Measuring Knowledge Capital Risk

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1 Introduction

The transition towards a service- and knowledge-based economy has been accompanied by a sharp increase in intangible assets, most notably in research and development (R&D) (Corrado et al., 2009b).

Knowledge capital, defined as a firm's accumulated investments in R&D, accounts for an increasing share of public firms' valuation (Belo et al., 2019). Notably, this form of capital exhibits a distinct risk profile compared to tangible, physical capital. For instance, companies heavily reliant on knowledge capital are more susceptible to the loss of critical personnel and modifications in patent enforcement.

Knowledge capital, brand capital, and organization capital are components of a firm's intangible capital. Spending on intangible assets qualifies as an investment since it reduces current consumption to increase future consumption (Corrado et al., 2009b,a). In this context, *brand capital* is defined as a firm's accumulated expenses in advertising (Belo et al., 2019); *organization capital* is defined as the set of unique systems and processes employed in an enterprise and positively correlated with the firm's managerial quality scores (Eisfeldt and Papanikolaou, 2013; Bloom and Van Reenen, 2007).

Moreover, endogenous growth models, such as models with expanding varieties (Romer, 1990), and with quality ladders (Grossman and Helpman, 1991; Atkeson and Burstein, 2019), imply that research expenses can spur growth. Even though the two latter models consider R&D as intermediate expenses, supply-side valuation models such as Belo et al. (2013) argue that not only quasi-fixed physical capital and labor inputs but also knowledge and brand capital can determine a firm's market value.

Along these lines, Hall (2001); McGrattan and Prescott (2001); Vitorino (2014); Eisfeldt et al. (2020); Li et al. (2014) confirm that intangible capital matters for aggregate stock market valuations and, more specifically, firm-level valuations. Corrado et al. (2009b) estimated total intangible capital in 2003 to be 3.6 trillion, half of which as scientific and non-scientific R&D capital. Crouzet and Eberly (2022) found that the omission of knowledge capital and its associated rents can explain up to 2/3 of the investment gap (the difference between marginal q and average Q) in R&D intense sectors such as Healthcare and Chemicals.

The riskiness of intangible assets differs systematically from tangible ones (Hansen et al., 2005). Eisfeldt and Papanikolaou (2013) points out that shareholders cannot entirely appropriate the cash flows from the key talent of the firm since the firm must always compensate key talent by its outside option. Eisfeldt et al. (2018) shows that key talent partially owns the cash flow from intangible capital in the form of equity, finding that almost 40% of compensation to high-skilled labor happens as equity-based pay. Finally, Ai et al. (2019) predicts that collateralizable assets, which do not include some categories of intangibles, provide insurance against aggregate shocks in the economy and should earn a lower expected return.

Specifically, knowledge capital is risky. Firms spend on R&D to increase their future profitability, which is not guaranteed. For example, research conducted by a pharmaceutical firm can lead to successful new drugs that lead to patent rents for several years or to no result at all. The riskiness of innovation firms, and the growing empirical dispersion of Tobin's q, also explains the relation between Tobin's q and aggregate investment has become tighter since the mid-1990s (Andrei et al., 2019). The riskiness of a financially constrained firm increases with its R&D intensity (Li, 2011). Besides the uncertainty of research investments, a firm is also susceptible to writing off part of its knowledge capital, e.g., when it narrowly loses a patent race (Peters and Taylor, 2017).

Knowledge capital heavy firms are especially susceptible to loss of key talent. Eisfeldt and Papanikolaou (2013) find that firms are more likely to list "loss of key talent" as a risk factor in their 10-K reports when they have high organization capital. It makes sense that the same pattern is valid for knowledge capital heavy firms, which are highly dependent on specialized and scarce workforce.

Firms vulnerable to loss of key talent are especially susceptible to immigration-related risks, e.g., the H-1B visa annual quota shortages. The H-1B visa, introduced with the Immigration and Nationality Act of 1990, established temporary renewable visas for college-educated specialty professional workers, most of whom work in STEM occupations. Peri et al. (2015) shows that the growth in foreign-STEM workers may explain between 10 and 25% of the aggregate productivity growth and 10% of skill-bias growth between 1990 and 2010.

The current methods of identifying knowledge-heavy firms have proven to be insufficient due to a number of key issues. Firstly, there is a lack of consistency in the standards for R&D reporting across industries and firms. This discrepancy is further compounded by the fact that some firms do not disclose their R&D expenditure in their annual reports, making it challenging to accurately determine their level of knowledge intensity.

Secondly, the measures used to identify intangible assets, typically through indirect measures like Selling, General and Administrative expenses (SG&A), include components that are not related to knowledge, such as organizational capital. This can blur the distinction between knowledge-heavy and non-knowledge-heavy firms.

Lastly, relying on patents as a measure of a firm's knowledge intensity only tells part of the story. While patents reflect the final outcomes of R&D investments, they do not account for the internal learning processes that take place within firms, thus potentially undervaluing those that invest heavily in internal knowledge development, even if they do not have a high patent output.

Considering these shortcomings, several research questions emerge: Firstly, is it possible to better identify knowledge-heavy firms by performing text analysis on the risk factors reported in their annual reports? By analyzing the language and terminology used, can we glean more information about the firm's knowledge intensity?

Secondly, if we can indeed identify knowledge-heavy firms in this manner, does this information influence how agents price these firms? In other words, do market participants factor in different risks for knowledge-heavy firms compared to non-knowledge-heavy firms?

Finally, we must question if using topic modeling to categorize the firms' self-declared risk factors can provide a more sensible and accurate categorization of firms by risk. By examining the topics that firms themselves identify as risks, can we create a more nuanced classification system for firms based on the nature and magnitude of their risk exposure?

This study seeks to identify firms that are vulnerable to knowledge capital-related risks, by a textual analysis of the risk factors disclosed in their annual reports. Further, the paper seeks to quantify these risks through an examination of their concurrent return patterns.

2 Methodology and Data

Investing in innovation and learning inherently poses risks for firms. The uncertain outcomes of R&D investments can either yield significant breakthroughs or not, as manifested by the jumps in cash flow delineated by Andrei et al. (2019). As a result, firms with greater cumulative R&D investments, named as "knowledge capital" in Belo et al. (2019), tend to exhibit more volatile valuations. Nonetheless, the mere magnitude of accumulated R&D may not be the optimal metric for assessing knowledge capital risk and, in turn, the variations in cash flow. This raises the pivotal question: how should we best quantify the risk to which high knowledge capital firms are exposed?

Moreover, Kogan et al. (2017) demonstrate that the companies' market value surges within the following three days of the filing of potentially lucrative patents, that is, patents that have the potential to amplify a firm's revenue streams while simultaneously stifling competition. Yet, one must ponder whether the stock market, outside patent-filing moments, also internalizes the inherent risks of devoting a significant part of investments to a risky innovation process.

Firms in the innovation sector often share commonalities in their financing strategies. Young, R&D-intensive firms frequently face challenges in securing debt finance due to the unpredictable and fluctuating returns on R&D, and the potential adverse selection and moral hazard in the R&D financing market. Notably, fluctuations in the supply of equity finance were instrumental in shaping the R&D surge of the 1990s (Brown et al., 2009), pointing to a shared risk factor among these firms.

Additionally, measures of patent activity, such as the one in Kogan et al. (2017), are not flawless indicators of the risks associated with R&D-centric firms. Large firms and firms in specific industries are more prone to protecting their intellectual property, which shows that patent distribution does not directly mirror the exposure to knowledge capital risks (Mezzanotti and Simcoe, 2023).

The overarching aim of this paper is to unearth the shared risks intrinsic to the innovation lifecycle. In doing so, we endeavor to move beyond the conventional proxies of R&D and patents, acknowledging their inherent limitations in capturing this multifaceted risk.

2.1 Latent Dirichlet Allocation (LDA)

In this study, I use Latent Dirichlet Allocation (LDA), a topic modeling technique, to identify latent topics within a comprehensive corpus of 121,839 firm annual reports spanning the years 2006 to 2022.

Latent Dirichlet Allocation (LDA) is a generative statistical model that is widely employed for topic modelling within the field of natural language processing (NLP). Its effectiveness hinges on the fundamental assumption that each document in a given corpus can be seen as a mixture of a certain number of latent topics, denoted as $k \in 1, ..., K$, each of which carries a particular weight, $\omega_{i1}, ..., \omega_{iK}$. Each of these topics is assigned a word probability vector, θ_k, defining the likelihood of each word appearing under this topic Blei et al. (2003).

Under this model, if we denote X_i as the vector of word counts with length n_i in the ith document, the word distribution in a document is modeled as a multinomial distribution. The probability of X_i can be written as:

$$X_i \sim Multinomial\left(n_i, \omega_{i1}\theta_1 + \cdots + \omega_{iK}\theta_K\right) \tag{1}$$

This equation represents the fact that the observed words in the document are generated by a mixture of topics, with each topic contributing to the document with a certain weight.

The output of an LDA operation is twofold: firstly, it generates a list of topics, with each topic represented as a collection of words. Secondly, it offers a weight distribution across these topics for each document, indicating the degree to which each topic is present in a given document.

It is important to note that LDA is an unsupervised learning method. This means that it operates without any predefined labels, instead learning and inferring patterns directly from the data. This characteristic makes LDA a versatile tool, able to extract valuable insights from large and complex corpora of text data.

2.2 Data

I retrieve the annual reports (10-Ks) for all publicly listed firms since 2013 from the Securities and Exchange Commission's EDGAR database, using their API. A 10-K is a comprehensive document that provides an overview of the company's financial performance and operations over a year, offering a detailed picture of a company's business. To ensure transparency and accuracy, laws and regulations strictly prohibit companies from making false or misleading statements in their 10-Ks. Additionally, under the Sarbanes-Oxley Act, a company's Chief Financial Officer (CFO) and Chief Executive Officer (CEO) are required to certify the accuracy of the 10-K (SEC: Office of Investor Education and Advocacy (2011)).

Item 1A of a 10-K ("Risk Factors") includes information about the most significant risks that apply to the company or its securities. I extract the item 1A information from each 10-K using XML parsing and `BeautifulSoup`, and removed supposedly less meaningful characters such as punctuation and numbers.

2.3 Filtering firms

Following Golubov and Konstantinidi (2019); Stambaugh and Yuan (2016), I filter firms by considering only ordinary common shares, traded on NYSE, AMEX, and NASDAQ exchanges; and following Stambaugh and Yuan (2016) I exclude those whose prices are less than $5 in 2016 dollars.

Reporting risk factors is mandatory for most firms; however, there are exceptions for asset-backed issuers and smaller reporting companies. Asset-backed issuers are defined as issuers whose reporting obligation arises from either the registration of an offering of asset-backed securities under the Securities Act or the registration of a class of asset-backed securities. Firms that are not required to disclose risk factors either leave Item 1A empty or write a placeholder text specifying that, due to their nature, they are not required to disclose risk factors. Consequently, there is an abnormal frequency of 10-K filings with a significantly low number of words, as depicted in Figure 13. In subsequent stages, 1A texts with an insufficient word count are discarded. The threshold adopted was 200 words.

The total count of filtered firms by year is shown in Table 1.

Table 1: File Counts by Year

Year	Total_1As	Filtered
2006	5685	2466
2007	6445	2714
2008	6931	2305
2009	8244	2190
2010	8122	2290
2011	8019	2356
2012	7797	2316
2013	7560	2401
2014	7560	2518
2015	7531	2528
2016	7196	2431
2017	6896	2394
2018	6804	2418
2019	6683	2404
2020	6531	2332
2021	6936	2308
2022	6899	1885

2.4 Text conversion to bag-of-words

After filtering the firms, I employ the `spacy` Python library to conduct lemmatization on all the refined texts. Lemmatization transforms words into their base form, ensuring consistent semantics. As an illustration, words such as "take", "took", and "taken" are standardized to "take". Notably, `spacy` integrates with WordNet—a comprehensive English lexical database curated by Princeton University.

To extract significant collocations—like "patent application"—which provide richer semantic insights than individual words, this research adopts the collocation detection method outlined in Mikolov et al. (2013). This methodology yields pertinent bigrams and trigrams. A minimum occurrence threshold of 5 ensures that only the most statistically relevant combinations are incorporated into the dictionary.

This research compiles the entirety of discovered words, bigrams, and trigrams to formulate a dictionary.

Lastly, the texts are transformed into a bag-of-words model using both the dictionary and the n-gram processed texts. In this representation, each word's frequency in a document, denoted as c_{ij}, is preserved, but the sequence of words is omitted, leading to the final depiction of the corpus.

2.5 Topic modeling

Upon having the corpus and the dictionary, I employ unsupervised topic modeling—specifically, the Latent Dirichlet Allocation (LDA) technique—to analyze the entire set of documents. These documents encapsulate risk factors associated with diverse firms spanning multiple years. During the model's configuration, I designate a parameter to specify the number of topics, represented as k, and supply the model with the dictionary I previously crafted. Selecting an appropriate value for k is typically done *ad hoc*, with the primary consideration being interpretability, as highlighted by Gentzkow (2019).

A representative output from this modeling approach can be viewed in Figure 1.

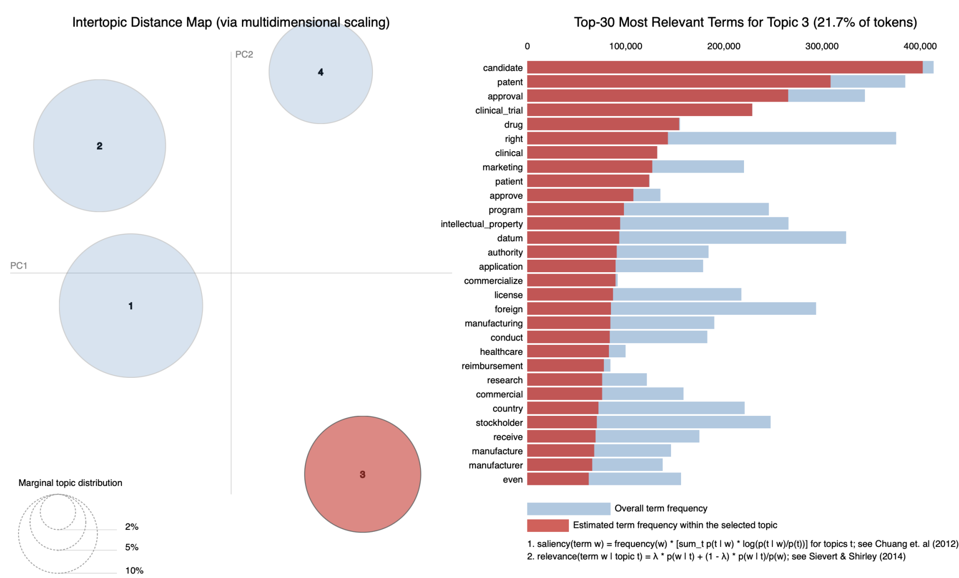

Figure 1: A graphic representation of a four-topic model on firms' risk factors since 2006.

After merging a four-topic map between firms and topic intensities to firms' identifying data, I obtain a topic map as shown in Table 2.

Table 2: Sample of topic map

conm	year	CIK	topic_0	topic_1	topic_2	topic_3
BOEING CO	2015	12927	0.875	0.109	0.016	0
UNIFI INC	2022	100726	0.893	0.107	0	0
UTAH MEDICAL PRODUCTS INC	2007	706698	0.021	0.457	0	0.519
SPOK HOLDINGS INC	2010	1289945	0.356	0.643	0	0
APTARGROUP INC	2015	896622	0.791	0.146	0	0.062
OASIS PETROLEUM INC	2018	1486159	1	0	0	0
PROGRESSIVE CORP-OHIO	2011	80661	0.051	0.238	0.711	0
RENTRAK CORP	2009	800458	0.017	0.982	0	0
UNVL STAINLESS ALLOY PRODS	2015	931584	0.957	0.042	0	0
QUALCOMM INC	2015	804328	0	0.998	0	0

3 Results

3.1 Defining `topic_kk`

For every topic map, I define `topic_kk` as the topic that has the highest loading within high-tech sectors in the economy, defined as SIC codes 283, 357, 466, 367, 382, 384, 737 (Brown et al. (2009)). Table 3 shows the average topic intensity for low- and high-tech firms for a four-topic model.

Table 3: Topic averages by hi-tech status

hi_tech	topic_0	topic_kk	topic_2	topic_3
0	0.49	0.22	0.27	0.03
1	0.1	0.58	0.02	0.3

As depicted in Figure 2, the mean topic intensity per year demonstrates a steady rise in the usage of knowledge-capital related language in firms' risk factors since 2009. This upward trend underlines the increasing emphasis placed on knowledge capital within these organizations.

Lastly, Figure 14 illustrates the accumulated assets of firms in the upper quartile of `topic_kk`, which shows a clear prevalence of firms in the Business Equipment, Chemicals, and Other sectors.

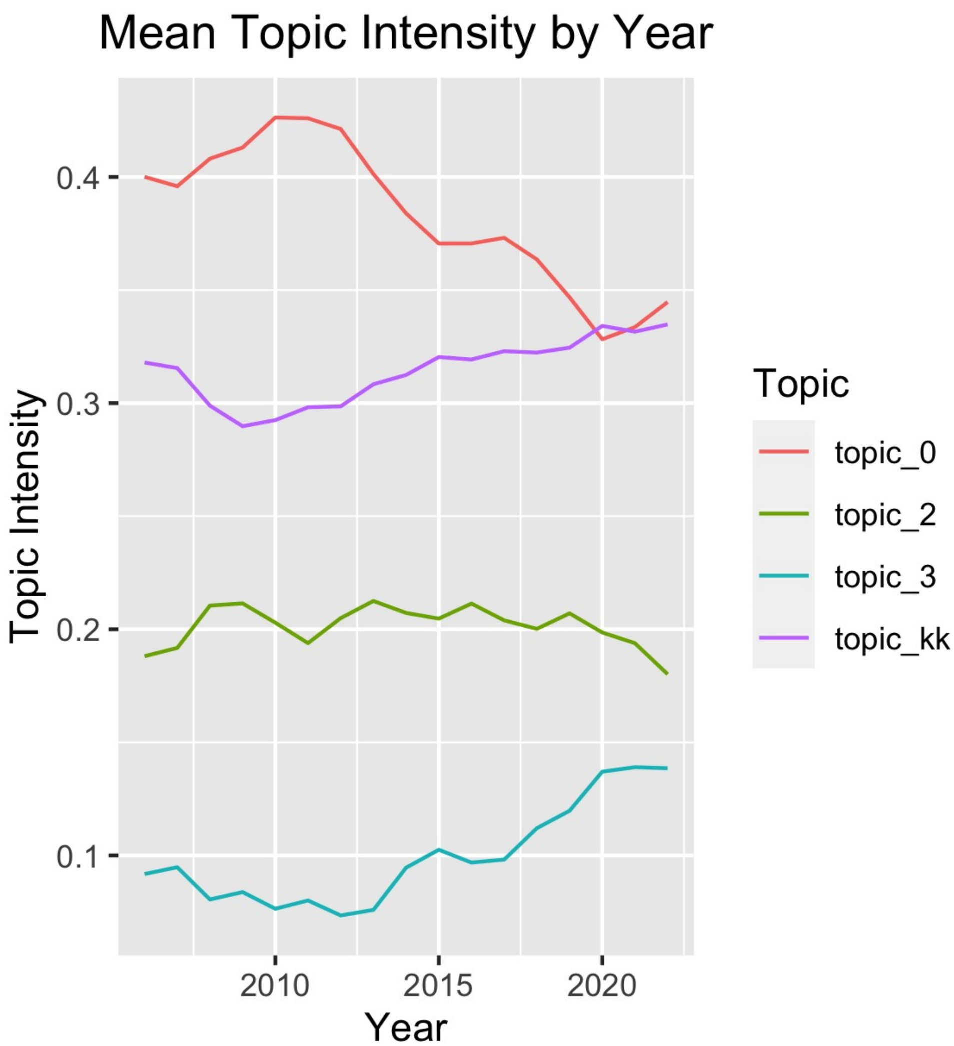

Figure 2: Mean annual topic intensity

3.2 Validating the text-based metric of knowledge-intensive firms

In this section, the text-based measure `topic_kk` is cross-examined with other potentially related measures drawn from existing literature.

Figure 3 presents a correlation matrix that delineates the relationship between the intensity of each topic and the average skill level of employees within a narrowly-defined industry, in accordance with the definition given by Belo et al. (2017). These authors define 'Skill' as the proportion of industry workers engaged in occupations that demand a high degree of training and preparation.

The determination of whether an occupation is high-skill is informed by the Specific Vocational Preparation (SVP) level for each occupation. This data is sourced from the 1991 edition of the Dictionary of Occupational Titles (DOT), published by the U.S. Department of Labor.

In Belo et al.'s (2017) classification, an occupation is considered high-skill if it possesses an SVP level of 7 or greater. This level implies a requirement of two or more years of preparation. Occupations failing to meet this threshold are classified as low-skill.

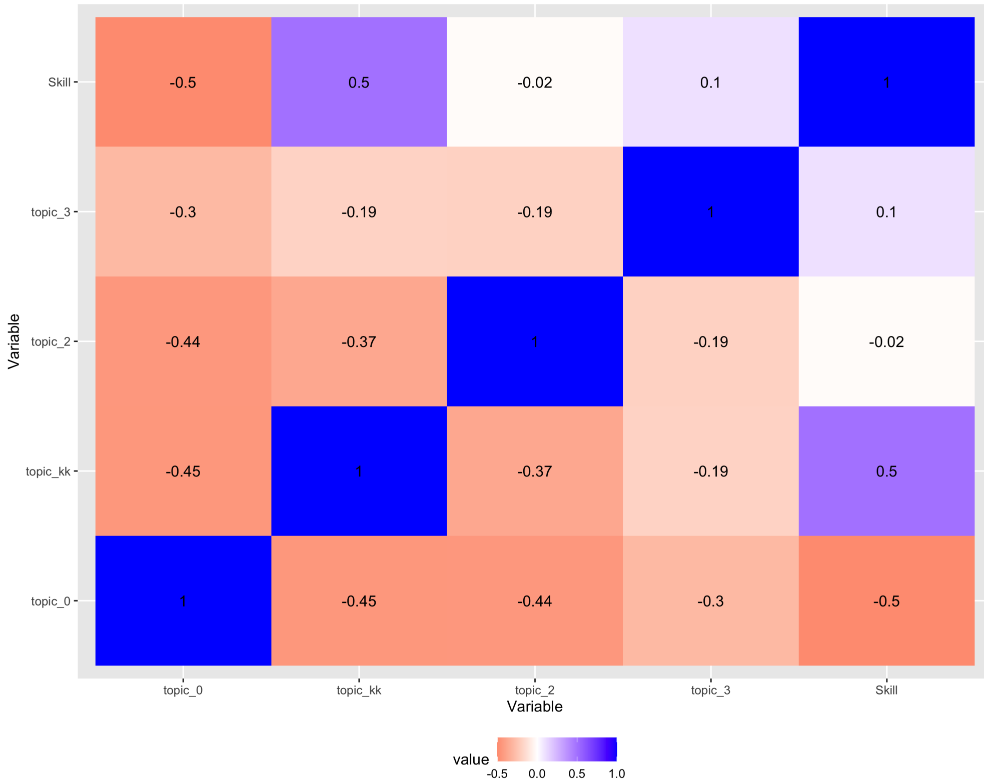

Figure 3: Correlation Matrix Showcasing the Relationship between Topic Intensity and Industry Employee Skill Level

The second component of the analysis, shown in Figure 4, computes the co-occurrences of quartiles for `topic_kk` and the accumulated patent-related market value within firms, in alignment with the methodology proposed by Kogan et al. (2017). Kogan et al. (2017) leveraged stock market data to estimate the value of individual patents filed by public corporations since 1926.

Quartiles for `topic_kk` are shown in Figure 5. In Figure 4, the vertical axis signifies annually assigned quartiles of the ratio between Accumulated Patent Value and Total Assets. The results imply a clear correlation between elevated accumulated patent value and increased loadings of `topic_kk`. A basic correlation analysis between average patent intensity and different topics is shown in Figure 6.

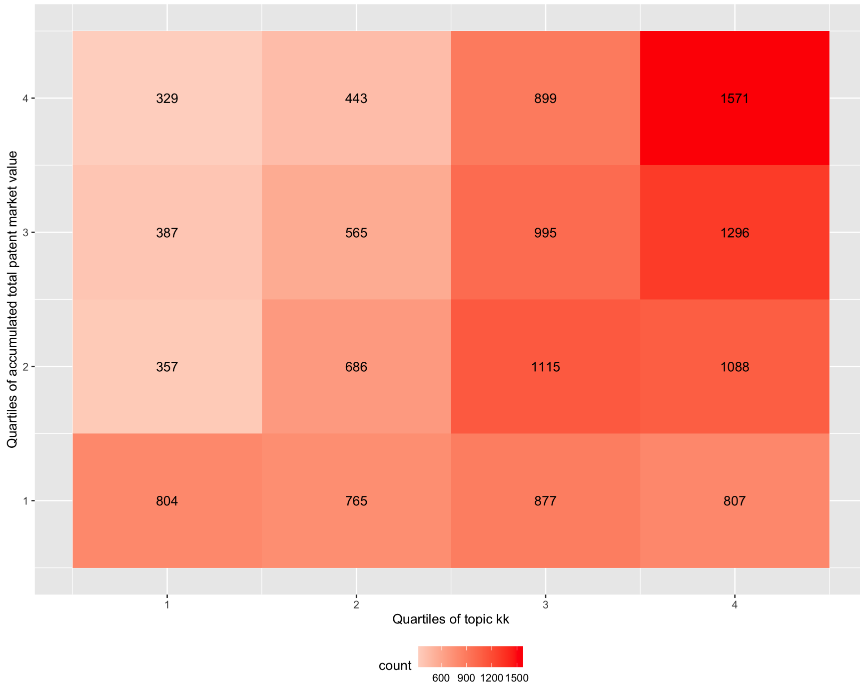

Figure 4: Quartiles of `topic_kk` vs. quartiles of accumulated total patent market value

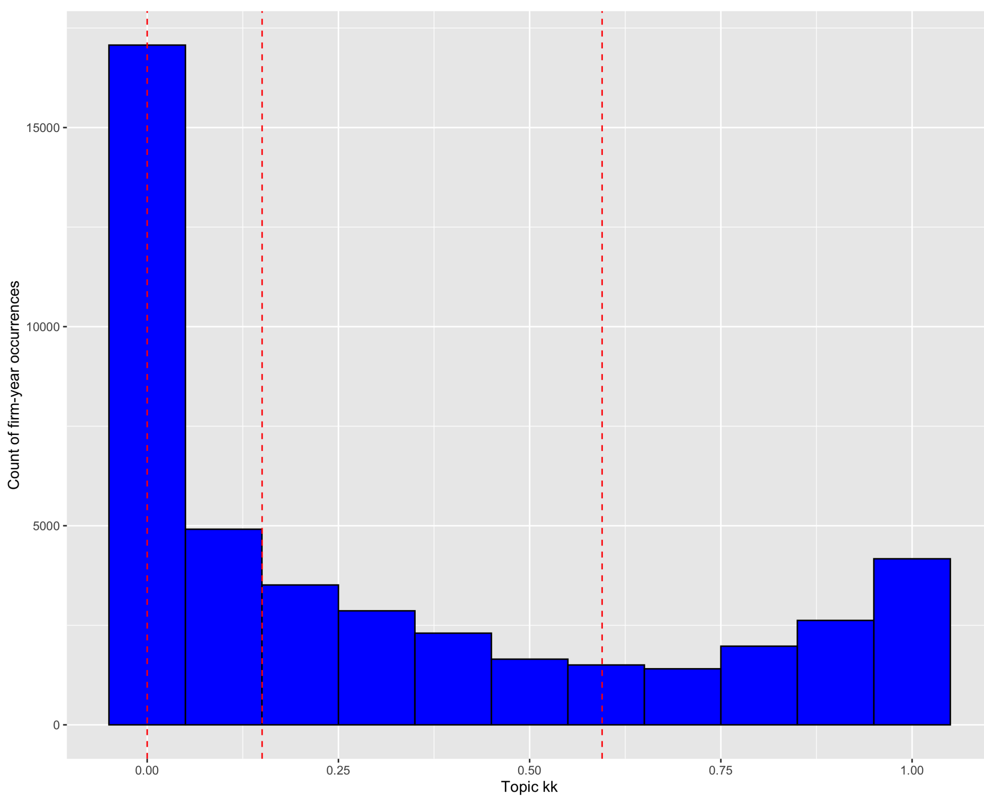

Figure 5: The histogram bars represent the frequency of `topic_kk` values, while the red dashed lines indicate the quartile dividers.

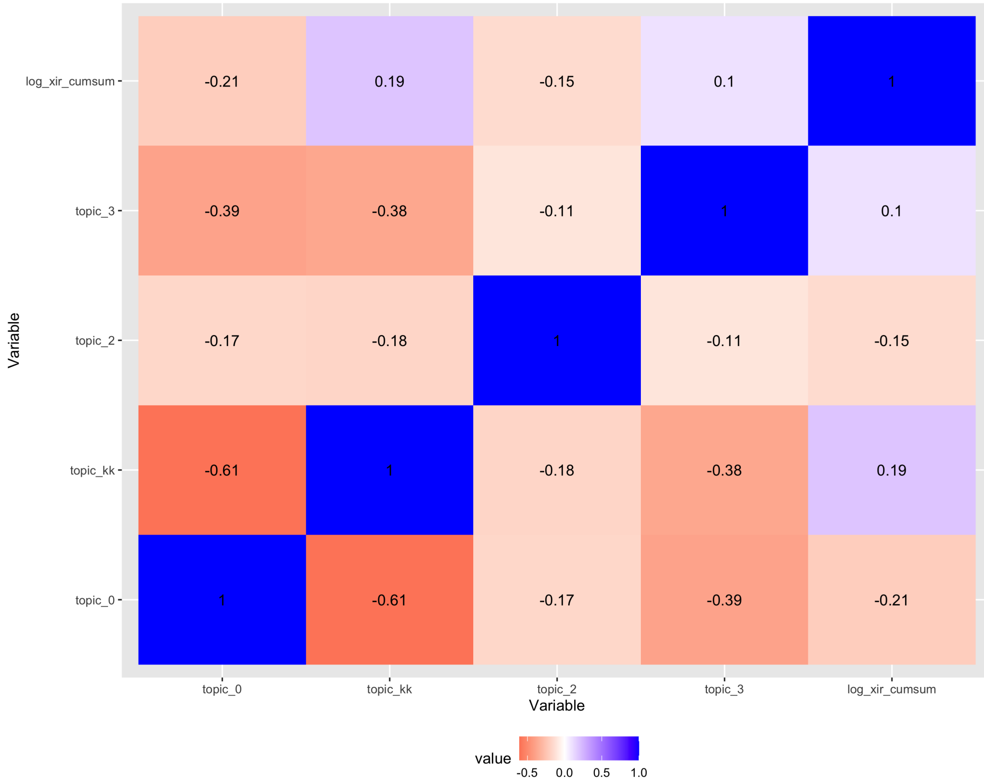

Figure 6: Correlation Matrix: Topic Intensities vs. Firms' Patent Intensities

Figure 7 demonstrates the correlation between `topic_kk` and knowledge capital, as per the definition provided by Peters and Taylor (2017). Notably, it appears that higher accumulated investments in R&D correspond to increased loadings of `topic_kk`.

Figure 7: Correlation Between Knowledge Capital Quartiles and `topic_kk` Quartiles: Higher R&D Investments Correlate with Higher Loadings of `topic_kk`

Lastly, Figure 14 illustrates the accumulated assets of firms in the upper quartile of `topic_kk`.

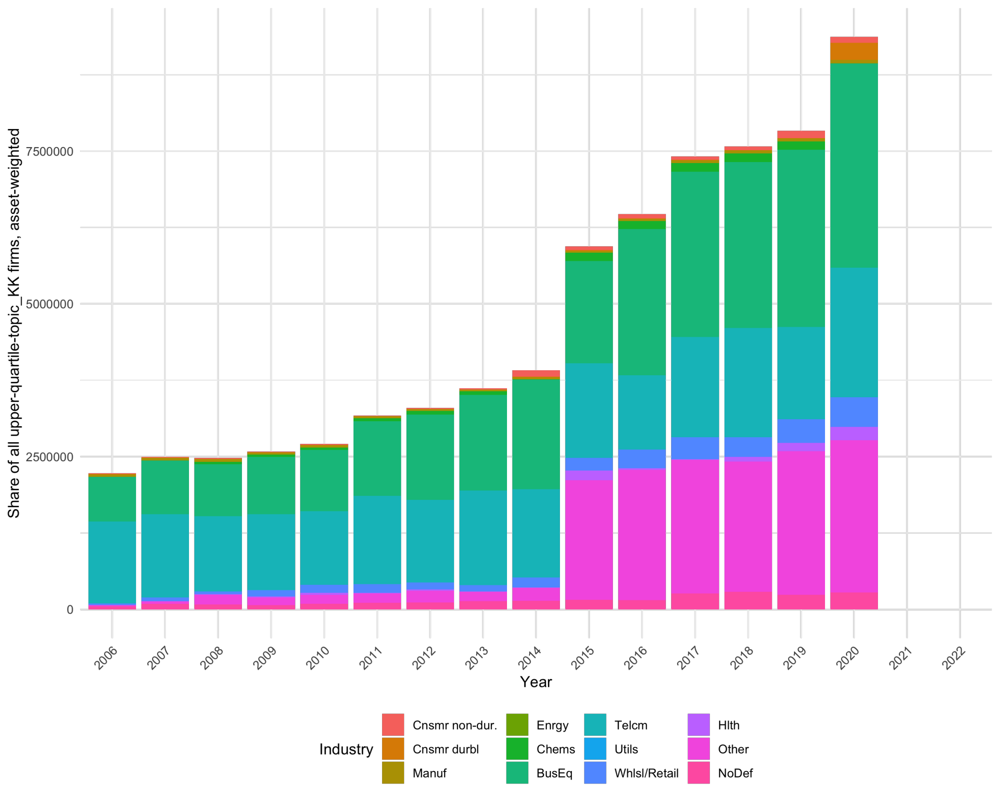

Figure 8: Accumulated Assets of Firms in the Upper Quartile of `topic_kk`

3.3 Implications for Asset Pricing

In this section, firms are matched based on their Central Index Key (CIK) and Permanent Company Number (PERMNO), facilitating a link between their annual reports and multiple other data sources. These sources encompass daily stock data (aggregated on a weekly basis), Compustat data, and metrics associated with firms' knowledge capital, their cumulative patent value, and the skill level prevalent within their respective industries as delineated in prior literature.

The investigation includes an analysis of value-weighted returns, partitioned according to diverse factors. Figure 9 illustrates value-weighted cumulative weekly returns, sorted by quartiles of `topic_kk` determined on an annual basis. The data signifies a correlation between enhanced `topic_kk` loadings and amplified weekly returns, a trend particularly prominent from 2011 onwards.

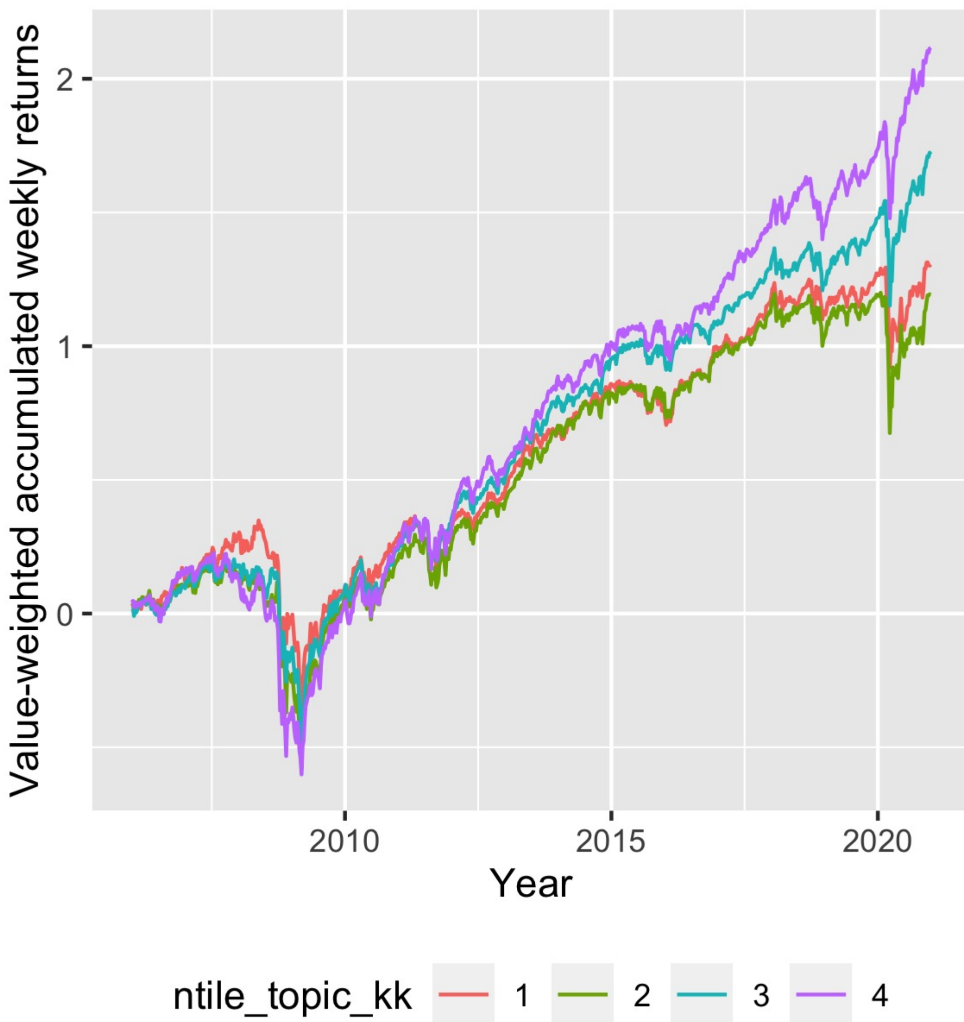

Figure 9: Value-weighted Accumulated Weekly Returns Segregated by Quartiles of `topic_kk`, Showing a Positive Correlation Especially Post-2011

In Figure 10, when constructing `topic_kk` quartiles for each yearly-industry subset based on the 12-industry Fama-French classification, the resulting patterns become less interpretable.

Figure 10: Value-weighted Returns Grouped by Yearly-Industry Subset Quartiles, Indicating Less Interpretable Patterns

Figure 11 displays value-weighted accumulated weekly returns, grouped by firms' maximum topic. Notably, firms with the maximum loading on `topic_kk` (topic 1) have outperformed their peers since 2008.

Figure 11: Firms with Maximum Loading on `topic_kk` Outperforming Peers Since 2008

Moving on to volatility patterns, Figure 12 presents the weekly standard deviation of returns within groups, categorized by the maximum topic. This analysis suggests that different topics are associated with varying cross-sectional volatility patterns.

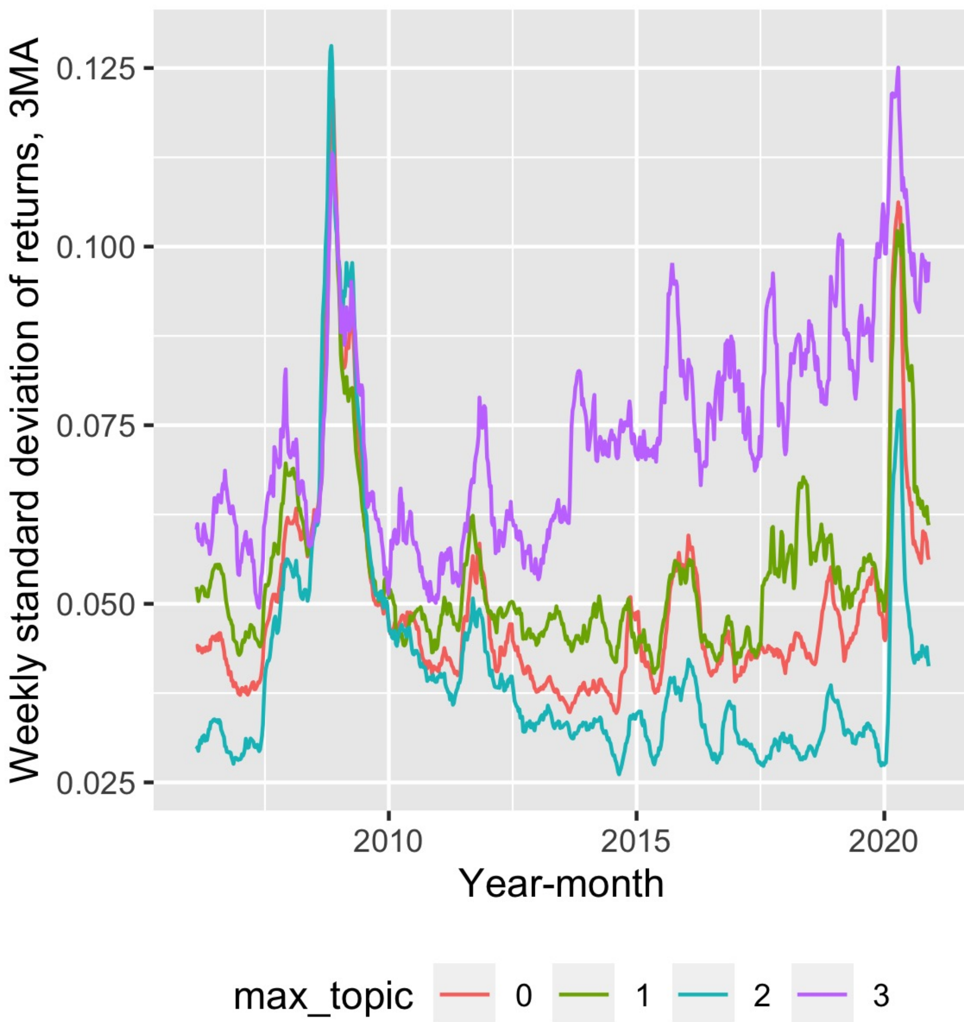

Figure 12: Weekly Standard Deviation of Returns Within Groups, Indicating Variations Across Different Topics

4 Next steps

This study is ongoing, with numerous opportunities for enhancement and further exploration. For instance, the hyperparameter selection process could be optimized, potentially through cross-validation techniques. Existing benchmarks for the choice of 'k', such as perplexity, are also being considered for testing.

In addition, the current methodology might evolve towards supervised models. For example, a prior for `topic_kk` could be imposed, comprising specific words such as "patents" or "intellectual property." So far, the learning process has been completely unsupervised.

Another area of interest is testing whether the derived topics can serve as factors in asset pricing models or if they can clarify any anomalies. Moreover, it would be valuable to examine whether the language associated with `topic_kk` has transformed over time. These areas of focus highlight the promising possibilities for further research and development in this study.

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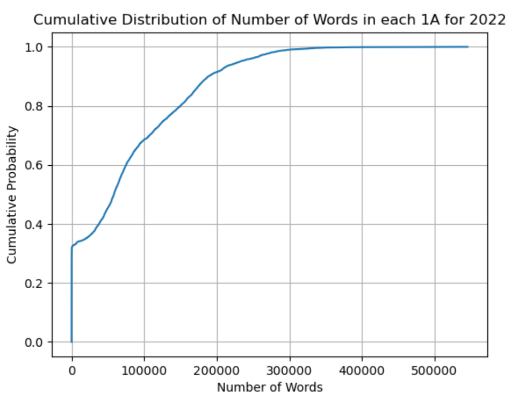
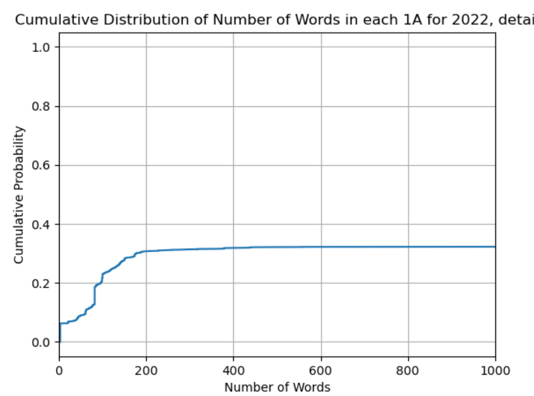
Appendix



(a) Cumulative Distribution of Number of Words



(b) Cumulative Distribution of Number of Words, Zoom

Figure 13: Cumulative Distribution of Number of Words in 2022

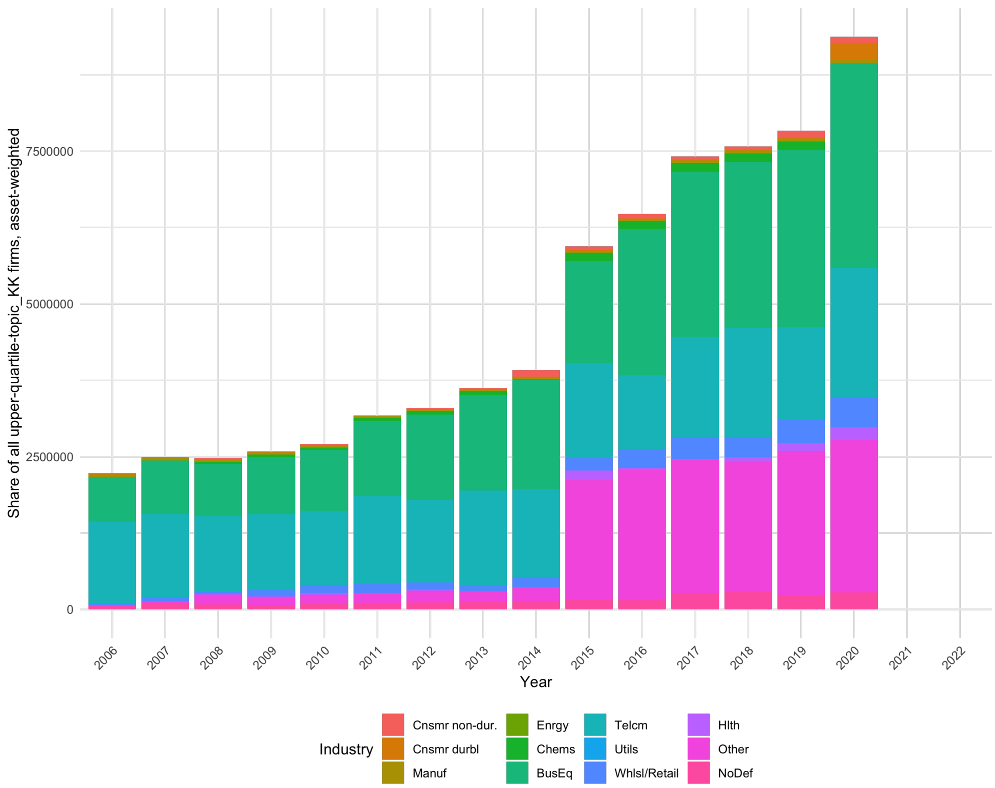


Figure 14: Accumulated Assets of Firms in the Upper Quartile of `topic_kk`