Risk Factors that Matter: Textual Analysis of Risk Disclosures for the Cross-Section of Returns

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Abstract

I introduce risk factors that not only explain the cross-section of returns, but also unambiguously represent economic risk for the firms, are interpretable, and come directly from the companies. I exploit machine learning and natural language processing techniques to identify from the 10-K annual reports the types of risks that firms face, and to quantify how much each firm is exposed to each type of risk. I employ the exposure of companies to each type of risk to construct portfolios exposed to specific risks and construct a factor model with these portfolios. The model is not rejected by the set of 49 Industry Portfolios using the GRS test, which is not the case for the Five Factor Model of Fama and French (2015).

Keywords Cross-Section of Returns, Factor Models, Machine Learning, Big Data, LDA, Text Analysis, NLP

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1 Introduction

The goal of most of the empirical cross-sectional asset pricing literature is to explain why different assets earn different returns, usually by specifying a linear factor model for excess returns:

$$r^e_{i,t+1} = \alpha_{i,t} + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1}, \tag{1}$$

with the important economic restriction[1] that $\alpha_{i,t} = 0$. There is no consensus on how to choose the factors, and researchers generally use one of three different approaches: empirical factors models explicitly designed to overcome anomalies (portfolios of returns that are known to generate α), factors constructed from economic theory and statistical factor models.

However, there have been major recent concerns about these approaches ,[2] the main ones being data mining, overfitting and p-hacking (that is, finding spurious correlations by repeatedly testing variations of the data); the lack of theories for factors or characteristics designed to address anomalies in the cross-section of returns;[3] and concerns about the absence of economic interpretability regarding purely statistical factors.[4] I propose a new way of modelling the cross-section of returns that avoids the usual concerns about factor models: I use machine learning techniques to extract from the 10-K Annual Reports all of the risks that companies disclose, and use these risks to construct a factor model with economically relevant risk factors.

Importantly, the machine learning approach that I use differs significantly from statistical factor models. A typical statistical factor model uses realized returns to find factors that best fit the cross-section. In my approach, I do not use information from the returns at all; I only use the information that companies disclose in their annual reports. Hence, the factors that I identify have a clear economic meaning and are fully and easily interpretable, rather than just being a linear combination of returns.

[1] Additionaly we require $E_t[\epsilon_{i,t}] = E_t[e_{i,t+1} f_{t+1}] = 0$ and $E_t[f_{t+1}] = \lambda_t$.

[2] See Cochrane (2011), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Hou, Xue, and Zhang (2017)

[3] Fama and French (1993): ”the choice of factors, especially the size and book-to-market factors, is motivated by empirical experience. Without a theory that specifies the exact form of the state variables or common factors in returns, the choice of any particular version of the factors is somewhat arbitrary”. See also Kelly, Pruitt, and Su (2018)

[4] See Kozak, Nagel, and Santosh (2018)

I use the risks revealed by the companies to solve the common concerns about factor models in the following way: First, to the best of my knowledge, this is the only paper to use the 10-K textual data to construct a factor model,[5] so the concerns about data mining or p-hacking should be minimal. Second, instead of defining some risk factors or characteristics that seem subjectively important, I take them directly from the firms, since they are the ones that best understand the risks they face. Finally, the factors unambiguously represent economic risk faced by the companies.

To accomplish this, I characterize the types of risks that public companies consider the most relevant and choose to disclose on their annual reports and quantify how much each company is exposed to each type of risk. Equipped with the per firm proportion of the exposure to the disclosed risks, I sort firms to get portfolios exposed to each specific risk, and form a factor model using the risks considered important by each of the firms. I test the capacity of these factors to price the cross-section of returns using the set of 49 industry portfolios.[6]

Although the main contribution is using machine learning techniques to discover interpretable and economically relevant risk factors, the model has an statistical fit significantly better than the Five-Factor Model of Fama and French (2015) in the test of the 49 industry portfolios. Crucially, it explains the cross-sectional variation of returns: the GRS statistic[7] that measures whether $\alpha_{it} \neq 0$ is .82, (compare to a GRS statistic of 1.55 for the Fama and French (2015) Model) and implies a p-value of 68 %, that is, we can very comfortably reject the null hypothesis that $\alpha_{it} \neq 0$, so there is no evidence of misspricing (for comparison, the p-value for the Fama and French (2015) Model is 4.4 %, that is, we cannot reject the null hypothesis that $\alpha_{it} \neq 0$). In short, the GRS test says that my model is a complete descriptions of expected returns for this set of portfolios.[8][9]

I extract the risks that companies disclose from the 10-K Annual reports using Latent Dirichlet Allocation (LDA),[10] a technique developed in the machine learning literature. LDA is a topic modelling technique that summarizes the risks that firms are concerned about, and how much time

[5] Note, however, that Israelsen (2014) was the first to apply LDA to construct portfolios, but uses them to perform factor analysis of the Fama-French factors

[6] I choose these portfolios as a test set following the critique of Lewellen, Nagel, and Shanken (2010).

[7] Gibbons, Ross, and Shanken (1989)

[8] See the Appendix for other test sets

[9] Additionaly, it succeeds in explaining a large fraction of the time series variation of the cross-section of returns (measured by an average R^2 of 63 %, comparable to the 68% average R^2 obtained with the Fama and French (2015) Model).

[10] Blei, Ng, and Jordan (2003)

each company spends discussing each risk.[11] With the additional assumption that if a company spends a longer time discussing a specific risk, they are more exposed to that risk,[12] we can quantify how much each firm is exposed to each type of risk.

Ex-ante, the risks reported by the companies could be either idiosyncratic or systematic. I select the systematic risks by choosing the portfolios with the highest Sharpe ratio[13] and use these portfolios to form a factor model. Note that no information about the 49 industry portfolios is used to select the portfolios that are going to form the factor model, so I avoid both p-hacking and data mining, in this sense, the test is actually an out-of-sample test. While choosing factors via the individual Sharpe ratio provides a great statistical fit, it is not the only criteria that can be used to select a the most important portfolios, see the Appendix for details.

The model has desirable properties over other models that also succeed in fitting the cross-section of stock returns. A salient branch of the literature is concentrated on explaining the cross-section of returns using statistical factors,[14] and while they provide an outstanding statistical fit, it is hard to understand the economics of these factors and whether they represent risk or are generated by behavioral patterns (Kozak, Nagel, and Santosh (2018)), whereas by design, the factors constructed from the firms' risk disclosures represent economic risk.

Another historically important branch of the literature explains anomalies (portfolios with $\alpha \neq 0$) by iteratively adding (some of) the existing anomalies as risk factors.[15] However adding anomalies as risk factors naturally generates too many factors, a "factor zoo" (Cochrane (2011)), and disentangling the true risk factors from the anomalies is a complicated endeavor.[16] To complicate things further, there are important concerns as to which of these anomalies are actually significant out-of-sample (Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016)), so adding them as risk factors is at best, risky. Since by design, all of the factors in the paper, represent risk, it suffices to identify which of these factors are priced to get a set of risk factors that explains the

[11] See Section 4 for a detailed explanation

[12] Gaulin (2017) and Campbell et al. (2014) find empirical evidence justifying this assumption: "the type of risk the firm faces determines whether it devotes a greater portion of its disclosures towards describing that risk type". See Section 3 for an extended discussion.

[13] Sharpe (1966)

[14] See Kelly, Pruitt, and Su (2018), Kozak, Nagel, and Santosh (2018) and Section 2 Related Literature

[15] See for example Fama and French (1992), Fama and French (1993), Fama and French (2015), Hou, Xue, and Zhang (2015), Stambaugh and Yuan (2017) among many, many others

[16] Feng, Giglio, and Xiu (2017) however, provide some hope to succeed.

cross-section.

Moreover, we know from Merton (1973) that the risk premia of every asset depends on the covariances of the firms' cash-flows with the market wealth and other state variables that affect the stochastic discount factor (SDF). Any characteristic of the firms that makes their dividends covary with either wealth or state variables would affect returns. Asking researchers to identify all of these variables seems like an unworkable task. Firms, however, have a better understanding of the risk they are facing. So instead of identifying all of the relevant characteristics, we can directly identify all of the risks perceived by the firms by recovering them from all of the firms' risk disclosures.

The paper continues as follows: Section 2 provides a (brief) literature review; Section 3 describes the data sets and addresses concerns about the reliability of the annual reports; Section 4 describes extensively the process to recover the types of risks from the annual reports; Section 5 describes the characteristics of these risks; Section 6 describes the risk factors and tests; and Section 7 concludes. The techniques used to extract the risks are fairly new to the finance field, so I encourage the reader to read Section 4 before Section 5 or Section 6.

2 Related Literature

My paper makes contributions in two different branches of literature: machine learning and big data methods in finance, and cross-sectional asset pricing.

There is a recent tradition of employing text analysis to study a variety of finance research questions (see Loughran and McDonald (2016) for a systematic review). There are some papers that employ text analysis to study a specific risk that the researchers have in mind (e.g. Hassan, Hollander, van Lent and Tahoun (2017) for political risk; Hanley and Hoberg (2017) for financial risk). I instead, do not specify any risk ex-ante and instead let them arise naturally from the data using unsupervised learning. One important predecessor of my paper is Israelsen (2014), who uses LDA to perform style analysis between disclosed risks and the Fama-French factors. I build on his paper by using the risks disclosed by the firms to form a factor model that explains the cross-section of returns.

My paper is of course related to the large literature on cross-sectional stock returns (see, e.g., Cochrane (1991); Berk, Green, and Naik (1999); Gomes, Kogan, and Zhang (2003); Nagel (2005); Zhang (2005); Livdan, Sapriza, and Zhang (2009);Eisfeldt and Papanikolaou (2013); Kogan and Papanikolaou (2014)). See Harvey, Liu, and Zhu (2016) for a recent systematic survey. However, to the best of my knowledge, this is the first paper to construct a successful factor model using all of the risks disclosed by the firms

3 Data

I use three sources of data: the 10-Ks Annual Reports, Compustat, and CRSP.

3.1 10-K Annual Reports

Firms disclose in their annual reports which types of risk they are facing. There can be some concerns about how true and informative these disclosures are, however, there exist ample evidence that risk disclosure are, indeed, useful and informative. First, firms are legally required to to discuss "the most significant factors that make the company speculative or risky" (Regulation S–K, Item 305(c), SEC 2005) in a specific section of the 10-K annual reports (Section 1A) and could face legal action if they fail to obey the regulation. Additionally, Campbell et al. (2014) find that "firms facing greater risk disclose more risk factors", "the type of risk the firm faces determines whether it devotes a greater portion of its disclosures towards describing that risk type", "managers provide risk factor disclosures that meaningfully reflect the risks they face" and "the disclosures appear to be (...) specific and useful to investors".

I extract the textual risk factors in Section 1A (mandatory since 2005) of each 10-K Annual Report. I collect the 10-Ks from 2005 to 2018 from the EDGAR database on the SEC's website. The 10-Ks come in many different file formats (.txt., .xml, and .html) and have different formatting, so it is quite challenging to automatically extract the Section 1A-Risk Factors, from the 10-K forms. I first detect and remove the markup language and then use regular expressions with predefined heuristic rules to extract these sections. I end up with a data set consisting of 79304 documents.

An excerpt of the 10-K annual report of Apple Inc. for the year 2010 illustrates the kind of disclosures that firms make. I incorporate suggested labels regarding the type of risk, as well as highlight possible key words in red. Note that both labels and key words are just for illustrative purposes, and there is no need to manually label the risks in the paper or define the keywords, since the risk factors will arise naturally using the LDA algorithm.

- Currency Risk: "Demand (...) could differ (...) since the Company generally raises prices on goods and services sold outside the U.S. to offset the effect of the strengthening of the U.S. dollar change".
- Supplier Risk: "The Company uses some custom components that are not common to the rest of the personal computer, mobile communication and consumer electronics industries."
- Competition Risk: "Due to the highly volatile and competitive nature of the personal computer, mobile communication and consumer electronics industries, the Company must continually introduce new products"

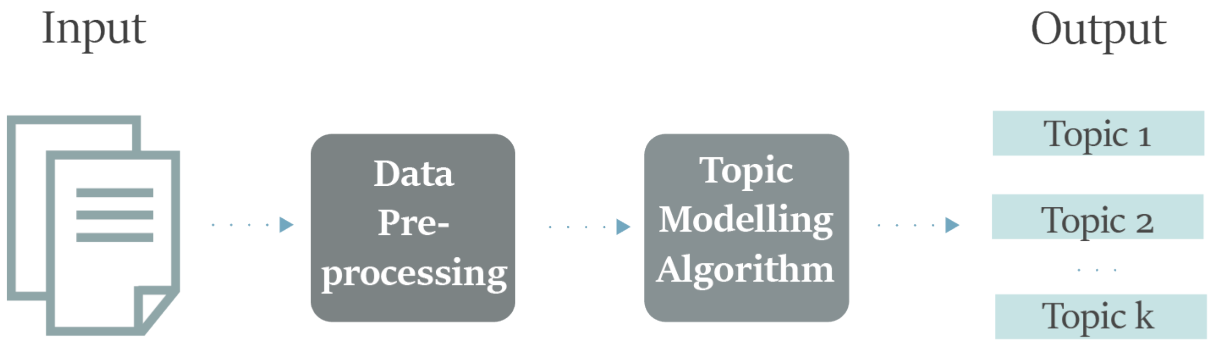
3.2 CRSP and Compustat

I follow the usual conventions regarding CRSP and Compustat data. I focus on monthly returns since the disclosures are done annually. For the accounting and return data, I use the the merged CRSP/Compustat database. I use annual firm-level balance sheet data from Compustat due to concerns about seasonality and precision; and monthly returns from CRSP. I use data from the same period as the one where 10-Ks are available: 2005-2018, although not all variables are available for every period. I exclude from the main analysis firms in industries with SIC codes corresponding to financial (SIC in [6000, 7000]).

The Five Factors of Fama and French (2015), the momentum factor, and the one-month Treasury-bill rate come from the French data library on Ken French's website. The Stambaugh and Yuan (2017) factors come from their website. The q-factors of Hou, Xue, and Zhang (2015) come from their website.

4 Text Processing

Figure 1: Steps for topic modelling



4.1 Bag of Words and Document Term Matrix

We need a way to represent text data for statistical purposes. The bag-of-words model achieves this task. Bag of Words considers text as a list of distinct words in a document and a word count for each word,[17] which implies that each document is represented as a fixed-length vector with length equal to the vocabulary size. Each dimension of this vector corresponds to the count or occurrence of a word in a document. Traditionally, all words are lowercased to reduce the dimension in half.

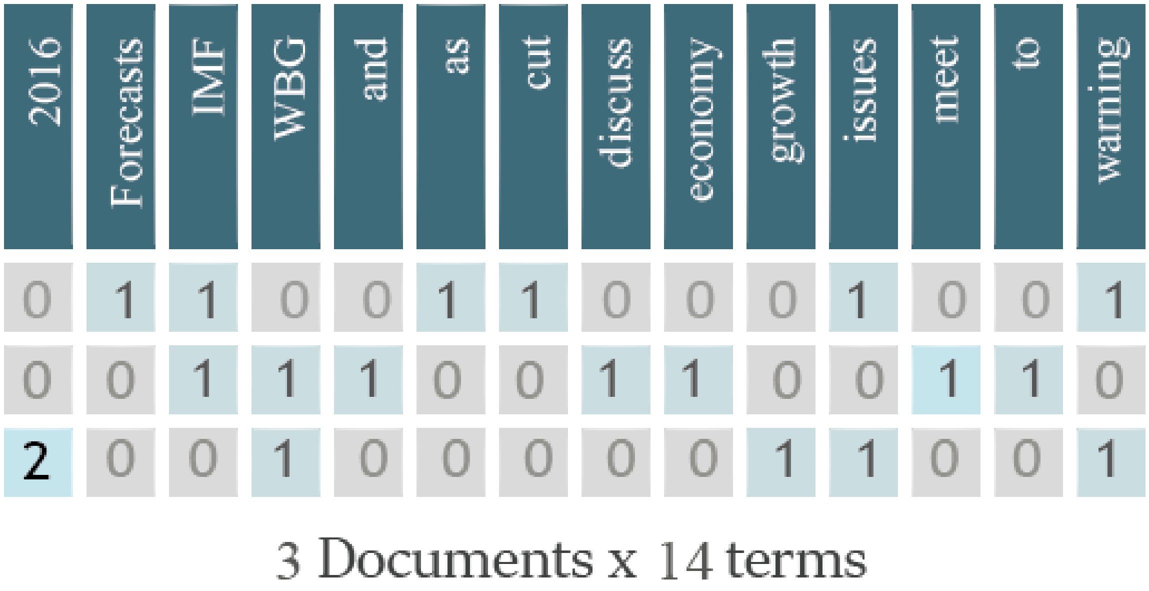
It is called a “bag” of words, because any information about the order or structure of words in the document is discarded. The model is only concerned with whether known words occur in the document, not where in the document. Notice that since we only consider the count, the order of the words is lost. When we consider several documents at a time, we end up with a Document Term Matrix (DTM), see Figure 2 for a simplified example. The DTM is typically very high dimensional ($>$ 10,000 columns), since we consider the space of all words used across all documents, it is also very sparse, since typically documents do not use the whole English vocabulary. Because of the huge dimension of the space, we need a dimentionality reduction technique, such as LDA.

Another subtle disadvantage is that it breaks multi-word concepts such as ”real state” into ”real” and ”state”, which have to be rejoined later, since counting those words separately will be

[17] Manning, Raghavan, and Schütze (2008)

different results than counting the multi-word concept.

Figure 2: Example of a very simple document term matrix



2016	Forecasts	IMF	WBG	and	as	cut	discuss	economy	growth	issues	meet	to	warning
0	1	1	0	0	1	1	0	0	0	1	0	0	1
0	0	1	1	1	0	0	1	1	0	0	1	1	0
2	0	0	1	0	0	0	0	0	1	1	0	0	1

3 Documents x 14 terms

4.2 Preprocessing

It is common to preprocess the raw text in several steps in order to make the topics more interpretable and to reduce the dimension. The purpose is to reduce the vocabulary to a set of terms that are most likely to reveal the underlying content of interest, and thereby facilitate the estimation of more semantically meaningful topics.

I remove common English words (the, and, or, ...) and additional terms that do not convey any meaning or are considered legal warnings in the 10-K (materially adverse, no assurance, ...) in order to extract only risk factors from the text. See the appendix for a full list and a detailed explanation.

Some words represent the same underlying concept. For example, "copy", "copied", and copying; all deal with either a thing made to be similar or identical to another or to make a similar or identical version of. The model might treat them differently, so I strip such words to their core. We can achieve this by either stemming or lemmatization. Stemming and Lemmatization are fundamental text processing methods for text in the English language.

Stemming helps to create groups of words which have similar meanings and works based on a set of rules, such as remove “ing” if words are ending with “ing”.[18] Different types of stemmers are available in standard text processing software such as NLTK (Loper and Bird (2002)), and within the stemmers there are different versions such as PorterStemmer, LancasterStemmer and SnowballStemmer. The disadvantages of stemming is that it cannot relate words which have different forms based on grammatical constructs, for example: ”is”, ”am”, and ”be” come form same root verb, ”be”, but stemming cannot prune them to their common form . Another example: the word better should be resolved to good, but stemmers would fail to do that. With stemming, there is lot of ambiguity which may cause several different concepts to appear related. Axes is both a plural form of axe and axis. By chopping of the ”s”, there is no way to distinguish between the two.

Lemmatization in linguistics is the process of grouping together the inflected forms of a word so they can be analyzed as a single item, identified by the word’s lemma, or dictionary form(Manning, Raghavan, and Schütze (2008)). In order to relate different inflectional forms to their common base form, it uses a knowledge base called WordNet. With the use of this knowledge base, lemmatization can convert words which have a different form and cannot be solved by stemmers, for example converting “are” to “be”. The disadvantages of lemmatization are that it is slower compared to stemming, however, I use lemmatization to preserve meaning and make the topics more understandable.

Phrase Modeling is another useful technique whose purpose is to (re)learn combinations of tokens that together represent meaningful multi-word concepts. We can develop phrase models by looking for words that co-occur (i.e., appear one after another) together much more frequently than you would expect them to by random chance. The formula to determine whether two tokens A and B constitute a phrase is:

$\frac{count(A,B)-count_{min}}{count(A)*count(B)} * N \geq threshold$, where:

- $count(A)$ is the number of times token A appears in the corpus

[18] Manning, Raghavan, and Schütze (2008)

- $count(B)$ is the number of times token B appears in the corpus
- $count(A, B)$ is the number of times the tokens A and B appear in the corpus in that order
- N is the total size of the corpus vocabulary
- $count_{min}$ is a parameter to ensure that accepted phrases occur a minimum number of times
- $threshold$ is a parameter to control how strong of a relationship between two tokens the model requires before accepting them as a phrase

With phrase modeling, named entities will become phrases in the model (so new york would become new_york). We also would expect multi-word expressions that represent common concepts, but are not named entities (such as real state) to also become phrases in the model.

4.3 Dictionary methods

The most common approach to text analysis in economics relies on dictionary methods, in which the researcher defines a set of words of interest and then computes their counts or frequencies across documents. However, this method has the disadvantage of subjectivity from the researcher perspective since someone has to pick the words. Furthermore, it is very hard to get the full list of words related to one concept and the dictionary methods assume the same importance or weight for every word. Since the purpose of the paper is to extract the risks that managers consider important with minimum researcher input, dictionary methods are unsatisfactory.

Furthermore, dictionary methods have other disadvantages, Hansen, McMahon, and Prat (2018) say: "For example, to measure economic activity, we might construct a word list which includes 'growth'. But clearly other words are also used to discuss activity, and choosing these involves numerous subjective judgments. More subtly, 'growth' is also used in other contexts, such as in describing wage growth as a factor in inflationary pressures, and accounting for context with dictionary methods is practically very difficult."

For the purpose of studying the cross-section of returns, the problem is similar to picking which characteristics are important for the returns. The dictionary methods would be equivalent to manually picking which characteristics would enter a regression. The following algorithm, Topic Modelling, is akin to automatic selection methods, such as LASSO (Tibshirani (1996)).

4.4 Topic Models

A topic model is a type of statistical model for discovering a set of topics that describe a collection of documents based on the statistics of the words in each document, and the percentage that each document spends in each topic. Since in this case, the documents are the risk disclosures from the annual statements and they only concern risks, the topics discovered will correspond to different types of risks.

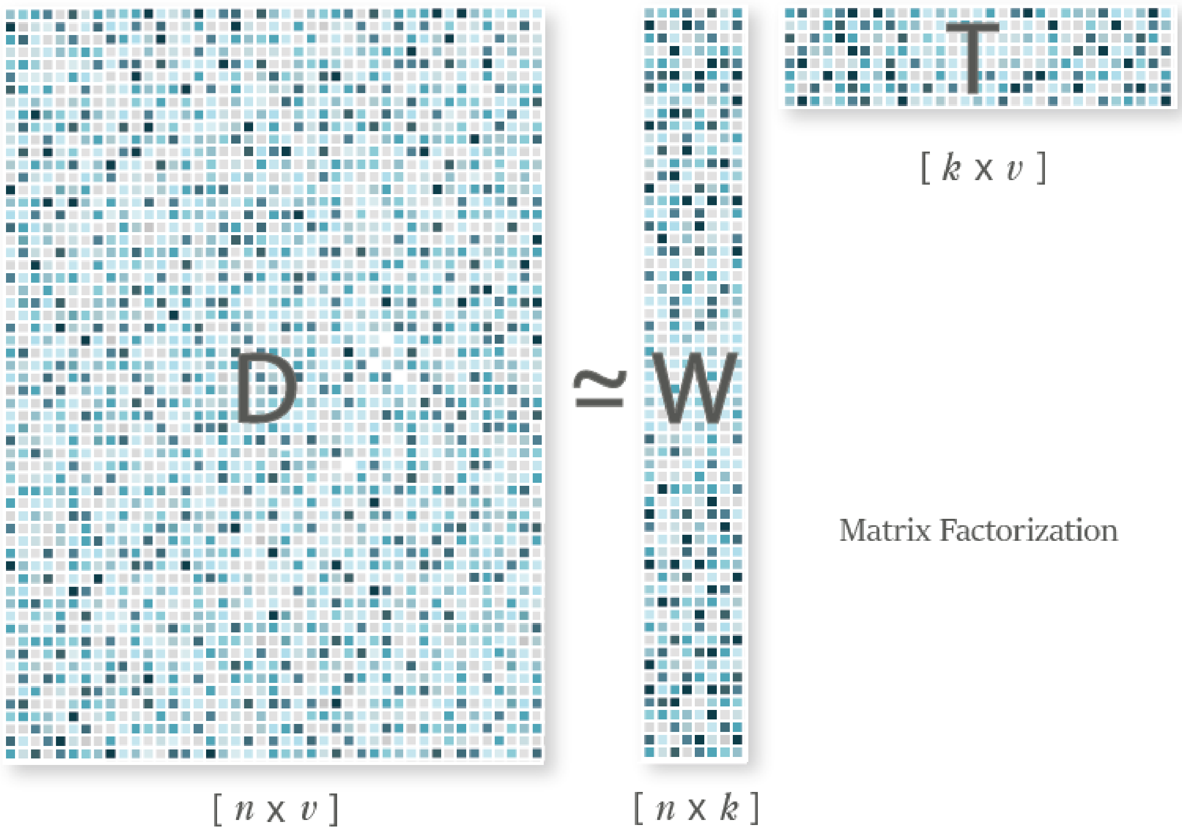
Intuitively, given that a document is about a particular topic, one would expect particular words to appear in the document more or less frequently. For example: "internet" and "users" will appear more often in documents produced by firms in the technology sector; "oil", "natural gas" and "drilling" will appear more frequently in documents produced by firms in the oil industry, while "company" and "cash" would appear similarly in both.

A document typically concerns multiple topics, or in this case risks, in different proportions; thus, in a company that is concerned with 20% about financial risks and 20% about internet operations, the risk report would approximately have around 8 times more technology words than financial words.

Because of the large number of firms in the stock market, the amount of time to read, categorize and quantify the risks disclosed by every firm is simply beyond human capacity, but topic models are capable of identifying these risks.

The most common topic model currently in use is the LDA model proposed by Blei, Ng, and Jordan (2003). The model generates automatic summaries of topics in terms of a discrete probability distribution over words for each topic, and further infers per-document discrete distributions over topics. The interaction between the observed documents and the hidden topic structure is manifested in the probabilistic generative process associated with LDA.

Figure 3: Intuition for Topic Modelling



4.5 LDA

In LDA each document can be described by a (probability) distribution over topics and each topic can be described by a (probability) distribution over words. In matrix algebra terms, we are factorizing the term-document matrix D into a matrix W mapping words to topics, and a matrix T mapping topics to words, similar to the factorization used in Principal Component Analysis, see Figure 3. In this way, LDA reduces the dimentionality of each document, from thousands of words, to the number of topics (25 in our case). However, LDA retains most of the information about the individual word counts, since the topics themselves are probability distribution over words

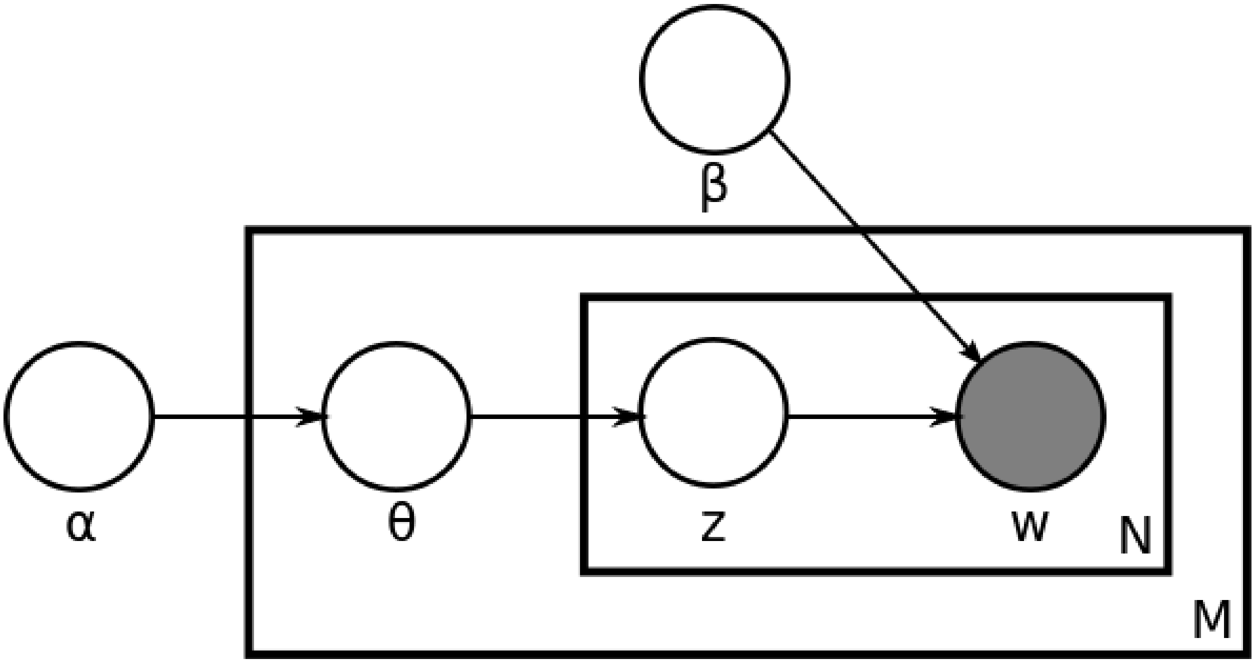
Formally, LDA is a Bayesian factor model for discrete data that considers a fixed latent set of topics. Suppose there are D documents that comprise a corpus of texts with V unique terms. The K topics (in this case, risk types), are probability vectors $\beta_k \in \Delta_{V-1}$ over the V unique terms in the data, where Δ_M refers to the M-dimensional simplex. By using probability distributions, we allow the same term to appear in different topics with potentially different weights. We can think of a topic as a weighted word vector that puts higher mass in words that all express the same underlying theme.[19]

In LDA, each document is described by a distribution over topics it belongs, so each document d has its own distribution over topics given by θ_d (in our case, how much each company discuss each type of risk). Within a given document, each word is influenced by two factors, the topics proportions for that document, θ_{dk}, and the probability measure over the words within the topics. Formally, The probability that a word in document d is equal to the nth term is $p_{dn}\theta_d^k$.

It is easier to frame LDA in the language of graphical models, see Figure 4. Where M is the set of all the documents; N is the number of words per document. Inside the rectangle N we see w: the words observed in document i, z: the random topic for jth word for document i, θ: the topic distribution for document i. α: the prior distribution over topics, intuitively controls the sparsity of topics within a document (i.e. how many topics we need to describe a document). β the prior distribution of words within a topic, controls how sparse are the topics in terms of words (i.e. how many words we need to describe a topic). There is a trade-off between the sparsity of the topics, i.e. how specialize they are, and the number of topics.

[19] See Blei, Ng, and Jordan (2003) and Hansen, McMahon, and Prat (2018)

Figure 4: LDA Graphical Model



4.5.1 Number of topics

The number of topics is a hyperparameter in LDA. Ideally, there should be enough topics to be able to distinguish between themes in the text, but not so many that they lose their interpretability. In this case 25 topics accomplish these task, and is consistent with the numbers used in the literature (Israelsen (2014), Bao and Datta (2014)).

There are technical measures such as perplexity or predictive likelihood to help determine the optimal number of topics from a statistical point of view. These measures are rarely use however, because these metrics are not correlated with human interpretability of the model and prescribe a very high number of topics, whereas for topic models, we care about getting interpretable topics (which correspond to the type of risks).

In the case of risk disclosures, a low number (< 20) gets few common risks that all firms in all industries face, and a big number (> 50) starts capturing very specific industry risks. Another issue is that with a big number of topics, very few firms will have significant exposure to each risk, and hence portfolios exposed to some risks will be poorly diversified. I set the number of topics equal to 25 after experimenting with different values.

A natural challenge is then to further reduce the extracted risks into a lower number of portfolios for the cross-section. I use the number of firms threshold, cross-validation, and with LASSO to address this challenge. See the section Portfolios for more detail.

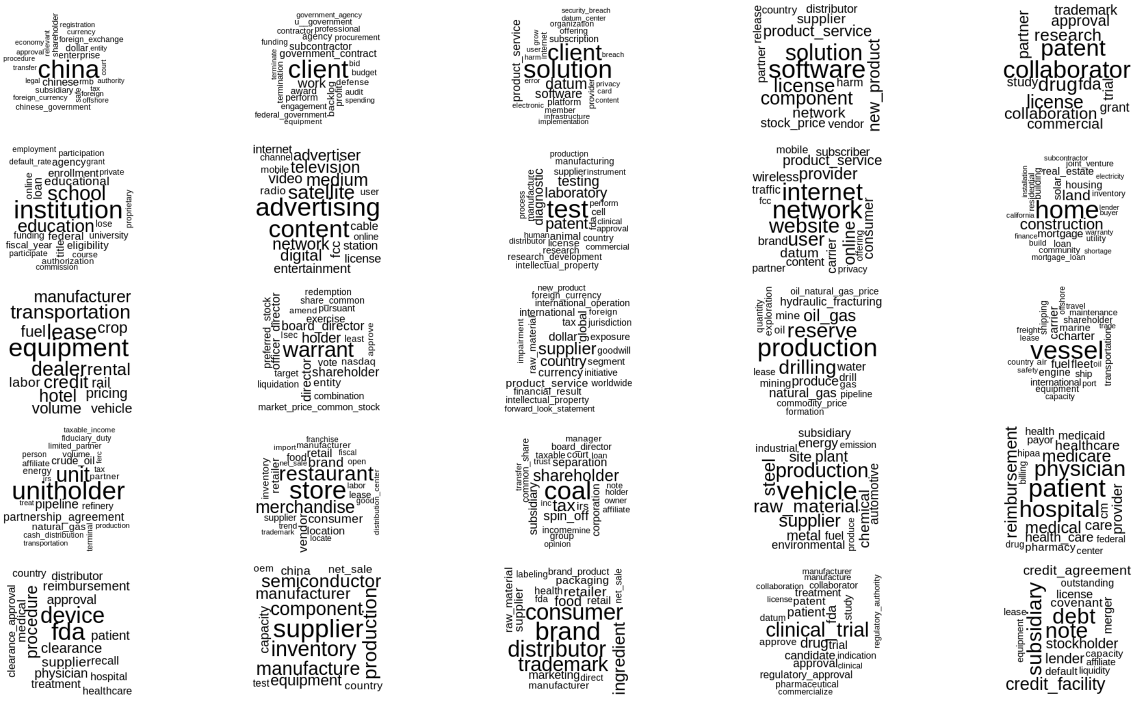
4.5.2 Estimation

The estimation of the posterior parameters is done using the open-source software GensimŘehůřek and Sojka (2010) which runs on Python. Gensim uses an online Variational Bayes algorithm. Because of the huge size of the collection of annual reports, the use of online algorithms allows us to not load every document into the RAM memory and hence we can estimate the model in a normal laptop. See the Appendix and Hoffman, Bach, and Blei (2010) for details.

5 Risk Topics and Risk Factors

We can get a general picture of the risks that firms are facing from Figure 5, where I present the 25 risk topics extracted from the 10-K annual report, recall from Section 4 that a topic is a probability distribution over words. I discuss here only the risks that I will use for the factor model, the ones with the highest Sharpe ratio, and discuss the rest in the Appendix.

Figure 5: Risk Topics



Wordcloud of the risks that firms face. A bigger font corresponds to a bigger weight for that word within each topic.

It is important to note that LDA does not give us labels for the topics, but nevertheless the topics are easily interpretable since they are characterized mostly by the most frequent words. Regardless, I name the topics for concreteness.

I refer to the topics as obtained using LDA as Risk Topics and the portfolios formed using these risks as Risk Factors.

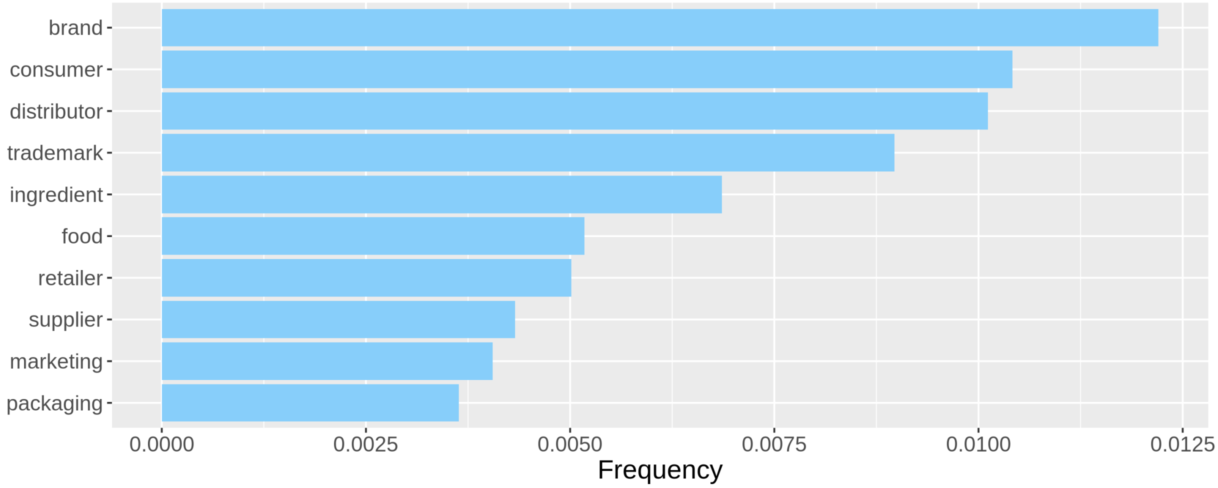
5.1 Portfolios

I construct portfolios exposed to each risk in the following way: For every topic, at June of every year I consider only the firms that spend more than 30% of their last risk disclosure available at the time discussing each risk, and form a value-weighted portfolio. Because most firms discuss multiple risks, 30% seems like a reasonable threshold. Regardless, I discuss other approaches in the Appendix.

To construct excess return portfolios, I substract the risk-free rate. Conceptually, because the firms that spend 0% of their risk disclosure discussing a specific risk, must be spending that time discussing other risks (I discard firms with no risk disclosures), if I substract portfolios composed of the remaining firms, I am effectively mixing risks in an unknown proportion, which would result in not understanding the risk the portfolio is representing, defeating the purpose of the exercise.

5.2 Consumer Demand Risk

Figure 6: Consumer Demand Risk Topic



Distribution of the 10 most frequent words for the Consumer Demand Risk Topic

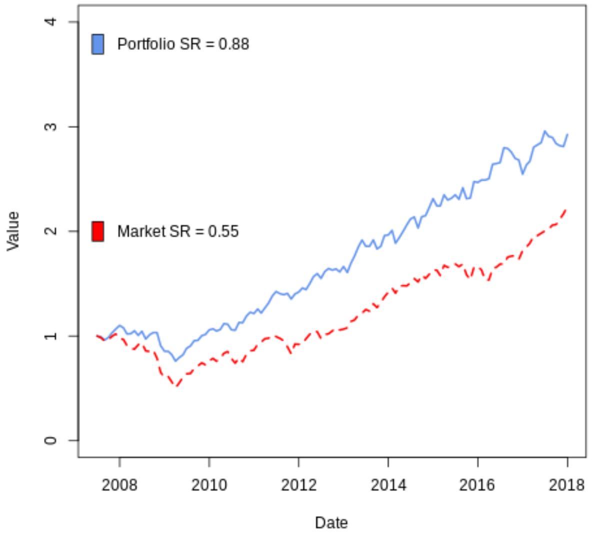
The Consumer Demand Risk Topic is characterized by words that have a direct relation to consumer demand, such as: "brand", "consumer", "food", "marketing"; as we can see from Figure 6. We can see in Table 1 that when we inspect the biggest companies that spend more than 30% of their risk disclosures commenting about the Consumer Demand Risk Topic, we can see companies that spend a lot of resources in attracting consumers: Coca-Cola, Colgate, Philip Morris, among others.

Table 1: Biggest 10 Companies that are exposed more than 30% to the Consumer Demand Risk

Company Name	Market Value (Millions)
COCA-COLA CO	185759
PEPSICO INC	144684
PHILIP MORRIS INTERNATIONAL	136203
ALTRIA GROUP INC	114095
MONDELEZ INTERNATIONAL INC	70849
COLGATE-PALMOLIVE CO	59474
GENERAL MILLS INC	37467
MONSTER BEVERAGE CORP	30224
CONSTELLATION BRANDS	28242
PERRIGO CO PLC	27041

The Consumer Risk Factor has the highest Sharpe ratio: .88. We can see from Figure 7 that while it fluctuates very much with the business cycles, specially during the financial crisis, it has a consistently higher performance than the market portfolio.

Figure 7: Cumulative Return of the Consumer Demand Risk Factor

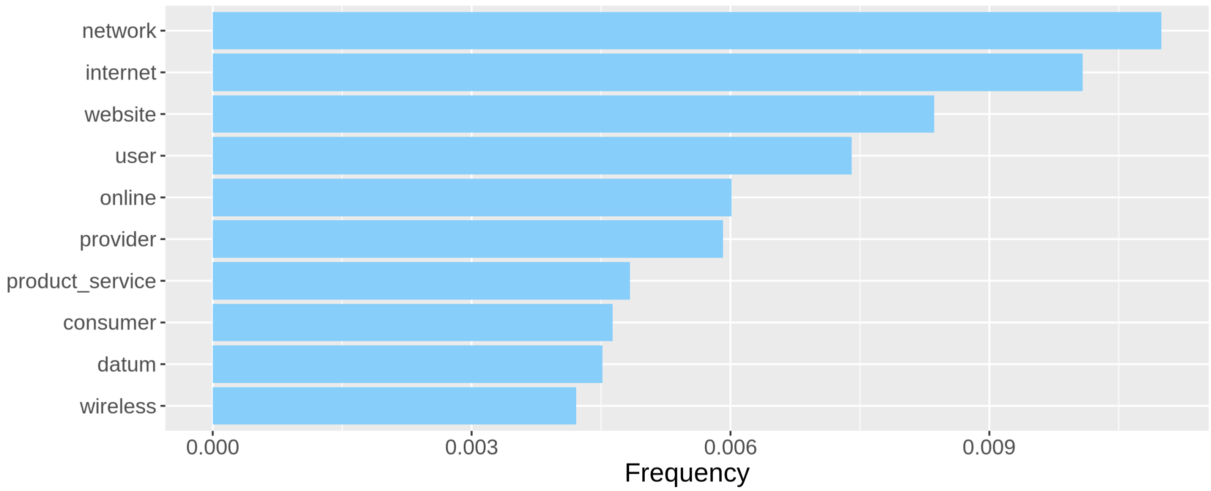


Cumulative return of investing one dollar in June 2007. Blue: Risk Factor, Red: Market Return, SR: Sharpe Ratio

5.3 Internet Risk

The Internet Risk Topic is characterized by words that have a direct relation to technology and web services, such as: ”network”, ”internet”, ”website”, ”user”; as we can see from Figure 8. We can see in Table 2 that when we inspect the biggest companies that spend more than 30% of their risk disclosures commenting about the Internet Risk Topic, we see the companies we expect: Microsoft, Amazon, Facebook, among others.

Figure 8: Internet Risk Topic



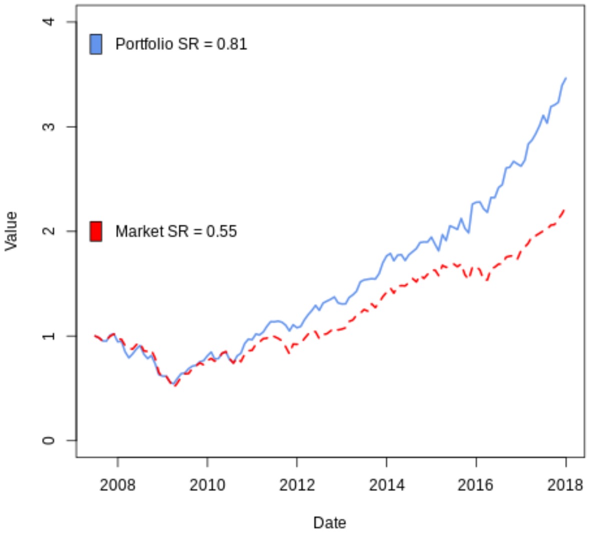
Distribution of the 10 most frequent words for the Internet Risk Topic

Table 2: Biggest 10 Companies that are exposed more than 30% to the Internet Risk

Company Name	Market Value (Millions)
MICROSOFT CORP	354392
AMAZON.COM INC	318344
FACEBOOK INC	297758
AT&T INC	211447
VERIZON COMMUNICATIONS INC	188262
BOOKING HOLDINGS INC	63253
NETFLIX INC	48948
EBAY INC	32536
T-MOBILE US INC	32015
ALTABA INC	31459

The Internet Risk Factor has a very high Sharpe ratio: .81. We can see from 9 that while it fluctuates very much with the business cycles, specially during the financial crisis, it has a higher performance than the market portfolio.

Figure 9: Cumulative Return of the Internet Risk Factor

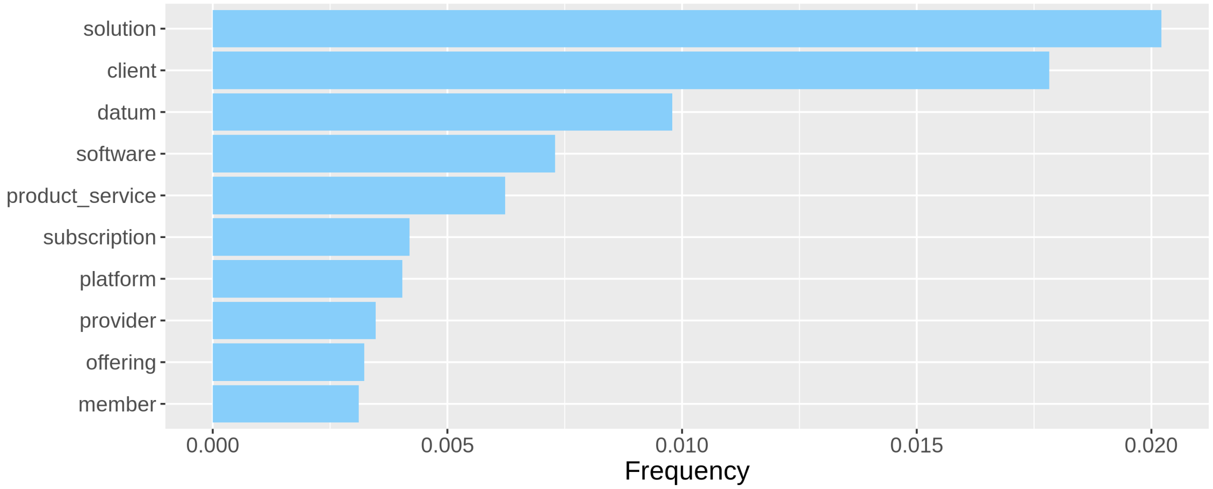


Cumulative return of investing one dollar in June 2007. Blue: Risk Factor, Red: Market Return, SR: Sharpe Ratio

5.4 Software Services Risks

The Software Services Risk Topic is characterized by words that have are related to software platforms, specially subscription services, such as: ”data”, ”subscription”, ”platform”, ”clients”; as we can see from Figure 10. We can see in Table 3 that when we inspect the biggest companies that spend more than 30% of their risk disclosures commenting about the Software Services Risk Topic, we see the companies that indeed conduct a lot of business in the software subscription space: Adobe, Linked In, Sales Force, among others.

Figure 10: Software Services Risk Topic



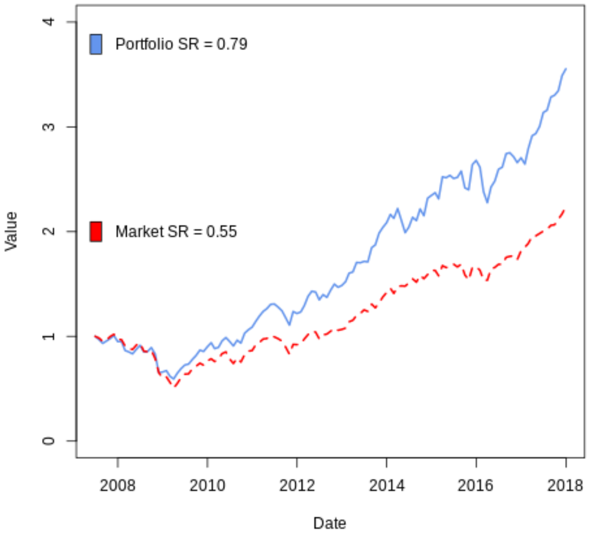
Distribution of the 10 most frequent words for the Software Services Risk Topic

Table 3: Biggest 10 Companies that are exposed more than 30% to Software Services Risks

Company Name	Market Value (Millions)
EXPRESS SCRIPTS HOLDING CO	59168
SALESFORCE.COM INC	45663
ADOBE SYSTEMS INC	45530
AUTOMATIC DATA PROCESSING	37419
COGNIZANT TECH SOLUTIONS	36552
LINKEDIN CORP	29722
S&P GLOBAL INC	26143
FISERV INC	20606
CERNER CORP	20455
FIDELITY NATIONAL INFO SVCS	19665

The Software Services Risk Factor has a very high Sharpe ratio: .79. We can see from 11 that while it fluctuates very much with the business cycles, more than the market, however it seems that this return is rewarded in with a high average return: 1.07 % monthly. Since most of the companies in the portfolio are in the business to business industry it seems intuitive that it varies much more than the market portfolio, since we know investment is very volatile.

Figure 11: Cumulative Return of the Software Services Risk Factor

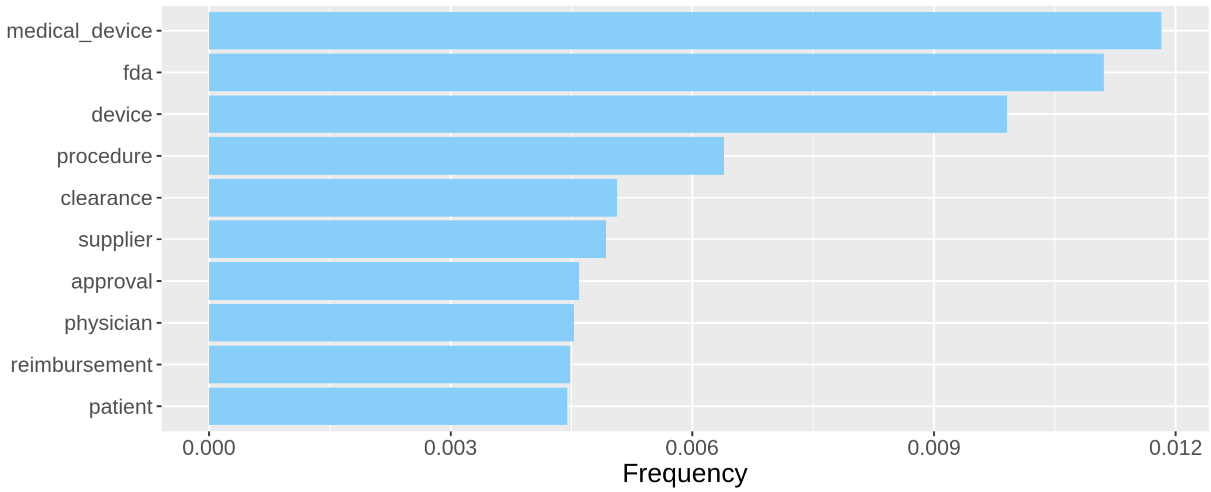


Cumulative return of investing one dollar in June 2007. Blue: Risk Factor, Red: Market Return, SR: Sharpe Ratio

5.5 Health and Innovation Risks

The Health and Innovation Risk Topic is characterized by words that have are related to medicine and innovation, such as: ”medical device”, ”FDA”, ”procedure”, ”patients”; as we can see from Figure 12. We can see in Table 4 that when we inspect the biggest companies that spend more than 30% of their risk disclosures commenting about the Health Service Risk Topic, we see the companies we expect: Microsoft, Amazon, Facebook, among others.

Figure 12: Health Services Risk Topic



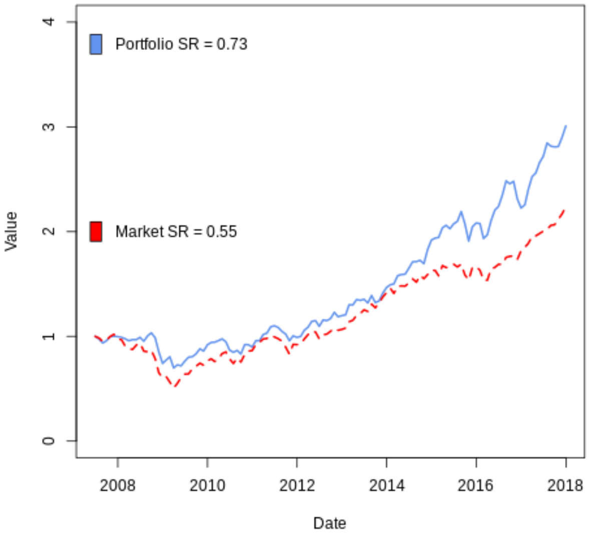
Distribution of the 10 most frequent words for the Health Services Risk Topic

Table 4: Biggest 10 Companies that are exposed more than 30% to Health Services Risks

Company Name	Market Value (Millions)
MEDTRONIC PLC	110732
ABBOTT LABORATORIES	66137
STRYKER CORP	34667
BOSTON SCIENTIFIC CORP	24832
BAXTER INTERNATIONAL INC	20893
ZIMMER BIOMET HOLDINGS INC	20795
INTUITIVE SURGICAL INC	20426
ST JUDE MEDICAL INC	17509
EDWARDS LIFESCIENCES CORP	17012
BARD (C.R.) INC	13961

The Health Services Risk Factor has a very high Sharpe ratio: .79. We can see from 13 that while it fluctuates very much with the business cycles, more than the market, however it seems that this return is rewarded in with a high average return: . Since most of the companies in the portfolio are in the business to business industry it seems intuitive that it varies much more than the market portfolio, since we know investment is very volatile.

Figure 13: Health Services Risk Factor

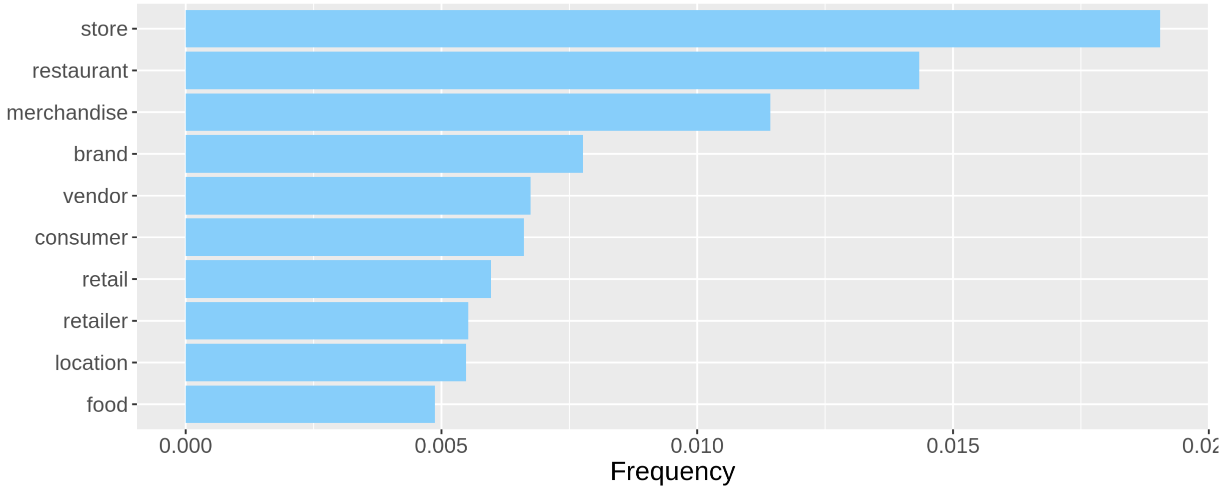


Cumulative return of investing one dollar in June 2007. Blue: Risk Factor, Red: Market Return, SR: Sharpe Ratio

5.6 Retail Risks

The Retail Risk Topic is characterized by words that have are related to Health, specially subscription services, such as: ”medical device”, ”FDA”, ”procedure”, ”patients”; as we can see from Figure 14. We can see in Table 5 that when we inspect the biggest companies that spend more than 30% of their risk disclosures commenting about the Health Service Risk Topic, we see the companies we expect: Microsoft, Amazon, Facebook, among others.

Figure 14: Retail Risk Topic



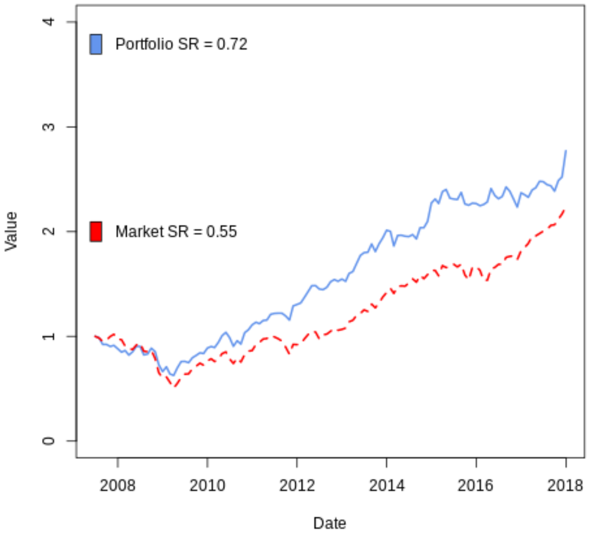
Distribution of the 10 most frequent words for the Retail Risk Topic

Table 5: Biggest 10 Companies that are exposed more than 30% to Retail Risks

Company Name	Market Value (Millions)
WALMART INC	209830
HOME DEPOT INC	157452
MCDONALD'S CORP	107129
NIKE INC	92880
STARBUCKS CORP	84413
LOWE'S COMPANIES INC	65211
COSTCO WHOLESALE CORP	61335
TJX COMPANIES INC	47267
TARGET CORP	43613
YUM BRANDS INC	30681

The Retail Risk Factor has a very high Sharpe ratio: .79. We can see from 15 that while it fluctuates very much with the business cycles, more than the market, however it seems that this return is rewarded in with a high average return: . Since most of the companies in the portfolio are in the business to business industry it seems intuitive that it varies much more than the market portfolio, since we know investment is very volatile.

Figure 15: Retail Risk Factor



Cumulative return of investing one dollar in June 2007. Blue: Risk Factor, Red: Market Return, SR: Sharpe Ratio

6 Factor Model Tests

[IN PROGESS]

I test the power of the risk factors discovered by testing them on the set of 49 industry portfolios, a set that is particularly hard to explain with the usual factors. Although the main contribution is using machine learning techniques to discover interpretable and economically relevant risk factors, the model has an statistical fit significantly better than the Five-Factor Model of Fama and French (2015) in the test of the 49 industry portfolios. Crucially, it explains the cross-sectional variation of returns: the GRS statistic[20] that measures whether $\alpha_{it} \neq 0$ is .82, (compare to a GRS statistic of 1.55 for the Fama and French (2015) Model) and implies a p-value of 68 %, that is, we can

[20] Gibbons, Ross, and Shanken (1989)

very comfortably reject the null hypothesis that $\alpha_{it} \neq 0$, so there is no evidence of misspricing (for comparison, the p-value for the Fama and French (2015) Model is 4.4 %, that is, we cannot reject the null hypothesis that $\alpha_{it} \neq 0$). In short, the GRS test says that my model is a complete descriptions of expected returns for this set of portfolios.[21][22]

Table 6: Selected characteristics of the Risk Factor Portfolios and the Market Portfolio

	Consumer Risk Factor	Internet Risk Factor	Software Risk Factor	Health Risk Factor	Sales Risk Factor	Market Portfolio
Mean	0.88	1.06	1.07	0.90	0.88	0.70
Sd.	3.46	4.52	4.69	4.28	4.27	4.41
Corr. with Mkt	0.70	0.82	0.90	0.75	0.81	1.00
Sr	0.88	0.81	0.79	0.73	0.72	0.55

7 Conclusion

Using machine learning and Natural Language techniques, I introduce factors that not only explain the cross-section of returns, but also unambiguously represent economic risk for the firms, are interpretable, and come directly from the companies. In this way, I address several concerns of the literature: data mining, overfitting and p-hacking; the lack of theories for factors or characteristics designed to address anomalies in the cross-section of returns and concerns about the absence of economic interpretability regarding purely statistical factors. The model is not rejected by the set of 49 Industry Portfolios using the GRS test, which is not the case for the Five Factor Model of Fama and French (2015). In my approach, I only use the information that companies disclose in their annual reports. Hence, the factors that I identify have a clear economic meaning and are fully and easily interpretable

[21] See the Appendix for other test sets

[22] Additionaly, it succeeds in explaining a large fraction of the time series variation of the cross-section of returns (measured by an average R^2 of 63 %, comparable to the 68% average R^2 obtained with the Fama and French (2015) Model).

References

Bao, Yang, and Anindya Datta. 2014. “Simultaneously Discovering and Quantifying Risk Types from Textual Risk Disclosures.” *Manage. Sci.* (Institute for Operations Research)(the Management Sciences (INFORMS), Linthicum, Maryland, USA) 60, no. 6 (June): 1371–1391. ISSN: 0025-1909. doi:10.1287/mnsc.2014.1930. https://doi.org/10.1287/mnsc.2014.1930.

Berk, Jonathan B., Richard C. Green, and Vasant Naik. 1999. “Optimal Investment, Growth Options, and Security Returns.” *The Journal of Finance* 54 (5): 1553–1607. ISSN: 1540-6261. doi:10.1111/0022-1082.00161. http://dx.doi.org/10.1111/0022-1082.00161.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. “Latent Dirichlet Allocation.” *J. Mach. Learn. Res.* 3 (March): 993–1022. ISSN: 1532-4435. http://dl.acm.org/citation.cfm?id=944919.944937.

Campbell, John L., Hsinchun Chen, Dan S Dhaliwal, Hsin min Lu, and Logan B. Steele. 2014. “The information content of mandatory risk factor disclosures in corporate filings” [in English (US)]. *Review of Accounting Studies* 19, no. 1 (March): 396–455. ISSN: 1380-6653. doi:10.1007/s11142-013-9258-3.

Cochrane, John H. 1991. “Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations.” *The Journal of Finance* 46 (1): 209–237. ISSN: 1540-6261. doi:10.1111/j.1540-6261.1991.tb03750.x. http://dx.doi.org/10.1111/j.1540-6261.1991.tb03750.x.

Cochrane, John H. 2011. "Presidential Address: Discount Rates." *The Journal of Finance* 66 (4): 1047–1108. doi:10.1111/j.1540-6261.2011.01671.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2011.01671.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2011.01671.x.

Eisfeldt, Andrea L., and Dimitris Papanikolaou. 2013. "Organization Capital and the Cross-Section of Expected Returns." *The Journal of Finance* 68 (4): 1365–1406. ISSN: 1540-6261. doi:10.1111/jofi.12034. http://dx.doi.org/10.1111/jofi.12034.

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2): 427–465. ISSN: 1540-6261. doi:10.1111/j.1540-6261.1992.tb04398.x. http://dx.doi.org/10.1111/j.1540-6261.1992.tb04398.x.

———. 1993. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics* 33 (1): 3–56. ISSN: 0304-405X. doi:https://doi.org/10.1016/0304-405X(93)90023-5. http://www.sciencedirect.com/science/article/pii/0304405X93900235.

———. 2015. "A five-factor asset pricing model." *Journal of Financial Economics* 116 (1): 1–22. ISSN: 0304-405X. doi:http://dx.doi.org/10.1016/j.jfineco.2014.10.010. http://www.sciencedirect.com/science/article/pii/S0304405X14002323.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu. 2017. "Taming the Factor Zoo."

Gaulin, Maclean Peter. 2017. "Risk Fact or Fiction: The Information Content of Risk Factor Disclosures." *Dissertation.*

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken. 1989. "A Test of the Efficiency of a Given Portfolio." *Econometrica* 57 (5): 1121–1152. ISSN: 00129682, 14680262. http://www.jstor.org/stable/1913625.

Gomes, João, Leonid Kogan, and Lu Zhang. 2003. "Equilibrium Cross Section of Returns." *Journal of Political Economy* 111 (4): 693–732. doi:10.1086/375379. eprint: https://doi.org/10.1086/375379. https://doi.org/10.1086/375379.

Hansen, Stephen, Michael McMahon, and Andrea Prat. 2018. "Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach*." *The Quarterly Journal of Economics* 133 (2): 801–870. doi:10.1093/qje/qjx045. eprint: /oup/backfile/content_public/journal/qje/133/2/10.1093_qje_qjx045/1/qjx045.pdf. http://dx.doi.org/10.1093/qje/qjx045.

Harvey, Campbell R., Yan Liu, and Heqing Zhu. 2016. ". . . and the Cross-Section of Expected Returns." *The Review of Financial Studies* 29 (1): 5–68. doi:10.1093/rfs/hhv059. eprint: /oup/backfile/content_public/journal/rfs/29/1/10.1093_rfs_hhv059/2/hhv059.pdf. http://dx.doi.org/10.1093/rfs/hhv059.

Hoffman, Matthew, Francis R. Bach, and David M. Blei. 2010. "Online Learning for Latent Dirichlet Allocation." In *Advances in Neural Information Processing Systems 23,* edited by J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor, R. S. Zemel, and A. Culotta, 856–864. Curran Associates, Inc. http://papers.nips.cc/paper/3902-online-learning-for-latent-dirichlet-allocation.pdf.

Hou, Kewei, Chen Xue, and Lu Zhang. 2015. "Digesting Anomalies: An Investment Approach." *The Review of Financial Studies* 28 (3): 650–705. doi:10.1093/rfs/hhu068. eprint: /oup/backfile/content_public/journal/rfs/28/3/10.1093/rfs/hhu068/3/hhu068.pdf. +%20http://dx.doi.org/10.1093/rfs/hhu068.

———. 2017. *Replicating Anomalies.* Working Paper, Working Paper Series 23394. National Bureau of Economic Research, May. doi:10.3386/w23394. http://www.nber.org/papers/w23394.

Israelsen, Ryan D. 2014. "Tell It Like It Is: Disclosed Risks and Factor Portfolios." *Working paper.*

Kelly, Bryan, Seth Pruitt, and Yinan Su. 2018. "Characteristics Are Covariances: A Unified Model of Risk and Return," Working Paper Series, no. 24540 (April). doi:10.3386/w24540. http://www.nber.org/papers/w24540.

Kogan, Leonid, and Dimitris Papanikolaou. 2014. "Growth Opportunities, Technology Shocks, and Asset Prices." *The Journal of Finance* 69 (2): 675–718. ISSN: 1540-6261. doi:10.1111/jofi.12136. http://dx.doi.org/10.1111/jofi.12136.

Kozak, SERHIY, STEFAN Nagel, and SHRIHARI Santosh. 2018. "Interpreting Factor Models." *The Journal of Finance* 73 (3): 1183–1223. doi:10.1111/jofi.12612. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12612. https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12612.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken. 2010. "A skeptical appraisal of asset pricing tests." *Journal of Financial Economics* 96 (2): 175–194. ISSN: 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2009.09.001. http://www.sciencedirect.com/science/article/pii/S0304405X09001950.

Livdan, Dmitry, Horacio Sapriza, and Lu Zhang. 2009. "Financially Constrained Stock Returns." *The Journal of Finance* 64 (4): 1827–1862. ISSN: 1540-6261. doi:10.1111/j.1540-6261.2009.01481.x. http://dx.doi.org/10.1111/j.1540-6261.2009.01481.x.

Loper, Edward, and Steven Bird. 2002. "NLTK: The Natural Language Toolkit." In *Proceedings of the ACL-02 Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics - Volume 1,* 63–70. ETMTNLP '02. Philadelphia, Pennsylvania: Association for Computational Linguistics. doi:10.3115/1118108.1118117. https://doi.org/10.3115/1118108.1118117.

Loughran, TIM, and BILL McDonald. 2016. "Textual Analysis in Accounting and Finance: A Survey." *Journal of Accounting Research* 54 (4): 1187–1230.

Manning, Christopher D., Prabhakar Raghavan, and Hinrich Schütze. 2008. *Introduction to Information Retrieval.* New York, NY, USA: Cambridge University Press. ISBN: 0521865719, 9780521865715.

McLean, R. David, and Jeffrey Pontiff. 2016. "Does Academic Research Destroy Stock Return Predictability?" *The Journal of Finance* 71 (1): 5–32. doi:10.1111/jofi.12365. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12365. https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12365.

Merton, Robert C. 1973. "An Intertemporal Capital Asset Pricing Model." *Econometrica* 41 (5): 867–887. ISSN: 00129682, 14680262. http://www.jstor.org/stable/1913811.

Nagel, Stefan. 2005. "Short sales, institutional investors and the cross-section of stock returns." *Journal of Financial Economics* 78 (2): 277–309. ISSN: 0304-405X. doi:https://doi.org/10.1016/j.jfineco.2004.08.008. http://www.sciencedirect.com/science/article/pii/S0304405X05000735.

Řehůřek, Radim, and Petr Sojka. 2010. "Software Framework for Topic Modelling with Large Corpora" [in English]. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks,* 45–50. http://is.muni.cz/publication/884893/en. Valletta, Malta: ELRA, May.

Sharpe, William F. 1966. “Mutual Fund Performance.” *The Journal of Business* 39 (1): 119–138. ISSN: 00219398, 15375374. http://www.jstor.org/stable/2351741.

Stambaugh, Robert F., and Yu Yuan. 2017. “Mispricing Factors.” *The Review of Financial Studies* 30 (4): 1270–1315. doi:10.1093/rfs/hhw107. eprint: /oup/backfile/content_public/journal/rfs/30/4/10.1093_rfs_hhw107/2/hhw107.pdf. +%20http://dx.doi.org/10.1093/rfs/hhw107.

Tibshirani, Robert. 1996. “Regression Shrinkage and Selection via the Lasso.” *Journal of the Royal Statistical Society. Series B (Methodological)* 58 (1): 267–288. ISSN: 00359246. http://www.jstor.org/stable/2346178.

Zhang, Lu. 2005. “The Value Premium.” *The Journal of Finance* 60 (1): 67–103. ISSN: 1540-6261. doi:10.1111/j.1540-6261.2005.00725.x. http://dx.doi.org/10.1111/j.1540-6261.2005.00725.x.

Hanley , Kathleen Weiss and Hoberg, Gerard, Dynamic Interpretation of Emerging Risks in the Financial Sector (February 28, 2018). Available at SSRN: https://ssrn.com/abstract=2792943 or http://dx.doi.org/10.2139/ssrn.2792943

Hassan, Tarek A. and Hollander, Stephan and van Lent, Laurence and Tahoun, Ahmed, Firm-Level Political Risk: Measurement and Effects (December 2017). Available at SSRN: https://ssrn.com/abstract=28 or http://dx.doi.org/10.2139/ssrn.2838644