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Honors Seminar

How Robustly Is a Firm's Stakeholder Reputation Incorporated into its Financial Risk?

I. Introduction

Previous research has shown that firms with high quality non-financial stakeholder reputations are less prone to bankruptcy and more resilient during bankruptcy scenarios. Enhancing non-shareholder reputation may thus function as a cushion for firms to lower overall risk and can increase shareholder value as a result, if applied cost-effectively (Lin & Dong, 2018).

The prominence of the ESG movement in recent years has led firms to realize the importance of evaluating such risks alongside traditional risk models. Despite the rise of "greenwashing" – or presenting an environmentally responsible public image while making insignificant internal changes – firms have made legitimate efforts to mitigate such risks (Atz et al., 2021). For example, Chevron has donated $2 billion towards social initiatives in the past decade alone, despite (or maybe because of) the negative reputation and importance of financial discipline associated with the oil industry.

One may thus raise the question: are firms overspending, underspending, or sufficiently spending on mitigating reputational risk? This approach distills a firm's reputation into just a financial perspective, with a focus on downside potential. Such a narrow gauge is primarily beneficial for bondholders, who can apply this framework to evaluate the value-creation from non-core spending.

To answer this question, I reviewed existing literature on the topic and performed an analysis across sectors and specific reputational facets to determine points of spending misalignment. This study expands on existing literature by providing sector breakdowns and subsample breakdowns while previous studies have only analyzed overall market effects of stakeholder reputation. Sector analysis allows for a more granular understanding of the data and accounts for different fundamental drivers of reputation and value between different industries. Subsample analysis allows me to fine-tune the groups of companies which contribute to my results.

I analyzed a sample of yearly data for 323 S&P 500 companies from the period 2015 – 2020. The findings of the overall study are inconclusive due to low R^2 coefficients but may indicate potential mispricing in the Energy, Materials, Industrials, Consumer Staples, and Real Estate sectors. The subsequent portions of the paper adhere to the following structure. Section 2 will provide background information and review literature pertaining to stakeholder reputation and financial risk. Section 3 will explain the methodology and data sources behind my analysis. Section 4 will discuss my findings and limitations. Section 5 will conclude with the implications of this research and provide areas for further exploration.

II. Hypothesis Development and Related Literature

Theoretical Background & Definitions

Financial markets tend to be robust in incorporating contemporary trends and ideas. However, broad-ranging biases tend to accrue within market prices as a function of longer-term uncertainty. While corporate cash flow models cluster risk into factors such as size risk and market risk (Fama & French, 1993), bankruptcy risk provides the most objective and uniform method with which to assess a firm's continuation probability (Merton, 1972). A business which can no longer fund itself will cease to exist. Under a legitimate bankruptcy pretense, previously cooperative parties must compete in a zero-sum fashion for materialized stores of value. I will thus apply the principles of bankruptcy risk as my definition of financial risk.

Stakeholder reputation may encompass any peer-to-peer relationship between a firm and a counterparty, with a more streamlined approach classifying important relationships based on primary interactions, such as employees, shareholders, customers, and managers (Godfrey, 2005). However, the difficulty in measuring and comparing these micro-interactions means that a more practical gauge of reputation is institutional public perception. Despite its limitations, this definition of reputation conveniently also allows for firm disclosure and performance. A firm's decision to disclose information limits institutional assessment, and institutions typically fill in gaps negatively due to firms' bias towards disclosing positive information.

Hypothesis 1:

Financial risk efficiently prices stakeholder reputation

Attig and his co-authors found in their 2013 paper that strong sustainability practices have a positive material impact on credit ratings (Attig et al., 2013). The authors employ a regression of credit ratings on an ordinal scale against MSCI ESG metrics between 1991 – 2010. Their results exhibit a positive relationship between scores and credit ratings and provide regression coefficients of a 0.1-point increase in credit score for a 1-point increase in any given ESG metric. In their 2017 paper, Chen and Lee provide a managerial perspective on how to balance the reputational effects of CSR against the financial and opportunity costs of implementing CSR strategies (C.Y. Chen & Lee, n.d.). Specifically, the authors reveal the importance of stakeholder critical mass before CSR initiatives create positive net present value.

These studies provide a practical framework which management of large public companies may use to incorporate CSR strategy into risk mitigation efforts. Additionally, the increased media presence of ESG and CSR in the past decade has brought the importance of stakeholder relations into the spotlight as well as an influx of data. Thus, unlike in Attig's original 2013 study, I expect firms in recent years to have adjusted their practices such that the relationship between stakeholder reputation and credit risk will be better priced in.

Hypothesis 2:

Environmental reputation will tend to be fairly priced relative to other variables

In his 2018 paper, Monnin provides a framework with which to incorporate climate risk into bankruptcy risk by incorporating the net present value of potential climate liabilities into a firm's Merton Model measure of value (Monnin, 2018). As firms have tracked and scrutinized climate and emissions specific risk more heavily and objectively than other risks associated with reputational capital, I expect that environmental-related effects will be sufficiently priced in.

Hypothesis 3:

Firms with either high existing chance of bankruptcy or high volatility and leverage see outsized impact of non-environmental CSR variables

In their 2018 paper, Lin and Dong find that greater moral capital accrued from corporate social responsibility (CSR) engagement gives firms a greater chance of emerging from bankruptcy, with proceedings taking less time and generating more favorable restructuring terms for stakeholders (Lin & Dong, 2018). The authors draw from Godfrey's 2005 work on the signaling effects of moral capital to argue that strong CSR engagement may thus function as insurance for distressed firms and generate value where other intangible sources fail to do so.

In contrast, however, Hock and his co-authors found that within the EU, "environmental sustainability has almost no effect on companies with a low credit rating. In contrast, environmental sustainability has a considerable influence on the credit risk premium of companies that have high credit ratings and good creditworthiness" (Hock et al., 2020). The author employs similar techniques to Attig but focuses specifically on MSCI environmental score.

Together, this suggests that within the distressed subsample, non-environmental scores should have higher regression coefficients and greater likelihood of market mispricing. Additionally, since high leverage and high volatility together create a greater chance of bankruptcy, I expect to see similar effects among that subsample.

III. Data and Research Design

Sample Selection

The starting point for my sample was the S&P 500, which encompasses five hundred of the largest public companies in the United States. I excluded all firms without sufficient annual ESG score data ranging from 2015 –

2020 from the sample. I also classified firms into sectors based on GICS standards to allow sector-specific subsample analyses.

Dependent Variable: Natural Log of CDS Spreads

Single-name CDS contracts represent a standardized and liquid means of trading and thus quantifying a firm's bankruptcy risk, reflecting investors beliefs on both probability of default and recovery rate. CDS contracts may be employed to hedge or speculate on credit risk, making them the most widely used credit derivative instrument as well as a key source of information for broader credit markets (Hock et al., 2020). CDS data was easy to find from Bloomberg and offered daily granularity stretching back over 7 years. We apply the natural logarithm operator to CDS spreads to improve the skew and distributional behavior.

Primary Independent Variable: ESG Scores

Without a robust unified set of standards to draw from to evaluate a firm's reputational capital, stakeholders must either: (i) attempt high-effort parsimonious sifting through the mess of data, or (ii) rely on third-party aggregators like MSCI and Refinitiv for "scores" on companies. While the second method limits the transparency and accountability of the process, it provides enough comparative properties with which to analyze large US corporations (Attig et al., 2013). I took the ESG dataset from Refinitiv, partially covered the S&P 500 (323 companies) and offered 6 years of annual score data between 2015 and 2020 for each of those companies.

Controls: Market Debt/Equity, Market Cap, Trailing 12M Volatility, Treasury Rates, Operating Margin

The financial factors I controlled for were leverage, size, volatility, and risk-free rates. Leverage, measured in this study by market debt/market equity, indicates a company's indebtedness. Merton in his 1974 paper asserted that greater leverage leads to increased probability of default, which thus increases CDS spreads (Merton, 1974). Greater size, as measured by market capitalization, should correspond to greater financial flexibility, and thus is expected to have a negative relationship with CDS spreads (Attig et al., 2013). I measured annualized volatility by trailing 12M standard deviation of stock returns. Under the Merton model, one may regard equity as a call option above debt – with a zero or negative equity value corresponding to a default scenario. Thus, greater volatility should correspond to greater likelihood of default and thus higher credit spreads (Hock et al., 2020). Risk-free rates are provided by the minimum 10-year US treasury rate over the year analyzed. According to Fu and Li's 2021 paper, risk-free rate possesses significant explanatory power for CDS spreads (Fu & Li, 2021). I believe that bonds with higher rates should be more prone to fluctuations as a result of convex payoff features, although rates remained consistently low throughout the observation period. Lastly, operating margins stand as a proxy for profitability, with the assumption that more profitable firms are better creditors (Attig et al., 2013).

Design: Observational Study, OLS Regression

Without experimental control over firms' decision-making or a natural experiment event, I decided to run an observational study over the aforementioned datasets. I applied the standard OLS first differences' model to control for firm fixed effects by regressing the natural log of changes in CDS spread against changes in ESG scores and the controls. I evaluated each ESG variable separately to determine their individual effects using the following equation:

$$-\Delta \ln(CDS) = \alpha + \beta_1 \Delta \frac{Debt}{Equity} + \beta_2 \ln\,(Mkt.Cap) + \beta_3 \Delta Vol + \ \beta_3 UST + \ \beta_4 \Delta Marg + \ \beta_5 \Delta ESG + \ \varepsilon$$

Subsamples: Leverage, Size, Risk, Volatility

I reapplied the same model to subsamples of high vs. low leverage (n = 694, n = 921, cutoff debt/equity = 20%), large vs. small market cap (n = 795, n = 820, cutoff ln(Mkt Cap) = 3.5), high CDS spread (n = 382, cutoff ln(CDS) = 4.5), and high volatility and leverage (n = 409, cutoff vol = 25%, cutoff debt/equity = 20%).

IV. Results:

The results of my overall least-squares regression as well as my initial subsample analyses are shown in Table 1. Leverage, volatility, risk-free rates, and ESG scores are statistically significance under the whole sample OLS model. Leverage, volatility, and risk-free rates display the expected positive relationship with CDS spreads, while size and operating margin do not have a noticeable effect on CDS spreads. Treasuries are the most statistically significant variable. My ESG coefficient result indicates that greater scores correspond with lower CDS spreads, in contrast to my assertion in Hypothesis 1, which states that firms efficiently price stakeholder reputation into financial risk.

None of the subsample analyses indicate statistically significant effects of the ESG independent variable. From the data available, one may conclude that firms with greater credit risk actually experience minimized effects of reputational capital. Changes in ESG scores produce minimal effects on both the High CDS Risk and High Leverage & Volatility subsamples relative to the whole sample. The greater R-squared coefficient in these subsamples indicates this result is more meaningful than my overall result. This finding contradicts my assertion in Hypothesis 3 that firms with higher chance of bankruptcy will see outsized impact of non-environmental CSR variables. Such deviation may be explained by Lin and Dong's differentiation between Moral Capital and Exchange Capital, which was not performed in my analysis. Under that proposed differentiation, a firm liquidates its Exchange Capital along with other intangibles for minimal value during bankruptcy proceedings, while the firm more resiliently preserves Moral Capital (Lin & Dong, 2018).

Table 1: Regression results of the whole sample and the subsamples

	Dependent Variable: Change in LN (CDS Spread)						
	Whole Sample	Leverage		Market Cap		CDS Risk	Volatility & Leverage
		High	Low	High	Low	High	High
Constant	-0.638***	-0.836***	-0.4***	-0.762***	-0.5***	-0.793***	-1.261***
	(0.057)	(0.076)	(0.091)	(0.103)	(0.106)	(0.103)	(0.098)
Δ Debt/Equity	0.026***	0.015	0.009	0.032*	0.002	-0.013	0.002
	(0.009)	(0.014)	(0.013)	(0.017)	(0.031)	(0.02)	(0.017)
LOG (Mkt Cap)	-0.0	0.123***	-0.0	0.079***	-0.0	0.052*	0.124***
	(0.001)	(0.022)	(0.001)	(0.023)	(0.0)	(0.028)	(0.024)
Δ Volatility	0.271***	0.292***	0.399***	0.307***	0.213***	0.281***	0.369***
	(0.021)	(0.025)	(0.043)	(0.034)	(0.026)	(0.037)	(0.029)
Treasury	27.061***	38.751***	17.91***	31.351***	24.259***	34.884***	63.004***
	(2.363)	(3.12)	(3.843)	(3.653)	(3.026)	(4.43)	(4.115)
Δ Op. Margin	-0.003	-0.009	-0.0	0.01	-0.012	-0.005	-0.013
	(0.009)	(0.026)	(0.01)	(0.014)	(0.011)	(0.022)	(0.026)
Δ Overall ESG	-0.146**	-0.11	-0.139	-0.122	-0.134	-0.105	0.008
	(0.07)	(0.101)	(0.146)	(0.098)	(0.103)	(0.101)	(0.104)
R^2	0.153	0.385	0.136	0.193	0.13	0.266	0.562
Adj. R^2	0.15	0.379	0.129	0.187	0.123	0.255	0.554
Obs.	1615	570	747	795	820	382	327
F stats	48.36	58.78	19.46	31.34	20.18	22.7	68.42

In Table 1, we report estimated coefficients and standard errors (in parentheses) of my OLS regression model measuring the dependent variable of changes in changes in natural log of firm CDS spreads against overall ESG score as well as financial controls. I apply my model for the whole sample and various subsamples, based on Debt/Equity Ratio (cutoff = 20%), Natural Log Market Capitalization (cutoff = 3.5), CDS Implied Risk (cutoff = 4.5), and a Volatility & Leverage combination (cutoff vol = 25%, cutoff debt/equity = 20%). ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

I next examine the sector-specific effects of each ESG subscore, as reflected in Table 2. Filtering out only for statistically significant results, the materials sector is most prone to market mispricing with three out of the seven total statistically significant results. Materials is also the only sector with significant negative score coefficients, suggesting the Materials sector undervalues reputational advantages. One explanation for this discrepancy is the dramatic cyclicality within the sector – with firms exposed to both financial cycles and commodity cycles – which may prompt firms to reinvest in reputation suboptimally to preserve optionality. The energy, corporate reputation positively relates to CDS spreads with a high R-squared, which may be a product of high regulation. None of the subscores are specifically over-prominent. However, the presence of the Communications-Environmental entry suggests that I did not robustly incorporate environmental reputation in Hypothesis 2 – though one may perform a more rigorous assessment to confirm or deny this result. It is also worth noting that the reduced sample sizes due to subsampling deter the validity of results such as the Communications-Environmental and Real Estate-Corporate entries, which have 40 and 30 observations, respectively.

Table 2: Regression results of subsample defined by specific ESG subscores and industry

	Dependent Variable: Change in LN (CDS Spread)							
	All	Energy	Materials			Con. Stap.	Comm.	Real Estate
	Econ	Corporate	Overall	Econ	Social	Corporate	Environ	Corporate
Constant	-0.577***	-1.912***	-0.876***	-0.686***	-0.89***	-0.383***	-1.031***	-0.407
	(0.06)	(0.295)	(0.182)	(0.184)	(0.183)	(0.144)	(0.236)	(0.298)
Δ Debt/Equity	0.024***	0.118**	-0.001	-0.001	-0.001	0.006	0.091***	0.01
	(0.009)	(0.055)	(0.043)	(0.041)	(0.043)	(0.024)	(0.027)	(0.062)
LOG (Mkt Cap)	-0.0	0.282**	0.064	0.085	0.065	0.021	-0.044	-0.134
	(0.001)	(0.133)	(0.066)	(0.063)	(0.066)	(0.074)	(0.073)	(0.22)
Δ Volatility	0.273***	0.499***	0.15**	0.166***	0.146**	0.179***	0.163	0.18
	(0.021)	(0.102)	(0.062)	(0.059)	(0.062)	(0.067)	(0.127)	(0.107)
Treasury	23.675***	68.23***	43.538***	32.209***	44.171***	21.699***	38.029***	14.687
	(2.587)	(11.031)	(6.131)	(6.662)	(6.148)	(5.957)	(11.105)	(9.871)
Δ Op. Margin	-0.003	0.002	-0.031	-0.035	-0.027	-0.401***	0.017	-0.028
	(0.009)	(0.019)	(0.054)	(0.052)	(0.054)	(0.153)	(0.152)	(0.155)
Δ ESG	-0.144***	1.061*	-0.284**	-0.309***	-0.257**	0.723***	1.779*	0.646**
	(0.038)	(0.539)	(0.119)	(0.081)	(0.116)	(0.241)	(0.897)	(0.287)
R^2	0.158	0.771	0.424	0.474	0.419	0.243	0.419	0.282
Adj. R^2	0.155	0.745	0.385	0.438	0.379	0.206	0.314	0.094
Obs.	1615	60	95	95	95	130	40	30
F stats	50.29	29.76	10.79	13.22	10.57	6.6	3.97	1.5

In Table 2, I report estimated coefficients and standard errors (in parentheses) of my OLS model applied to GICS sector-specific subsample and ESG subscore (overall, economic, environmental, corporate, social) combinations. The data is filtered to only include entries which were found to exhibit statistically significant ESG scores. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

I then further subsampled by combining both of the above techniques to classify companies based on Financial, Sector, and Score characteristics. After filtering out for statistical significance of the given score, I display the results in Table 2. This technique created several unusably small samples, such as the High CDS Communications entry, which had an R-squared coefficient of 83.4% but only consisted of 13 entries (df = 6). Interestingly, from the remaining data, Large Cap Consumer Discretionary firms and High Volatility Industrials firms overemphasize social reputation. Meanwhile, High Volatility Financials underemphasize corporate reputation – though it is important to note that financial companies tend to be more regulated around volatility. These results suggest that assessments which employ greater granularity may discover effects which do not exist on the broader sample.

Table 3: Regression results of subsample defined by specific ESG subscores and industry

	Dependent Variable: Change in LN (CDS Spread)									
	Large Cap		High CDS Risk					High Vol		
	Cons. Disc.	Utilities	Healthcare	Comm.	Utilities	Real Estate		Industrials	Cons. Stap.	Financials
	Social	Econ	Social	Overall	Social	Overall	Social	Social	Environ	Corporate
Constant	-1.057***	-0.35	-1.648*	-0.862***	1.535	-0.091	-0.208	-1.012***	-1.543***	-0.742***
	(0.251)	(0.446)	(0.729)	(0.231)	(0.933)	(0.343)	(0.325)	(0.155)	(0.223)	(0.188)
Δ Debt/Equity	0.028	0.068	-0.041	-0.072	-0.542*	0.0	0.012	0.016	0.032	-0.041
	(0.038)	(0.096)	(0.097)	(0.038)	(0.268)	(0.065)	(0.061)	(0.028)	(0.038)	(0.03)
LOG (Mkt Cap)	0.028	1.318***	0.306	-0.182	1.591	-0.11	-0.182	-0.0	-0.089	0.14
	(0.024)	(0.385)	(0.508)	(0.1)	(1.678)	(0.213)	(0.201)	(0.0)	(0.11)	(0.148)
Δ Volatility	0.6***	-0.076	0.655**	-0.032	-0.781*	0.123	0.163	0.557***	0.392***	0.128**
	(0.091)	(0.058)	(0.268)	(0.112)	(0.341)	(0.11)	(0.104)	(0.069)	(0.087)	(0.059)
Treasury	47.021***	2.408	73.718**	58.732***	4.378	-4.017	1.192	45.135***	77.516***	49.842***
	(9.9)	(11.586)	(30.748)	(11.182)	(29.076)	(12.286)	(11.581)	(6.082)	(9.477)	(8.322)
Δ Op. Margin	0.102	0.085	-0.447	0.364*	0.635	0.013	0.02	-0.002	0.679**	0.01
	(0.064)	(0.204)	(0.362)	(0.174)	(0.632)	(0.15)	(0.14)	(0.1)	(0.308)	(0.038)
Δ ESG	0.713**	-0.551***	-2.019**	1.61**	-3.87***	0.634**	0.828**	0.275**	-0.843**	-0.671**
	(0.317)	(0.193)	(0.654)	(0.534)	(1.118)	(0.291)	(0.289)	(0.116)	(0.347)	(0.307)
R^2	0.513	0.386	0.605	0.834	0.645	0.247	0.346	0.485	0.74	0.372
Adj. R^2	0.47	0.274	0.341	0.669	0.378	-0.004	0.128	0.455	0.694	0.329
Obs.	75	40	16	13	15	25	25	112	41	95
F stats	11.92	3.45	0.341	5.04	2.42	0.98	1.59	16.45	16.13	8.69

In Table 3, we report estimated coefficients and standard errors (in parentheses) of my OLS model with all ESG subscores applied subsamples chosen for both industry and financial characteristics: Debt/Equity Ratio (cutoff = 20%), Natural Log Market Capitalization (cutoff = 3.5), CDS Implied Risk (cutoff = 4.5), and a Volatility & Leverage combination (cutoff vol = 25%, cutoff debt/equity = 20%). I filter the data to only include entries which exhibit statistically significant ESG scores. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Lastly, I used a test for correlation between the different ESG scores to contextualize the added value gained by analyzing different scores as different variables. Table 4 below shows that all scores have a positive correlation to one another. Additionally, the overall ESG score has a correlation over 55% with all of the other scores, suggesting each component adds minimal information. Indeed, a PCA analysis confirms that one requires only two principal components to explain 97% of all variances between the five scores (PC1 = 65%, PC2 = 22%). A firm which finds itself leading or lagging in specific scores may thus focus on Lin and Dong's Moral and Exchange Capital as proxy levers to adjust business practices for cost-based risk-mitigation efforts (Lin & Dong, 2018).

Table 4: ESG subscore correlation matrix

	Overall	Economic	Environmental	Corporate	Social
Overall	1.00	0.71	0.63	0.59	0.77
Economic	0.71	1.00	0.20	0.17	0.40
Environmental	0.63	0.20	1.00	0.47	0.52
Corporate	0.59	0.17	0.47	1.00	0.48
Social	0.77	0.40	0.52	0.48	1.00

In table 4, we report the Pearson correlation between changes in my ESG subscores. The sample comprises 1615 US firm-year observations, covering 323 unique firms over the 2015-2020 period.

Limitations

This analysis performed in this report is an observational study, meaning all findings are associations and one cannot imply causal inference. It is likely that I have not controlled for all relevant underlying firm financial factors, such as stock price returns and intangible assets, which can may mitigate or even reverse any effects displayed. In particular, the low R-squared coefficients displayed in my OLS models suggests that error sources remain unaccounted for in my analysis. Abnormally high condition numbers and kurtosis among the samples suggests that this model breaks the assumptions of fit and normality inherent in the accurate application of OLS models. The linear model itself may be an incorrect functional classification of ESG score, with other works proposing U-shaped and logistic curves as more adequate payoff diagram. Additionally, endogeneity is highly likely since firms can adapt management practices as well as transparency to “game” ESG scores for maximal value creation.

Data quality was also a concern throughout the study. ESG scores are a crude proxy for reputation and come laden with subjectivity and biases of the issuer. Unlike CDS spreads, which are a traded instrument linked with other financial products, there are no objective cross-references for accountability of ESG scores. Sample data was also sparse and did not include explicit control for time-based movements.

V. Concluding Remarks

Under the corporate social responsibility movement, both the academic and business communities have recognized that firms implementing sustainable practices better address broad stakeholder needs and more holistically manage risk (Atz et al., 2021). This analysis allows both firm management as well as investors with a tangible way to quantify the impact on firm value for each marginal score improvement in various ESG criteria, and thus allows for more informed and efficient capital allocation in the context of reputation. An educated view on the risk-mitigating effects of ESG across categories and industries would inform regulators, rating agencies, and the academic community on which aspects of corporate social responsibility to focus their efforts on in measuring and managing.

This report finds that there still exist statistically significant points of discrepancy between firms’ actual and optimal reputational budgets, which creates material credit risk effects. Despite extensive existing research into the question, markets have not yet determined accurate means to price reputational risk in the context of other financial risks. Materials, Real Estate, and Consumer Staples firms can particularly benefit from stronger incorporation of reputation gauges. Additionally, as firms move closer to bankruptcy, non-reputational financial risks take priority and mitigate reputational effects, as consistent with Godfrey’s 2005 paper.

Greater data frequency and transparency will dramatically improve the robustness of these results as well as provide runway for more sophisticated models. Specifically, statistically significant small-subsample results may be re-evaluated. Future research should explore other statistical models, such as time-series, cross-sectional, and logistic regression as well as economic optimization models, such as nonzero-sum matrix games and network cooperation models (e.g., giant component analysis). Fine-tuned analyses which include basic economic assumptions of firm psychology offer greater likelihood of results as well as more practical value than a simple OLS regression.

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