A Topic Modelling Method for Automated Text Analysis of the Adoption of Enterprise Risk Management

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Abstract: This paper presents a topic modelling method for automated text analysis of the adoption of enterprise risk management by publicly traded firms. The topic modelling method applies the Latent Dirichlet Allocation algorithm on corporate annual financial disclosures to identify whether firms have adopted enterprise risk management. The preliminary results indicate that the firms that have adopted enterprise risk management have a smaller reduction in daily abnormal returns during the recession period of the COVID-19 financial market shock in 2020 (the first quarter of 2020 when the stock market crashed) and a larger increase in daily abnormal returns during the recovery period (the second and third quarters of 2020 when the stock market recovered). Moreover, there is no evidence that the adoption of enterprise risk management reduces the volatility of stock returns of publicly traded firms during the COVID-19 financial market shock in 2020.

1 INTRODUCTION

Enterprise Risk Management (ERM) is a holistic risk management approach to managing all risks within an organization as a portfolio, and it has been adopted by a significant portion of publicly traded firms since the 1990s (Arena et al., 2011). ERM is believed to add value to a firm from both the micro-level and the macro-level by creating competitive advantages, increasing risk awareness, creating synergies among diversified business units, and reducing the cost of risk (Ai et al., 2018; Clarke & Varma, 1999; Doherty, 2000; Nocco & Stulz, 2006). Many rating agencies, professional associations, legislative bodies, regulators, and international standards organizations endorse and promote ERM (Gatzert et al., 2016; Hoyt & Liebenberg, 2011; Khurana et al., 2004; Nair et al., 2014).

Despite the positive effects of ERM on risk identification, risk mitigation, information sharing, and the potential corresponding benefits to firm performance and value, previous empirical research indicated mixed results on the role of ERM during and after a systematic crisis. Some research showed that firms with sophisticated risk management experienced a higher failure rate in turbulent environments because of overconfidence in the benefits of risk management (Baxter et al., 2013; Bromiley et al., 2001). For example, insurance companies such as Countrywide Mortgage faced bankruptcy during the 2008 financial crisis, despite having strong ERM (Bromiley et al., 2015).

Starting in 2019, the outbreak and spread of the COVID-19 virus severely impacted global economics and organizational performance. COVID-19 has negatively impacted the financial performance of many industries, such as transportation, mining and real estate (He et al., 2020; Mazur et al., 2020). This has resulted in a decline in gross domestic product and international trade globally (Iyke, 2020). The COVID-19 financial market shock in 2020 is of great interest to the risk management research community because it has created tremendous challenges and difficulties for risk management.

In this paper, we propose a topic modelling method for automated text analysis of the adoption of ERM of publicly traded firms, and examine the impact of COVID-19 on ERM. The proposed topic modelling method applies the Latent Dirichlet Allocation algorithm on corporate annual financial disclosures to identify whether publicly traded firms have adopted ERM. The output of the proposed topic modelling method is then combined with the financial market data for further analysis of the impact of ERM

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during the COVID-19 financial market shock in 2020.

The remainder of the paper is organized as follows. Section 2 formulates the research problem. Section 3 describes the topic modelling method. Section 4 presents the results of the topic modelling method to examine the impact of ERM during the COVID-19 pandemic. Section 5 presents the conclusions.

2 RESEARCH PROBLEM

A significant portion of publicly traded firms has adopted ERM since the 1990s (Arena et al., 2011). As previous empirical research indicated mixed results on the role of ERM during and after a systematic crisis (Baxter et al., 2013; Bromiley et al., 2001), the impact of ERM during the COVID-19 financial market shock in 2020 remains unclear. Pagach and Wieczorek-Kosmala (2020) conceptually examined the impact of COVID-19 on ERM and provided important yet unanswered research questions on the role of ERM in response to the COVID-19 pandemic:

1. Does the financial market recognize the benefits of ERM during the COVID-19 financial market shock in 2020?
2. Does ERM help reduce the volatility of firm stock market returns during the COVID-19 financial market shock in 2020?

Based on the previous research literature (Alexander, 2008; Azar, 2014; Arena et al., 2011; Beasley et al., 2008; Carpenter & Guariglia, 2008; Eckles et al., 2014; Farrell & Gallagher, 2015; Gatzert & Martin, 2015; Hentschel & Hall, 1991; Hoyt & Liebenberg, 2011; Liebenberg & Hoyt, 2003; (Farrell & Gallagher, 2015; Lu et al., 2020; Nocco & Stulz, 2006; Olowe, 2009; Pagach & Warr, 2010; Stulz, 1996; Traub, 2019; Wang, et al., 2009), we examine the following two hypotheses.

H1: During the COVID-19 financial market shock in 2020, the firms that have already adopted ERM experienced higher abnormal returns compared with firms that do not adopt ERM.

H2: During the COVID-19 financial market shock in 2020, the firms that have already adopted ERM experienced lower stock return volatility compared with firms that do not adopt ERM.

We collected the stock market data for the first three quarters of 2020 from the Capital IQ Security Daily database, as well as all corporate annual financial disclosures since 1985 of all publicly traded firms in the US. The first confirmed COVID-19 case in the US was recorded on January 20, 2020 (Taylor, 2020). During February, the spread of the coronavirus in the US was relatively slower compared with other regions, such as Asia and Europe. The month of March marked the sign of a full outbreak in the US. On March 6, 2020, the US government announced the COVID-19 Emergency Relief Aid Program. The US S&P 500 Index Prices in the first 3 quarters of 2020 are shown in Figure 1. For the COVID-19 financial market shock in 2020, we define the first quarter of 2020 as the recession stage, and the second and third quarters of 2020 as the recovery stage.

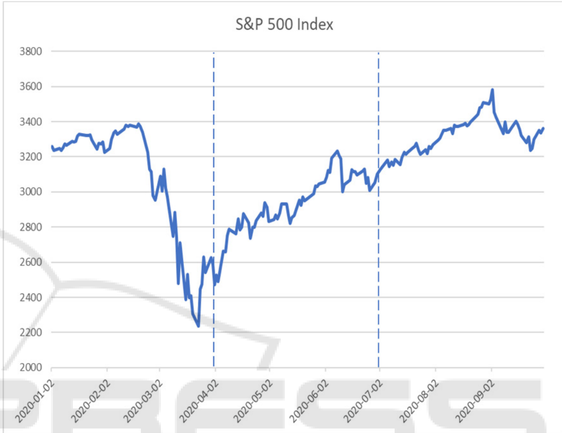

Figure 1: The US S&P 500 Index Prices in the first three quarters of 2020.

We are interested in how ERM impacts both firm stock performance and volatility of returns. Therefore, we have two sets of dependent variables. We use daily *abnormal return* (AR) to measure a firm's stock market performance (Albuquerque, Koskinen, Yang, & Zhan, 2020). To calculate AR, we first calculated the three-year average beta between 2017 and 2019 using the capital asset pricing model. AR is calculated as the residual returns after the market-induced return is removed. We first run the regression based on the market model as follows.

$$R_{it}=\alpha_i + \beta_i * R_{mt} \quad (1)$$

where i, t, m represents the publicly traded firm i, date t, and industry m; R_{it} is the risk-adjusted daily return; α_i is the constant; β_i is the three-year average beta; and R_{mt} is the risk-adjusted market daily return. We then calculate AR as the difference between the risk-adjusted return and the risk-adjusted market return as follows.

$$AR_{it}=R_{it} - (\alpha_i + \beta_i * R_{mt}) \quad (2)$$

We use the standard deviation of a firm's risk-adjusted daily return to measure a firm's stock return risk.

We then use the difference-in-difference (diff-in-diff) regression method to test the hypothesis H1. We regress AR on the diff-in-diff estimator and all other control variables at the firm-day level as follows.

$$AR_{it} = \alpha + \beta_1 * (ERM_i * COVID_t) + \beta_2 * ERM_i + \beta_3 * COVID_t + X'\delta + \lambda_m + \varepsilon_{it} \quad (3)$$

where i, t, m represents the publicly traded firm i, date t, and industry m; ERM_i =1 represents the adoption of ERM by the publicly traded firm i before 2020, and 0 otherwise; $COVID_t$=1 if the date is March 6, 2020 or after, and 0 otherwise, because the US government announced the COVID-19 Emergency Relief Aid Programs on March 6, 2020; X' is the vector of control variables; λ_m is the industry fixed effects; and ε_{it} is the error term. As expressed in the hypothesis H1, we expect the coefficient β_1 to be positive. This diff-in-diff estimation has an advantage in estimating the marginal effects of the treatment group versus the control group in different periods. In order to further control for time-invariant factors that may bias the diff-in-diff coefficient, we also run a firm-day fixed effect regression with the same diff-in-diff estimator as follows.

$$AR_{it} = \alpha + \gamma_1*(ERM_i*COVID_t) + \gamma_2 K_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (4)$$

where K_{it} is the daily price range; μ_i is the firm fixed-effects and θ_t is the day fixed-effects. Please note that the independent variable ERM_i and all firm-year level control variables are absorbed in the firm fixed-effects.

The hypothesis H2 investigates ERM's impact on stock return volatility. We use the cross-sectional estimation by regressing the standard deviation of daily abnormal returns on the independent variable ERM_i and the vector of firm-year level control variables. Stock volatility is calculated based on the stock returns in the first quarter, the first two quarters, and the first three quarters, respectively. We include industry fixed-effects for all stock volatility risk regressions as follows.

$$Volatility_i = \alpha + \beta*ERM_i + X'\delta + \lambda_m + \varepsilon_i \quad (5)$$

where $Volatitity_i$ is the stock return volatility of the publicly traded firm i.

The independent variable ERM_i in the regressions (3), (4) and (5) is the adoption of ERM by the publicly traded firm i. The adoption of ERM by a publicly traded firm in the US can be found in one of corporate annual financial disclosures such as the 10-K, DEF-14A and PRE-14A filings. Because there are a large number of publicly traded firms in the US in our dataset, each with multiple financial disclosure filings every year, it is impossible to manually identify the adoption of ERM in the corporate annual financial disclosures. We propose a topic modelling method for automatically identifying the adoption of ERM by a publicly traded firm.

3 AUTOMATED TEXT ANALYSIS OF THE ADOPTION OF ERM

3.1 The Proposed Topic Modelling Method

In machine learning, *topic modelling* refers to a variety of algorithms for discovering the abstract "topics" in a collection of text documents. The Latent Dirichlet Allocation (LDA) algorithm is the most popular topic modelling algorithm that has been extensively studied (Blei, Ng, & Jordan, 2003). It is capable of generating a probabilistic model of a mixture of hidden topics, each of which is defined as a probability distribution over the vocabulary. Recently, the LDA algorithms have been studied for analyzing corporate annual financial disclosures of publicly traded firms (Bao & Datta, 2014; Dyer et al., 2017; Toubia et al., 2019).

The objective of using the LDA algorithm in our study is to automatically identify the adoption of ERM by publicly traded firms in their annual financial disclosures, including the 10-K, DEF-14A and PRE-14A filings.

Our method for automated text analysis of corporate annual financial disclosures of publicly traded firms is summarized in Figure 2. First, we apply several data preprocessing steps to transform all original corporate annual financial disclosures into text documents that are suitable for the input of the LDA algorithm. Second, we apply the LDA algorithm to extract different topics of the text documents. If the topics related to the adoption of ERM are among the top topics identified by the LDA algorithm and more important than other irrelevant topics, then we conclude the corresponding corporate annual financial disclosure contains the information of such an ERM adoption by the firm. Third, we perform a data-driven validation procedure to validate the results of the LDA algorithm. Finally, we perform an event analysis to identify the starting year of the adoption of ERM.

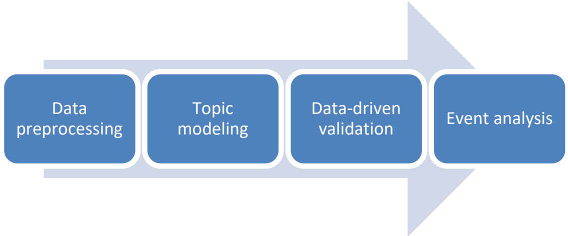

Figure 2: The method for automated text analysis of corporate annual financial disclosures of publicly traded firms.

3.2 The LDA Algorithm

The Latent Dirichlet Allocation (LDA) algorithm is the most popular topic modelling algorithm that has been extensively studied (Blei, Ng, & Jordan, 2003). It is a generative machine learning model that explains a set of observed words through unobserved topic groups. A text document is associated with a small number of topics, and each word's presence in the document is attributable to one of the document's topics. Figure 3 illustrates the probabilistic graphical representation of the LDA model (Blei, Ng, & Jordan, 2003).

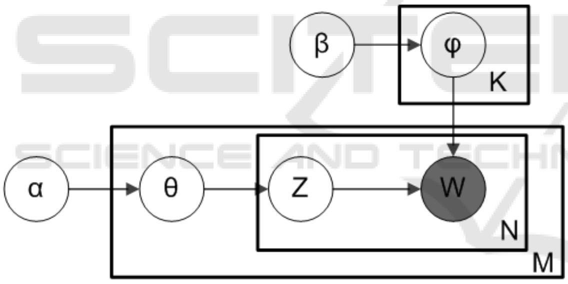

Figure 3: The LDA model.

The notations in Figure 2 are as follows.

- M: the number documents
- N: the number of words in a document m
- K: the number of possible topics
- α: the parameter of the Dirichlet prior on the per-document topic distribution
- β: the parameter of the Dirichlet prior on the per-topic word distribution
- θ: the topic distribution for a document m
- ϕ: the word distribution for a topic k
- Z: the topic for a word n in a document m
- W: the specific word

The only observable variable of the LDA model is W, and the other variables are latent variables. The input variable of the LDA algorithm is a set of M text documents, and the desired output of the LDA algorithm is θ, the topic distribution of every document. If the topics related to the adoption of ERM are among the top topics identified by the LDA algorithm and more important than other irrelevant topics, then we conclude the corresponding corporate annual financial disclosure indicates an ERM adoption by the firm.

Using the LDA algorithm to identify the adoption of ERM has at least two major advantages compared to the traditional manual identification process used in research literature (Berry-Stölzle & Xu, 2018; Hoyt & Liebenberg, 2011). First, the LDA algorithm is consistent and free from human errors. This makes data replicability relatively easy compared with the human judgment process. The process is objective in the sense that it does not have a preference over, or against, any specific firm. Human judgment, in contrast, is sometimes biased due to personal preferences, physical and psychological conditions, and personal errors. Second, the LDA algorithm can process a huge number of documents while the human manual process cannot.

Moreover, for automatic text analysis of identifying the adoption of ERM in the corporate annual financial disclosures, the LDA algorithm is capable of yielding much more accurate results than the exact keyword matching, another alternative automated process. For example, the sentence "This combination of legal and management experiences enables Mr. Carter to provide guidance to the Company in the areas of legal risk oversight and enterprise risk management, corporate governance, financial management and corporate strategic planning" in a corporate annual financial disclosure could yield a positive adoption of ERM by the exact keyword matching of "enterprise risk management", but a negative adoption by the LDA algorithm as the topic "enterprise risk management" is not more important (i.e., has a higher probability) than the irrelevant topics "corporate governance" and "financial management".

3.3 Data-Driven Validation

The use of the LDA algorithm for identifying the adoption of ERM by a firm in a corporate annual financial disclosure is rule-based. In the algorithm, a corporate annual financial disclosure indicates an ERM adoption by the firm when the topics of the financial disclosure related to the adoption of ERM are more important and thus have higher probabilities than other irrelevant topics.

As the LDA algorithm is an unsupervised learning algorithm, it is difficult to assess the quality of its results. We perform a data-driven validation procedure to establish the robustness of the results of the LDA algorithm. First, we manually label a small set of corporate financial disclosures on the adoption of ERM. Second, we use this training data set to train a supervised classification model using the logistic regression algorithm on all topics identified by the LDA algorithm. Third, we use this trained classification model to predict each financial disclosure whether it is about the adoption of ERM. Finally, the prediction results are then compared with the rule-based results from the LDA algorithm in order to establish the robustness of the results of the LDA algorithm.

3.4 Event Analysis

We identify the starting year of the adoption of ERM by the firms in their corporate annual financial disclosures. This can be achieved by a simple event analysis, where a firm's corporate annual financial disclosures had a change of topics regarding ERM.

4 RESULTS

4.1 Description of the Data

We used the data of the U.S. publicly traded firms for our study by combining the Compustat Capital IQ database and the Compustat Security Daily databases. Since we are interested in how ERM influences financial market risk and returns during the COVID-19 financial market shock in 2020, we can only include firms that still exist at the beginning of 2020. To construct the dataset, we first obtain financial information for all firms that still exist in Compustat Capital IQ by 2019. The stock market information for these firms was then collected from the Compustat Security Daily database between January 1st, 2020 and September 30th, 2020. To show the preliminary results, we randomly selected 1500 firms for our study. After removing firms with missing values in key variables, we were able to retain 1468 firms. This gives us a total of 274,520 firm-day observations.

4.2 Robustness of the LDA Algorithm Results

We randomly selected 50 corporate annual financial disclosures from the1468 firms in our dataset, and manually labelled them on the adoption of ERM. We use this training data set to train a supervised classification model using the logistic regression algorithm on all topics identified by the LDA algorithm. We use this trained classification model to predict each financial disclosure whether it is about the adoption of ERM. Finally, the prediction results are then compared with the rule-based results from the LDA algorithm.

For all 50 financial disclosures, we found that the rule-based results from the LDA algorithm are all identical to the classification results of the logistic regression classifier. With 100% accuracy for the 50 randomly selected corporate annual financial disclosures, the robustness of the LDA algorithm results is established.

4.3 Impact of ERM on Abnormal Returns

Table 1 shows the results for the AR regression for the hypothesis H1. The coefficient for the diff-in-diff estimator is positive and significant in all models. Moreover, the significance level of the diff-in-diff estimator increases as we include longer post-COVID period ($\beta1=0.150$, $p=0.043$ for Quarter 1; $\beta1=0.118$, $p=0.003$ for Quarter 1 & 2; $\beta1=0.146$, $p=0.000$ for Quarters 1, 2 & 3, respectively), indicating that ERM's impact on the abnormal return during the COVID-19 pandemic is long-term. The coefficients of the diff-in-diff estimator are similar in the firm fixed-effects models (Models 2, 4, & 6). Therefore, the hypothesis H1 is supported.

4.4 Impact of ERM on Stock Return Volatility

Table 2 shows the regression results for the hypothesis H2. The results show that ERM does not have a significant impact on the stock return volatility during both the recession period and the recovery period. The results are consistent when we use other measurements of stock return volatility, such as the standard deviation of daily abnormal returns and the standard deviation of the daily price range. Therefore, the hypothesis H2 is not supported.

5 CONCLUSIONS

The proposed topic modelling method for automated text analysis of the adoption of ERM by publicly traded firms is superior to the traditional manual process and alternative automated process. We have demonstrated the effectiveness and robustness of the

Table 1: Difference in Difference Regression of Abnormal Return on ERM.

	Quarter 1		Quarter 1&2		Quarter 1, 2, & 3	
	Model 1	**Model 2**	**Model 3**	**Model4**	**Model 5**	**Model 6**
ERM	-0.019		-0.065+		-0.079*	
	(0.040)		(0.038)		(0.038)	
COVID Dummy	-0.258***		0.171***		0.082***	
	(0.045)		(0.026)		(0.024)	
ERM X COVID Dummy	**0.150***	**0.147***	**0.118****	**0.109****	**0.146*****	**0.141*****
	(0.074)	**(0.074)**	**(0.040)**	**(0.040)**	**(0.038)**	**(0.038)**
Size	-0.020*		-0.028***		-0.035***	
	(0.008)		(0.006)		(0.005)	
Leverage	0.000		0.001		0.002	
	(0.003)		(0.002)		(0.003)	
ROA	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
Capital Expenditure	0.010**		0.024***		0.017***	
	(0.003)		(0.003)		(0.003)	
Book-to-Market Ratio	-0.001		-0.003*		-0.004**	
	(0.001)		(0.001)		(0.001)	
AD Intensity	-0.067		-0.018		0.135	
	(0.406)		(0.284)		(0.172)	
Dividend Per Share	-0.001		-0.005		-0.005	
	(0.004)		(0.004)		(0.004)	
Financial Slack	0.000		-0.002		-0.035	
	(0.081)		(0.061)		(0.054)	
Daily Price Range	0.011	0.013	0.010	0.031	0.011	0.032+
	(0.009)	(0.011)	(0.008)	(0.021)	(0.008)	(0.018)
Constant	0.326***	-0.225+	0.125*	-0.248+	0.191**	-0.252+
	(0.079)	(0.130)	(0.059)	(0.131)	(0.061)	(0.130)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Industry Fixed Effects	Yes	No	Yes	No	Yes	No
F (df1, df2)	-	32.90***	-	25.31***	-	24.07***
		(63, 1468)		(126, 1468)		(190, 1468)
R^2	0.003	-	0.001	-	0.001	-
Observations	90,857	90,857	182,395	182,395	274,520	274,520

Table 2: Cross-sectional Regression of Stock Market Volatility on ERM.

	DV=SD(Daily Return)			DV=SD(DailyAbnormal Return)		
	Model 1 Q 1	Model 2 Q 1&2	Model 3 Q 1, 2, & 3	Model 4 Q 1	Model 5 Q 1&2	Model 6 Q 1, 2, & 3
ERM	0.060	0.040	0.089	-0.039	-0.031	0.032
	(0.113)	(0.106)	(0.101)	(0.165)	(0.139)	(0.126)
Size	-0.316***	-0.362***	-0.418***	-0.501***	-0.518***	-0.540***
	(0.026)	(0.022)	(0.021)	(0.026)	(0.022)	(0.021)
Leverage	0.026	0.025	0.022	0.027	0.024	0.022
	(0.036)	(0.033)	(0.034)	(0.035)	(0.033)	(0.033)
ROA	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditure	0.049***	0.048***	0.037***	0.040*	0.040*	0.030*
	(0.011)	(0.011)	(0.010)	(0.019)	(0.017)	(0.014)
Book-to-Market Ratio	-0.012***	-0.015***	-0.013***	0.004	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.020)	(0.016)	(0.013)
AD Intensity	-1.798	-0.841	-0.520	-2.037	-0.945	-0.644
	(2.813)	(1.669)	(1.268)	(3.104)	(1.776)	(1.331)
Dividend Per Share	-0.020*	-0.009	-0.006	-0.032+	-0.016	-0.013
	(0.010)	(0.016)	(0.015)	(0.017)	(0.020)	(0.017)
Financial Slack	-0.856***	-0.899***	-0.892***	-1.167***	-1.117***	-1.046***
	(0.242)	(0.220)	(0.201)	(0.293)	(0.254)	(0.227)
Constant	6.600***	6.525***	6.680***	6.840***	6.795***	6.939***
	(0.384)	(0.393)	(0.405)	(0.458)	(0.441)	(0.484)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.370	0.454	0.517	0.372	0.459	0.510
Observations	1468	1468	1468	1468	1468	1468

results of the proposed method. Using the output of the proposed method, we have validated the hypothesis on the relationship between ERM and abnormal returns of the firms. In particular, the firms that have adopted ERM have a smaller reduction in abnormal returns during the recession period of the COVID-19 pandemic (the first quarter of 2020 when the stock market crashed) and a larger increase in abnormal returns during the recovery period (the second and third quarters of 2020 when the stock market recovered). Moreover, we have found no evidence that ERM reduces the volatility of stock returns of publicly traded firms. Based on these findings, we would suggest that investors are more confident about the financial outcome of the firms with an ERM adoption during the COVID-19 pandemic.

REFERENCES

Ai, J., Bajtelsmit, V., & Wang, T. 2018. The Combined Effect of Enterprise Risk Management and Diversification on Property and Casualty Insurer Performance. *Journal of Risk and Insurance*, 85(2): 513-543.

Arena, M., Arnaboldi, M., & Azzone, G. 2011. Is enterprise risk management real? *Journal of Risk Research*, 14(7): 779-797.

Azar, S. A. 2014. The determinants of US stock market returns. *Open Economics and Management Journal*, 1(1).

Bao, Y. & Datta, A. 2014. Simultaneously discovering and quantifying risk types from textual risk disclosures. *Management Science*, 60(6): 1371-1391.

Baxter, R., Bedard, J. C., Hoitash, R., & Yezegel, A. 2013. Enterprise risk management program quality: Determinants, value relevance, and the financial crisis. *Contemporary Accounting Research*, 30(4): 1264-1295.

Beasley, M., Pagach, D., & Warr, R. 2008. Information conveyed in hiring announcements of senior executives overseeing enterprise-wide risk management processes. *Journal of Accounting, Auditing & Finance*, 23(3): 311-332.

Beasley, M. S., Clune, R., & Hermanson, D. R. 2005. Enterprise risk management: An empirical analysis of factors associated with the extent of implementation. *Journal of accounting and public policy*, 24(6): 521-531.

Berry-Stölzle, T. R. & Xu, J. 2018. Enterprise risk management and the cost of capital. *Journal of Risk and Insurance*, 85(1): 159-201.

Blei, D. M., Ng, A. Y., & Jordan, M. I. 2003. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3: 993-1022.

Bromiley, P., Miller, K. D., & Rau, D. 2001. Risk in strategic management research. *The Blackwell handbook of strategic management*: 259-288.

Bromiley, P., McShane, M., Nair, A., & Rustambekov, E. 2015. Enterprise risk management: Review, critique, and research directions. *Long Range Planning*, 48(4): 265-276.

Carpenter, R. E. & Guariglia, A. 2008. Cash flow, investment, and investment opportunities: New tests using UK panel data. *Journal of Banking & Finance*, 32(9): 1894-1906.

Clarke, C. J. & Varma, S. 1999. Strategic risk management: the new competitive edge. *Long Range Planning*, 32(4): 414-424.

Doherty, N. 2000. Integrated risk management: Techniques and strategies for managing corporate risk. New York, NY: McGraw Hill Companies.

Dyer, T., Lang, M., & Stice-Lawrence, L. 2017. The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, 64(2-3): 221-245.

Eckles, D. L., Hoyt, R. E., & Miller, S. M. 2014. The impact of enterprise risk management on the marginal cost of reducing risk: Evidence from the insurance industry. *Journal of Banking & Finance*, 43: 247.

Farrell, M. & Gallagher, R. 2015. The valuation implications of enterprise risk management maturity. *Journal of Risk and Insurance*, 82(3): 625-657.

Gatzert, N. & Martin, M. 2015. Determinants and value of enterprise risk management: Empirical evidence from the literature. *Risk Management and Insurance Review*, 18(1): 29-53.

Gatzert, N., Schmit, J. T., & Kolb, A. 2016. Assessing the risks of insuring reputation risk. *Journal of Risk and Insurance*, 83(3): 641-679.

Gordon, L. A., Loeb, M. P., & Tseng, C.-Y. 2009. Enterprise risk management and firm performance: A contingency perspective. *Journal of Accounting and Public Policy*, 28(4): 301-327.

Grace, M. F., Leverty, J. T., Phillips, R. D., & Shimpi, P. 2015. The Value of Investing in Enterprise Risk Management. *Journal of Risk and Insurance*, 82(2): 289-316.

He, P., Sun, Y., Zhang, Y., & Li, T. 2020. COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, 56(10): 2198-2212.

Hoyt, R. E. & Liebenberg, A. P. 2011. The value of enterprise risk management. *Journal of Risk and Insurance*, 78(4): 795-822.

Iyke, B. N. 2020. COVID-19: The reaction of US oil and gas producers to the pandemic. *Energy Research Letters*, 1(2): 13912.

Liebenberg, A. P. & Hoyt, R. E. 2003. The determinants of enterprise risk management: Evidence from the appointment of chief risk officers. *Risk Management and Insurance Review*, 6(1): 37-52.

Mazur, M., Dang, M., & Vega, M. 2020. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance Research Letters: 101690.

Nair, A., Rustambekov, E., McShane, M., & Fainshmidt, S. 2014. Enterprise risk management as a dynamic capability: A test of its effectiveness during a crisis. *Managerial and Decision Economics*, 35(8): 555-566.

Nocco, B. W. & Stulz, R. M. 2006. Enterprise risk management: Theory and practice. *Journal of Applied Corporate Finance*, 18(4): 8-20.

Olowe, R. A. 2009. Stock return, volatility and the global financial crisis in an emerging market: The Nigerian case. *International Review of Business Research Papers*, 5(4): 426-447.

Pagach, D. & Wieczorek-Kosmala, M. 2020. The Challenges and Opportunities for ERM Post-COVID-19: Agendas for Future Research. *Journal of Risk and Financial Management*, 13(12): 323.

Pagach, D. P. & Warr, R. S. 2010. The effects of enterprise risk management on firm performance. Available at SSRN 1155218.

Stulz, R. M. 1996. Rethinking risk management. *Journal of Applied Corporate Finance*, 9(3): 8-25.

Toubia, O., Iyengar, G., Bunnell, R., & Lemaire, A. 2019. Extracting features of entertainment products: A guided latent dirichlet allocation approach informed by the psychology of media consumption. *Journal of Marketing Research*, 56(1): 18-36.

Wang, J., Meric, G., Liu, Z., & Meric, I. 2009. Stock market crashes, firm characteristics, and stock returns. *Journal of Banking & Finance*, 33(9): 1563-1574.