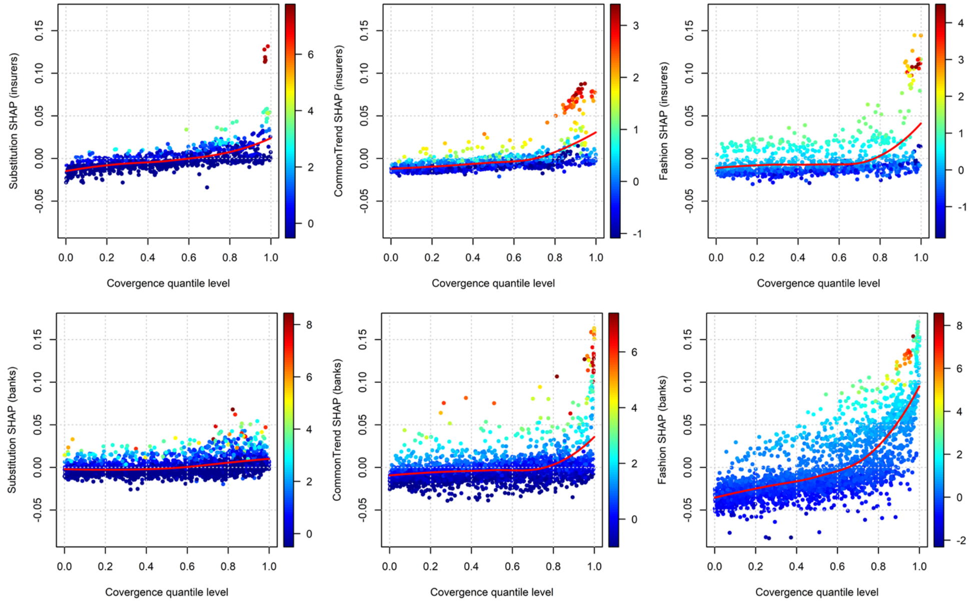

FIGURE 9 Sensitivity analysis based on Shapley values: feature contributions to predicted value, against quantile level of predictions; color represents the feature value. Top: insurers; bottom: banks.

empirical measure. Finally, the color of the plotted points represents the value of the feature examined. If we focus specifically on the right of each plot in Figure 9, for example, $u \in [0.8, 1)$, we consider those firm-years for which the highest convergence is observed. We can see that for such companies, which are most relevant for considerations of high industry convergence, the contribution of *Fashion* tends to be the most important one, particularly in the case of banks. At the same time, for those insurers that have a very high level of *Convergence_inter*, the feature contributions of *Substitution* and *CommonTrend* are also high.

In Figure 10, we plot the attributions $\phi_j(\mathbf{x}_i)$ against the feature values $x_{i,j}$—the colors now represent the response quantile level u_i (top row: insurers; bottom row: banks).[1] The picture is consistent for both industries. We observe that the relationships between covariates $x_{i,j}$ and attributions $\phi_j(\mathbf{x}_i)$ are clearly increasing, with the points at the top right typically displaying high values of the response variable, *Convergence_inter*. The steeper increase in the plot for *Fashion* once again confirms the dominant effect of this variable.

5.3 | Reconsidering contagion risk prediction

Figure 7 (top left panel) reveals an increasing time trend of *Convergence_inter*, indicating the potential for contagion risks arising in the future. Furthermore, as shown by Figures 1 and 8, there is an important industry effect, with the attention of insurance risk managers to directed

[1]Note that for a linear model of the form $\hat{g}(\mathbf{x}_i) = \sum_j \beta_j x_{i,j}$, Shapley value attributions take the form $\phi_j(\mathbf{x}_i) = \beta_j x_{i,j}$, thus reproducing the modeled linear effects.

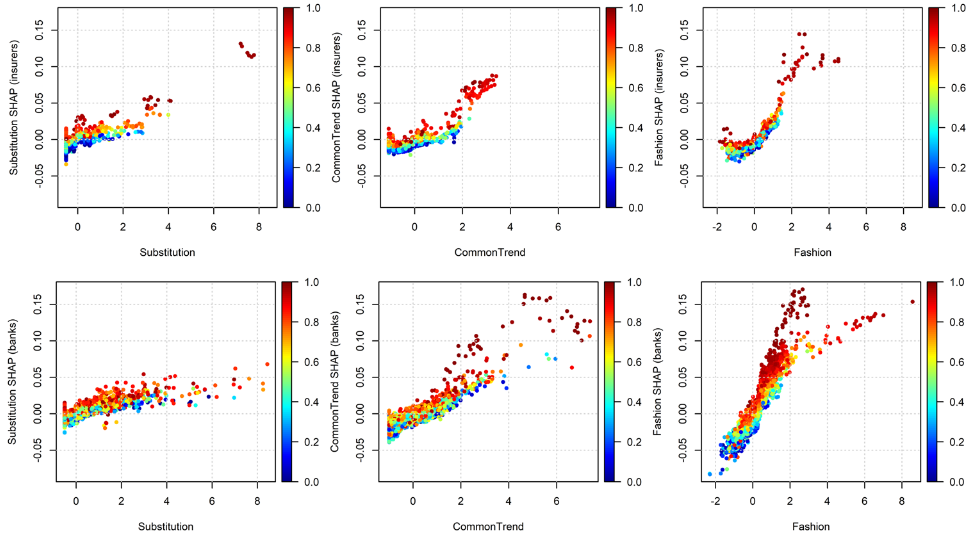

FIGURE 10 Sensitivity analysis based on Shapley values: feature contributions to predicted value, against feature values; the colors represent the quantile level of predictions. Top: insurers; bottom: banks.

in towards the banking industry to a greater extent than the reverse taking place. This is consistent with the econometric finding that "banks create significant systemic risk for insurers but not vice versa" (Chen et al., 2014); see also Elyasiani et al. (2016); Kaserer and Klein (2019).

Our analysis showed that *Convergence_inter* is increasing in all three variables representing the antecedents of attention that we identified. This lends empirical support to the theoretical framework developed in Section 2. We find that the most important antecedent of convergence in the attention of risk managers is *Fashion*—this is consistently implied by all three importance and sensitivity measures that we used. *CommonTrends* is the second most important antecedent, while *Substitution* has the least bearing on the attention of risk managers (though here we have a differential effect between insurers and banks, with the former more attuned to this issue).

Taking stock, we have arrived at the following point: in Section 3.4, we have established that our *Convergence_inter* measure is a predictor of cross-industry contagion risk. Here we have shown that *Convergence_inter* is itself dominated by *Fashion*. This begs the question: does *Fashion* predict contagion risk?

To address the question, we return to the setting of Section 3.4 and repeat the regression of contagion risk on lagged Convergence (focusing on the Inter-industry case), but this time controlling for *Fashion*. Figure 11 shows the ALE plots resulting from this analysis, when using a Gradient Boosting model. Comparing to Figure 3, we see that the effects of *Year* and *Convergence_inter* are fundamentally unchanged. The effect of *Fashion* on predictions is an order of magnitude smaller in scale and also negative. This relation indicates that, to best predict cross-industry contagion risk from *Convergence_inter*, the (minor) impact of *Fashion* should be "stripped out." Again we validate these results by panel regression, reported in Table 7 in the Appendix 1, which gives consistent conclusions. This analysis indicates that the consideration of *Fashion* can be a useful control for predicting contagion risk, alongside our measure of convergence. However, *Fashion* does not appear to be in itself a driver of contagion

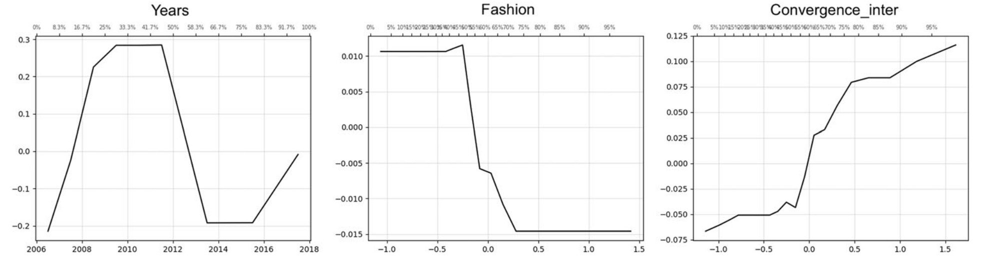

FIGURE 11 ALE plots for the prediction of inter-industry contagion risk from convergence in attention controlling for *Fashion*. ALE, Accumulated Local Effects.

risk (as also attested by regressing stock correlations on *Fashion* only, see Table 7)—at least when considering a 1-year horizon.

6 | CONCLUDING REMARKS

In this paper, we contribute to the study of the convergence between the insurance and banking industries. The specific contribution of this paper is fourfold. First, we theoretically connect industry convergence with the context of decision-making through the lens of the ABV of the firm. Then, building on strategic management theory, we establish a framework for antecedents of convergence in attention, and their potential implications for contagion risk. Second, we operationalize the theoretical framework in the insurance/banking context, using text data from risk disclosures and tools from machine learning, to create measures of convergence in attention and its antecedents. Third, we demonstrate empirically that the suggested measure of convergence in attention is a predictor of contagion risk, as manifested through stock correlations, both across and within the insurance and banking industries. Finally, based on the theoretical framework and regression and sensitivity analyses, we identify the dominant antecedent of cross-industry convergence in attention.

We find that the dominant antecedent of convergence is management fashions. At the same time, we also find that the variable representing management fashions is not a predictor of contagion risk; instead, it is a source of noise contaminating—but not drowning out—the useful signal provided by our proposed convergence measure. This tension leads to two key implications.

First, since convergence in attention does predict contagion risk, we conclude that 10-K reports are both the trace of institutional forces and a signal that their authors send to stakeholders, thus potentially influencing (and coordinating) action. This observation reinforces the need for improved corporate governance (Eling & Marek, 2014; Howard, 2010; O'Connor, 2002) and, in particular, inclusive and participatory approaches (Renn et al., 2022; Schweizer et al., 2022).

Second, the locus of attention matters. Much of the convergence in attention is driven by considerations that do not predict stock correlations between the banking and insurance industries, as they reflect narratives that may pervade but are not specific to the insurance/banking systems. Nonetheless—though we cannot present empirical evidence in that direction—we believe that the growing dominance of management fashions in regulatory reports remains a substantive issue for contagion risk, at it may progressively erode the informativeness of risk disclosures and/or manifest as managers' group think, with adverse consequences in the longer term, given the dynamic relation between attention and action. This challenge is also salient to other risk contexts, for example, mandated climate risk reporting frameworks (Di Marco et al., 2023; Task Force on Climate-related Financial Disclosures, 2022).

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author, Lei Fang, upon reasonable request.

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APPENDIX 1: REGRESSION TABLES AND HYPERPARAMETERS

See Tables 3–7.

TABLE 3 Model selection: Cross-validation results when using the convergence measures to predict contagion risk in Section 3.4.

Model	Parameter	Value	Inter-industry	Value	Intra-industry
Elastic Net	Regularization parameter	0.0001	0.9893	0.0001	0.9746
		0.001	0.9892	0.001	0.9745
		0.01	0.9886	0.01	0.9738
		0.1	0.9916	0.1	0.9774
		0.5	1.0007	0.5	1.0005
Random Forest	Number of trees in the forest	450	1.1129	10	1.1666
		500	1.1128	100	1.1147
		550	1.1128	1000	1.1056
		600	1.1137	10000	1.1057
Gradient Boosting	Number of boosting stages	40	0.8601	10	0.8971
		46	0.8590	50	0.8512
		47	**0.8588**	75	0.8500
		48	0.8591	**76**	**0.8499**
		50	0.8591	77	0.8500
		75	0.8609	100	0.8522

TABLE 4 Hyperparameters for Elastic Net, Random Forest, and Gradient Boosting regressions in Section. For Elastic Net Regression and Random Forests, we use defaults. For Gradient boosting, we use grid search and inspect learning curves to avoid overfitting.

Model	Hyperparameter	Default value
Elastic Net Regression	Maximum iterations	1000
	Tolerance for stopping criteria	0.0001
	The order in which features are updated	Cyclic
	Fit an intercept term	True
Random Forest Regressor	Function to measure split quality	Squared error
	Maximum depth	None (expand fully)
	Minimum samples to split a node	2
	Minimum samples at a leaf node	1
	Bootstrap samples are used when building trees	True
Gradient Boosting Regressor	Loss function	Squared error
	Learning rate	0.05
	Maximum depth	2
	Subsample fraction	0.8
	Split quality criterion	Friedman MSE
	Tolerance for stopping criteria	0.0001
	Minimum samples to split an internal node	3
	Minimum samples at a leaf node	4
	Number of iterations with no change for early stopping	5
	Proportion of training data as validation for early stopping	0.1

TABLE 5 Panel data regression results: Convergence as a predictor of contagion risk.

	Inter-industry		Intra-industry		Inter-industry		Intra-industry	
Feature	**Coef.**	***p*-Value**	**Coef.**	***p*-Value**	**Coef.**	***p*-Value**	**Coef.**	***p*-Value**
Convergence	0.0639	0.0029	0.0995	0.0000	0.0364	0.0831	0.0694	0.0003
Insurance Industry	−0.0418	0.4487	−0.1019	0.1729	−0.1070	0.0903	−0.2758	0.0004
F-statistic (robust)	4.7573	0.0086	12.641	0.0000	41.492	0.0000	63.670	0.0000
Hausman Test	RE		RE		RE		RE	
Year dummies controlled	No		No		Yes		Yes	

TABLE 6 Model selection: Cross-validation results when regressing the inter-industry convergence on its theorized antecedents, in Section 5.

Regression model	Parameter	Param value	Average MSE
ElasticNet	Regularization parameter	0.0001	0.003537
		0.001	0.003536
		0.01	0.003782
		0.1	0.013622
		0.5	0.013699
RandomFores	Number of trees in the forest	10	0.003047
		100	0.002461
		500	0.002379
		550	0.002377
		600	0.002379
		1000	0.002389
GradientBoosting	Number of boosting stages to perform	10	0.004606
		50	0.002710
		100	0.002587
		1000	0.002519
		10,000	0.002818

TABLE 7 Panel data regression results: Convergence and Fashion as predictors of inter-industry contagion risk.

Feature	Coeff. (Model 1)	*p*-Value	Coeff. (Model 2)	*p*-Value
Fashion	−0.0230	0.2712	−0.0049	0.7951
Convergence_inter	0.0475	0.0409	—	—
InsInd	−0.1064	0.0915	−0.1152	0.0736
F-statistic (robust)	38.794	0.0000	41.473	0.0000
Hausman Test	RE		RE	
Year dummies controlled	Yes		Yes	

APPENDIX 2: ROBUSTNESS TESTS OF CHANGING TOPICS NUMBER

See Figures 12 and 13.

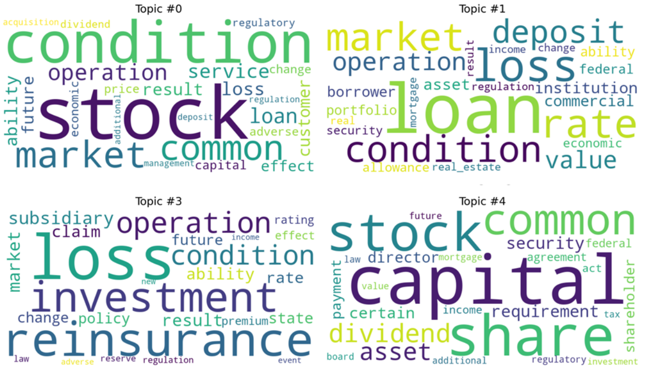

FIGURE 12 LDA output: word clouds ($K = 5$).

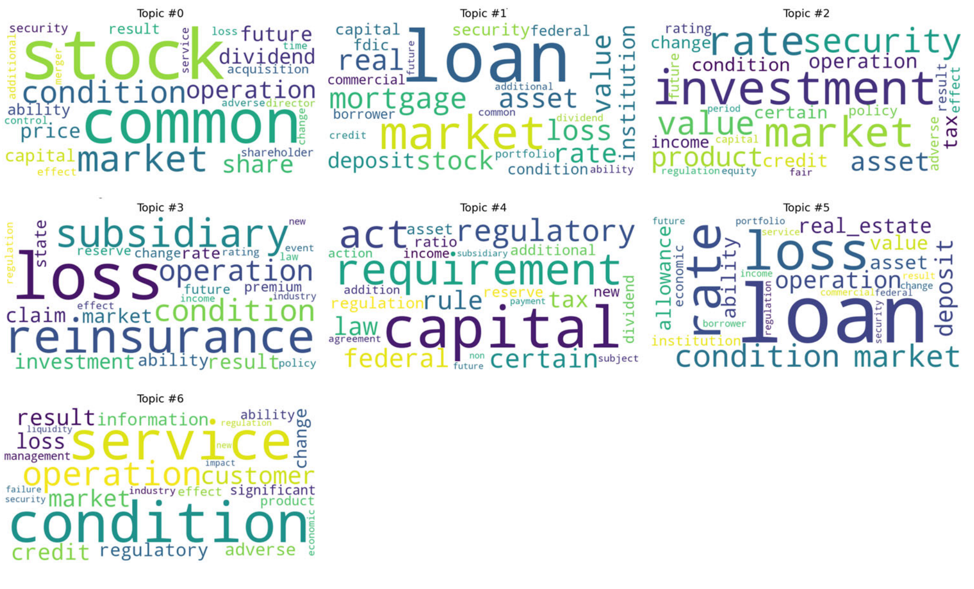

FIGURE 13 LDA output: word clouds ($K = 7$).

In the 5-topic and 7-topic models, most word clouds contain multiple overlapping themes and/or replications of themes across word clouds, making it difficult to assign each to a single conceptual category. For example, in the 5-topic model, Topic 2 reflects a combination of market and operational factors, while Topic 3 combines reinsurance losses with investment and operations. In the 7-topic model, Topics 1 and 5 both prominently feature loans as the most important word. This thematic blending and replication limit interpretability.