CORPORATE GOVERNANCE AND RISK TAKING

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ABSTRACT

This dissertation examines the effect of various corporate governance mechanisms on firm risk taking. The first essay examines the effect on firm risk through the CEO ability channel, while the second essay examines the effect on firm risk through the institutional investor channel.

This first essay investigates CEO risk management ability. Using CEO education as a proxy for ability I examine the relationship between CEO education and various types of risk: (1) market risk, (2) credit risk, and (3) operational risk. Propensity score methods are used as a way to deal with the endogenous matching problem which exists in the executive compensation literature. These methods are proposed as an alternative to the managerial fixed effects approaches such as "spell fixed effects" and the mover dummy variable method (MDV). While the managerial fixed effects methods would fail when the explanatory variables of interest are time-invariant, it is possible to capture this variation in managerial effects by using propensity score methods. I find that the effect on the various types of risks varies by the type of risk and by the type and quality of education. Firms with CEOs that have law degrees and actuarial credentials are associated with fewer operational risk events. While firms with CEOs that have MBA degrees are able to manage market risk better than their peers. Overall, the quality of CEO education matters, and in many cases it is associated with a simultaneous reduction in firm risk and increase in firm value.

This second essay investigates the impact of institutional shareholder ownership on firm risk taking. I find a negative relationship between the aggregate institutional ownership percentage and firm risk taking. I also find that institutional ownership concentration induces risk taking. In addition, the effect on firm risk is stronger when institutional shareholders have majority control. The results provide support for both the prudent-man law and the large institutional shareholder hypotheses. Furthermore, the results are robust to quasi-experimental approaches including propensity score matching and doubly robust estimation. These findings provide additional evidence on the benefits and incentives of institutional shareholder monitoring.

Dedicated to my mother of blessed memory

Svetlana Davydova Z"L

אורה בת לייב ז״ל

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CHAPTER 1

IS CEO EDUCATION LINKED WITH RISK MANAGEMENT ABILITY?

1.1. Introduction

In order to evaluate ex-ante CEO performance it is important to have a measure of CEO ability or skill. The board and the shareholders want to make sure that the firm hires the most skilled CEO for the job. The CEO's ability should in turn be reflected in firm performance. A major difficulty is finding a good measure of CEO ability. To overcome this difficulty, CEO education has been one proxy proposed in the literature (e.g., Palia, 2000; Pérez-González, 2006).

This study contributes to the literature by linking CEO education with risk management ability, and by providing an alternative approach to handle the endogenous matching problem which plagues the executive compensation literature. The property-liability insurance industry provides a good testing ground for the link between CEO education and risk management ability. Property-liability insurance CEOs are in the business of managing risk. While risk is a key component of all CEO compensation packages, it is mostly based on market risk (i.e., option compensation). Also CEOs in most industries may not necessarily have training in risk management.

However, property-liability insurance CEOs have risk management training which includes pure risks and speculative risks. Therefore, unlike in most other industries, it is easier to identify if insurance CEOs have risk management ability.

In this study, I examine the link between the education of property-liability insurance executives and three types of risk: (1) market risk, (2) credit risk, and (3) operational risk. I use different risk measures so the results will not be driven by any particular risk. I find that the relationship between CEO education and firm risk varies largely by the type of risk and by the type and quality of education. Taking into account the different measures of risk and the quality and type of education, I find that better educated CEOs can manage risks better.

Endogenous matching is a major concern when studying CEO characteristics across industries. One of the reasons for this problem is that firms in different industries select CEOs based on their particular firm characteristics (e.g., Bertrand and Schoar, 2003; Elsaid et al., 2012; Kaplan et al., 2012). An example given in Elsaid et al. (2012) is that riskier firms are less likely to hire CEOs with a degree from an ivy league institution. Graham et al. (2012) note that the matching issue is present in some form in any employer-employee matched data set.

However, since the sample used in this study consists of publicly traded property-liability insurance companies the endogenous matching problem is not severe for several reasons: (1) the firms are of comparable size, (2) the firms are exposed to the same types of risks, and (3) the firms face the same regulatory scrutiny. In addition, propensity score matching methods are proposed as a way to handle the endogenous matching problem. While there have been several managerial fixed-effects methods proposed to handle this problem in the literature such as "spell fixed effects" and the mover dummy variable (MDV) method, these methods fail when we want to estimate the effects of time-invariant variables such as education (Graham et al., 2012). By considering CEO education as a treatment effect, it is possible to compare treatment and control group firms and to estimate the effects of education on firm outcomes such as firm risk or firm value.

The remainder of the paper is organized as follows. A review of the relevant literature is presented in Section 1.2. Hypotheses about CEO credentials and risk are developed in Section 1.3. The data and variable selection is described in Section 1.4. The methodology is described in Section 1.5. The results and robustness checks are presented in Section 1.6. Section 1.7 concludes.

1.2. Literature Review

It is not easy to come up with a good proxy for CEO ability. However, education is a well known proxy for ability or skill. Several studies examine the link between CEO education and various firm characteristics such as firm performance.

1.2.1. CEO Education, CEO Ability, and Pay for Credentials

Spence (1973) showed that education is a useful signal on the job market. Several theoretical studies have also shown that differences in CEO skills are important in determining CEO pay (Rosen, 1981; Murphy and Zabojnik, 2004; Gabaix and Landier, 2008). Falato et al. (2012) find empirical support for "pay for credentials", and show that credentials such as education can be plausibly interpreted as signals of CEO abilities.

Palia (2000) compares CEO education quality at regulated utilities to those at manufacturing firms, and finds that CEOs in manufacturing firms have higher education quality. Barker and Mueller (2002) show that there are significant R&D spending increases in firms where CEOs have advanced science degrees. Butler and Gurun (2012) study CEO educational networks in mutual funds. They show that CEOs in companies with high levels of educationally connected ownership have significantly higher compensation than firms without educationally connected ownership.

1.2.2. CEO Education and Firm Performance

Pérez-González (2006) found that successor CEOs which did not attend selective colleges in family firms performed worse than those that came from selective colleges. Gottesman and Morey (2010) find no significant evidence that the type or selectivity of education of the CEO is related to firm financial performance. Elsaid et al. (2012) examine CEO successions and find no evidence that changing the education level of the successor CEO improves firm financial performance. While, Zhang and Rajagopalan (2010) find a negative relationship between the level of CEO education (e.g., undergraduate vs. graduate) and firm performance. Jalbert et al. (2010) find mixed results for the effect of CEO education variables on firm performance, although the results largely show no statistically significant relationship between firm performance and CEO education.

Bhagat et al. (2010) find that while CEO education is important in CEO hiring, it does not-affect long term performance of firms. This leads them to conclude that CEO education is not a good proxy for ability. However, Kaplan et al. (2012) show that using college selectivity is a valid measure to capture part of general CEO talent. They also document a positive relationship between CEO ability and firm performance. Similarly, Chevalier and Ellison (1999) analyze the performance of mutual fund managers and find that fund managers who attended more selective undergraduate institutions have better performance than fund managers who attended less selective undergraduate institutions.

1.3. Hypothesis Development

It has been shown that education is a signal of ability (e.g., Spence, 1973; Falato et al., 2012). There is also evidence of a positive relationship between CEO ability and firm performance (e.g., Kaplan et al., 2012). The selectivity of the institution that the manager attended was also shown to be an important measure of CEO talent (Chevalier and Ellison, 1999; Pérez-González, 2006; Kaplan et al., 2012). Building on this literature, I develop the hypothesis on the link between CEO education and firm risk via two channels.

The first channel which links CEO education and risk taking is the incentive compensation channel. Several studies have shown that CEO incentive compensation induces risk taking (e.g., Cohen et al., 2000; Chen et al., 2006; Coles et al., 2006). In addition, labor market signaling theories imply that there should be "pay for credentials" (Custódio et al., 2010; Falato et al., 2012). Therefore, if incentive compensation induces CEOs to take risk, and CEOs are compensated based on their credentials, then CEO credentials should also be related to risk.

The second channel which links CEO education and risk taking is the managerial risk aversion channel. It can be argued that education is a characteristic that is a determinant of risk aversion or managerial risk appetite. Halek and Eisenhauer (2001) surveyed a group of households and found some evidence of lower risk taking among high-school graduates and college attendees compared to dropouts, but they also found that risk-taking rises with years of education. Similarly for executives, MacCrimmon and Wehrung (1990) found that Canadian executives with lower education were more risk taking than American executives or Canadian executives with higher education. There is also evidence that managers with more education are more actively involved in corporate hedging as evidenced by their increased use of derivatives (Pennings and Garcia, 2004; Bodnar et al., 2013). In addition Belghitar and Clark (2012) find a negative and significant effect between CEO education and total and idiosyncratic risk. This leads to the main hypothesis:

H1: *There is a negative relationship between CEOs which graduated from top schools and firm risk.*

Corporations face many types of risk including market risk, credit risk, and operational risk. The skills required to manage market risk and credit risk are different than the skills required to manage operational risk. A key difference is that operational risk typically cannot be hedged and has a "fat tailed" loss distribution (Nocco and Stulz, 2006). Cummins et al. (2006) find that firms experience negative abnormal returns following public announcements of operational losses. In addition, Jarrow et al. (2010) show that the cost of operational risk can exceed the cost of default risk. The implication of these findings is that managing operational risk is as important if not more important than managing credit risk and market risk.

Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people, systems or from external events [1]. Legal risk is also included in this definition of operational risk. Bagley (2008) provides theoretical arguments for "legal astuteness" as a valuable managerial capability. There are several potential benefits of legal astuteness which include the ability to reduce transactions costs, the ability to convert regulatory constraint into opportunities, the ability to increase realizable value, as well as the ability to manage risk (Bagley, 2008). Similarly, Lewis et al. (2013) posit that those with a legal education exhibit greater risk aversion and have an inclination for risk mitigation. In addition, Bamber et al. (2010) find that managers with a legal background are sensitive to litigation risk. Therefore it would be expected that CEOs with a legal background should be more skilled in operational risk management. This leads to the next hypothesis:

H2: *There is a negative relationship between CEOs with a law degree and operational risk.*

Market risk and credit risk can be hedged using derivatives such as credit default swaps (CDS). CEOs with better ability should be able to ensure that their firms have good credit quality. This is especially true for property-liability insurers which face regulatory scrutiny from the state regulator. Most business programs, especially finance MBA programs typically train their students in option pricing and credit risk management. Bodnar et al. (2013) find a positive relationship between CEO education and the use of foreign currency derivatives. Chen et al. (2013) show that CEO ability heterogeneity and board recruiting ability is negatively related to

[1] Basel Committee on Banking Supervision, 2006. *International Convergence of Capital Measurement and Capital Standards*, Bank for International Settlements.

credit risk. Similarly Belghitar and Clark (2012) find that CEO education level is negatively related to firm volatility and default risk. One of the measures used by Chemmanur et al. (2009) to measure management quality is the percentage of MBAs on the management team. Chemmanur et al. (2009) show that better and more reputable managers can reduce information asymmetry facing their firm in the equity market, which is evidenced by lower leverage ratios of firms with a higher percentage of MBAs on the management team. This leads to the next two hypotheses:

H3: *There is a negative relationship between CEOs with a business degree and credit risk.*
H4: *There is a negative relationship between CEOs with a business degree and market risk.*

Professional certifications such as accounting certifications (CPA) and insurance certifications (e.g., CPCU, FCAS) provide additional information about ability. These certifications show that an individual met certain accepted standards in a particular area. Chemmanur et al. (2009) suggest that a higher percentage of CPAs on a management team implies management quality. For the property-liability insurance industry in particular, Chartered Property Casualty Underwriter (CPCU) and Fellow of the Casualty Actuarial Society (FCAS) certifications are well established for underwriting and actuarial expertise respectively. However, there is no prior evidence that indicates if these certifications are related to firm risk. This leads to the final hypothesis:

H5: *There is a relationship between CEOs with a professional certification and firm risk.*

1.4. Data and Variable Selection

The data comes from five main sources: (1) Compustat, (2) Execucomp, (3) Algorithmics Algo OpData, (4) CRSP, and (5) SNL Financial. Firm level accounting data is taken from Compustat as well as insurance specific data which is taken from SNL Financial. Operational loss data is taken from the Algo OpData database. The intersection of these databases yields a sample of 53 publicly traded property-liability insurance firms with a total of 522 firm-year observations from 1992-2010 in an unbalanced panel. The sample is representative of the property-liability insurance industry as a whole. In 2010, the sample contained 35 property-liability insurers which constituted approximately 44% of total property-liability industry premiums for that year[2].

CEO education data is obtained from Capital IQ, Lexis-Nexis, as well as web searches. Different variables are constructed for each type of degree such as business education (MBA and BUSINESS), law education (LAW), and quantitative education which includes science and mathematics degrees (QUANT). Rankings of colleges and universities are obtained from U.S. News and World Report. Several variables are constructed using education rankings to measure education quality. These variables include Top_50_LAW, if the CEO has a degree from a top 50 law school as well as Top_50_MBA, if the CEO has a degree from a top 50 business school. Data on CEO professional certifications such as Certified Public Accountant (CPA) are also

[2]This calculation is based on the property-liability industry data provided in the National Association of Insurance Commissioners (NAIC) annual report card which can be found on the NAIC website: http://www.naic.org/state_report_cards/report_card_la.pdf

obtained. Insurance-specific certifications such as CPCU, and FCAS are obtained as well. Variables based on certifications are constructed which include (INS_Cert) if the CEO has any insurance certifications, and CPA if the CEO has a CPA license. This data is then merged with the main sample.

I follow the corporate governance literature in selecting various control variables (e.g., Core et al., 2008; Graham et al., 2012). Specifically, I select variables such as firm size (ln(Assets)), leverage (Leverage), return on assets (ROA), and stock return (ret) for firm characteristics. In addition, I control for long-tail lines of business by including the variable, LONG_TAIL, which is the percent of net premiums written in long tail lines of business as in Pottier and Sommer (1999). Long tail insurance lines are those lines in which there is usually a long waiting period between the insured event and the final claim by the insurer, hence these business lines are associated with greater levels of uncertainty (Pottier and Sommer, 1999).

I also select variables such as CEO tenure (Tenure), CEO age (CEO_AGE), for managerial characteristics. The natural logarithm of total compensation (ln(TDC1)) is also used to control for the effect of managerial incentives. Annualized 12-month return volatility (σ_{ret}) is used as a measure of market risk. Two measures of credit risk are used: (1) Standard and Poor's (S&P) credit ratings as in Blume et al. (1998), (2) Distance-to-Default, which I measure as the natural logarithm of Z-score (ln(Z)) as in Laeven and Levine (2009). Operational risk frequency (Operational_Freq) and the natural logarithm of operational risk severity (Operational_Loss) are used as measures of operational risk based on the Algorithmics Algo OpData database. The variables are defined in Appendix A.

The descriptive statistics are reported in Table 1. Leverage ranged from .317 to 1.082 which suggests that the firms had a conservative amount of debt. The average Tobin's Q is 1.102 which means that most of the firms in the sample are not overvalued. CEO age ranges from 35 to 85. The rankings of undergraduate institutions attended by the CEOs range from 1-184 (USN_UG_Rank), while the rankings of the graduate institutions attended by the CEOs range from 1-135. The average CEO total pay is around $5 million. The oldest firm in the sample is Hartford Financial Services Group Inc. which was founded in 1810, and was 200 years old at the end of 2010.

1.5. Methodology

To investigate the relationship between CEO credentials and firm risk, different models are employed. Due to the differences among different types of risk, I estimate separate models for market risk, credit risk, and operational risk. The 12-month stock return volatility is used as measure of market risk. Standard and Poor's (S&P) long-term credit ratings as well as Z-score are used as proxies for credit risk. Finally, operational risk frequency and severity from publicly reported operational risk events are used to measure operational risk.

1.5.1. CEO Credentials and the Balance Between Performance and Risk

In order to take into account the risk-return tradeoff, I scale the annual average geometric return, ret, by the 12-month return volatility σ_{ret}. This allows me to estimate the relationship between CEO education and firm performance for each

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
	Firm Characteristics				
ln(Assets)	517	9.301	1.531	6.395	13.874
ret	475	0.080	0.204	-0.481	0.310
Leverage	517	0.764	0.104	0.317	1.082
ROA	517	0.026	0.028	-0.185	0.160
LONG_TAIL	428	58.476	36.570	0.504	100
Q	488	1.102	0.163	0.817	2.149
Firm_Age	343	48.079	42.664	1	200
	Risk Measures				
Operational_Loss ('000,000)	517	6.789	103.827	0	2330.2
Operational_Freq	517	0.091	0.365	0	3
σ_{ret}	498	0.075	0.043	0.024	0.453
Lower_Grade	243	0.477	0.501	0	1
ln(Z)	271	4.241	1.381	0.276	8.615
	CEO Characteristics				
TDC1	515	5062.028	5579.457	289.048	45549.5
CEO_Age	492	56.632	8.241	35	85
Tenure	517	7.035	11.070	0	45
LAW	517	0.118	0.323	0	1
GRAD	517	0.464	0.499	0	1
MBA	517	0.251	0.434	0	1
CPA	517	0.166	0.373	0	1
INS_Cert	517	0.170	0.376	0	1
Top_50_UG	517	0.335	0.472	0	1
Top_50_MBA	517	0.132	0.338	0	1
Top_50_GRAD	517	0.319	0.467	0	1
Top_50_LAW	517	0.062	0.241	0	1
ACTUARY	517	0.081	0.273	0	1
BUSINESS	517	0.544	0.499	0	1
QUANT	517	0.114	0.318	0	1
USN_UG_Rank	276	54.511	51.142	1	184
USN_GRAD_Rank	230	30.117	37.399	1	135

additional unit of risk. I estimate the relationship between CEO education and the balance between performance and risk in the following way:

$$\begin{aligned}\frac{ret_{it}}{(\sigma_{ret})_{it}} &= \alpha_i + \xi_t + \beta_1\text{Education}_{it} + \beta_2\text{CPA}_{it} + \beta_3\text{INS\_Cert}_{it} \\ &+ \beta_4\ln(\text{Assets})_{it} + \beta_5\text{Leverage}_{it} + \beta_6\ln(\text{TDC1}_{it}) \\ &+ \beta_7\text{CEO\_AGE}_{it} + \beta_8\text{Tenure}_{it} + \beta_9\text{LONG\_TAIL}_{it} + \varepsilon_{it},\end{aligned} \tag{1.1}$$

where Education_{it} is the set of the following CEO credentials: GRAD, Top_50_UG, Top_50_GRAD, Top_50_LAW, Top_50_MBA, LAW, MBA, ACTUARY, BUSINESS, and QUANT. Firm fixed-effects and year fixed-effects are denoted by α_i, and ξ_t respectively. The disturbance is denoted by ε_{it}.

1.5.2. CEO Credentials and Credit Risk

The effects of CEO credentials on credit risk are examined by looking at the probability that a firm will be in a certain rating category. The distribution of credit ratings is shown in Table 2. Roughly half of the sample has a rating of upper medium grade or above, while the other half is below upper medium grade (A-). Most studies which investigate credit ratings use ordered-probit models to estimate the effect of the independent variables on each rating category (e.g., Blume et al., 1998). However, due to the lack of heterogeneity and sample size in rating categories, an ordered-probit model would not be appropriate for this data.

To overcome this limitation, I construct a dummy variable Lower_Grade which takes the value 1 if the ratings are below A-, and 0 otherwise. This allows me to

Table 2: **Distribution of S&P Credit Ratings**

Rating	Description	Frequency	%
AAA	Prime Grade	3	1.21
AA, AA-	High Grade	5	2.02
A+, A, A-	Upper Medium Grade	121	49.00
BBB+, BBB, BBB-	Lower Medium Grade	112	45.34
BB+ , BB, BB-	Non-Investment Grade Speculative	6	2.43
Total		247	100

estimate a Probit model with Lower_Grade as the dependent variable:

$$\begin{aligned}\Phi^{-1}\Big(P(\text{Lower\_Grade}_{it} = 1)\Big) &= \beta_1 \text{Education}_{it} + \beta_2 \text{CPA}_{it} + \beta_3 \text{INS\_Cert}_{it} \\ &+ \beta_4 \ln(\text{Assets})_{it} + \beta_5 \text{ROA}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 ret_{it} + \beta_8 \ln(\text{TDC1}_{it}) \\ &+ \beta_9 \text{CEO\_AGE}_{it} + \beta_{10} \text{Tenure}_{it} + \beta_{11} \text{LONG\_TAIL}_{it} + \nu_{it},\end{aligned} \tag{1.2}$$

where $\Phi(\cdot)$ is the standard normal distribution.

Another measure proxy for credit risk is Z-score, which is a measure of distance-to-default. There are several advantages in using Z-score in lieu of credit ratings. Using Z-score captures more variation in firm credit quality than credit ratings since it is a continuous variable. A disadvantage of long-term credit ratings is that they do not change that much from year to year. In contrast, Z-score would better capture the yearly changes in credit quality. Another disadvantage of using S&P credit ratings is that the credit rating methodology is very opaque. Meanwhile, Z-score can be easily constructed from observable company financial statements. I estimate Z-score in the following way:

$$Z = \frac{(\text{ROA} + \text{CAR})}{\sigma(\text{ROA})}, \tag{1.3}$$

where σ(ROA) is the quarterly standard deviation of ROA, and CAR is the capital to assets ratio. Since Z-score is usually skewed, I follow Laeven and Levine (2009) and take the logarithm of Z. This allows me to estimate OLS panels for Z-score:

$$\begin{aligned} \ln(\text{Z}_{it}) &= \alpha_i + \xi_t + \beta_1\text{Education}_{it} + \beta_2\text{CPA}_{it} + \beta_3\text{INS\_Cert}_{it} \\ &+ \beta_4 \ln(\text{Assets})_{it} + \beta_5\text{ROA}_{it} + \beta_6\text{Leverage}_{it} + \beta_7 ret_{it} \\ &+ \beta_8 \ln(\text{TDC1})_{it} + \beta_9\text{CEO\_AGE}_{it} + \beta_{10}\text{Tenure}_{it} + \beta_{11}\text{LONG\_TAIL}_{it} + \nu_{it}. \end{aligned} \tag{1.4}$$

1.5.3. CEO Credentials and Operational Risk

Due to the differences between operational risk and market risk, different modeling approaches should be used. Chernobai and Yildirim (2008) show that operational risk frequency can be modeled in a similar way to doubly stochastic default in credit risk. In particular, they show that operational risk frequency can be modeled as a doubly stochastic Poisson process. Chernobai et al. (2011) use Poisson regression to model operational risk frequency. Therefore, I estimate the following Poisson regression:

$$\begin{aligned} \text{Operational\_Freq}_{it} &= \exp\Big(\beta_1\text{Education}_{it} + \beta_2\text{CPA}_{it} + \beta_3\text{INS\_Cert}_{it} + \beta_4 \ln(\text{Assets})_{it} \\ &+ \beta_5\text{ROA}_{it} + \beta_6\text{Leverage}_{it} + \beta_7 \ln(\text{TDC1}_{it}) \\ &+ \beta_8\text{CEO\_AGE}_{it} + \beta_9\text{Tenure}_{it} + \beta_{10}\text{LONG\_TAIL}_{it} + \eta_{it}\Big). \end{aligned} \tag{1.5}$$

It is also possible to estimate operational risk severity regressions using operational loss data. I estimate operational risk severity regressions in the following way:

$$\begin{aligned}\text{Operational\_Loss}_{it} &= \alpha_i + \beta_1 \text{Education}_{it} + \beta_2 \text{CPA}_{it} + \beta_3 \text{INS\_Cert}_{it} + \beta_4 \ln(\text{Assets})_{it} \\ &+ \beta_5 \text{ROA}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \ln(\text{TDC1}_{it}) \qquad (1.6) \\ &+ \beta_8 \text{CEO\_AGE}_{it} + \beta_9 \text{Tenure}_{it} + \beta_{10} \text{LONG\_TAIL}_{it} + \kappa_{it}.\end{aligned}$$

1.6. Results

The results for the balance between performance and risk are presented in Table 3. Panel A shows the firm fixed-effects regression estimates. The specification with Top_50_LAW was not estimated due to collinearity. None of the CEO education variables were statistically significant. Leverage is statistically significant and negative, which implies that each extra unit of debt corresponds decreased performance and increased risk.

Median regressions are estimated in Panel B of Table 3. The median regression is more robust than OLS since it is a non-parametric model and it is not sensitive to outliers. Therefore, it is worthwhile comparing the OLS results to the median regression results. The coefficients of MBA and BUSINESS are statistically significant and positive. This suggests that firms that have CEOs with MBA degrees as well as firms with CEOs that have a business graduate or undergraduate degree have higher return per unit of risk. These results support H4.

The results of the credit risk models are presented in Table 4. The specification with Top_50_LAW was not estimated because the standard errors in that specification were not reliable. Panels A and B show the Probit regression results. Panel A shows the raw pooled Probit coefficients, while Panel B shows the average marginal effects. The coefficients of Top_50_UG and ACTUARY are negative and significant. The marginal effect of Top_50_UG is also statistically significant, with a coefficient of -0.194. This means that firms with CEOs that attended selective undergraduate institutions on average will have a 19.4% reduction in the probability of being rated below A-. The marginal effect of ACTUARY is also statistically significant, with a coefficient of -0.205. This means that firms with CEOs that have actuarial credentials on average will have a 20.5% reduction in the probability of being rated below A-. However, the coefficients of Top_50_MBA and LAW are positive and significant, with significant marginal effects coefficients of 0.141 and 0.867 respectively. This implies that firms with CEOs that attended top MBA programs and firms with CEOs that have law degrees on average will have an 18% and an 86.7% increase in the probability of being rated below A- respectively. In addition, the CPA and INS_Cert variables are statistically significant and negative in specifications (2) and (3). This means that firms with CEOs that have CPA and insurance certifications are less likely to be rated below A-. The findings from the Probit regressions support H1 and H5.

The results of the Distance-to-Default models are presented in Panel C of Table 4. The specifications with Top_50_LAW and Top_50_MBA were not estimated because the standard errors in those specification were not reliable. The coefficient of Top_50_UG is positive and statistically significant. This suggests that firms with CEOs that attended more selective undergraduate institutions are associated with higher distance-to-default (or lower default probability). Meanwhile, the coefficients of MBA, BUSINESS, and CPA are statistically significant and negative. This suggests that firms with CEOs that have a business degree or an MBA not necessarily from a highly ranked school as well as a CPA are associated with lower distance-to-default (or higher default probability). It is interesting to note that while the coefficient of Top_50_MBA was positive, the coefficient of MBA was negative. Overall the results of the credit risk models support H1 as well as H5.

The results of the pooled Poisson regression are presented in Table 5. Surprisingly the coefficients of GRAD, MBA, and BUSINESS are positive and statistically significant. Perhaps, this is because operational risk is usually not part of the curriculum in most graduate or business programs. This means that firms that have CEOs with a graduate degree or an MBA or business education at either the undergraduate or graduate level are more likely to have more operational losses. Another explanation can be that CEOs with graduate degrees and MBAs are more overconfident than their peers. Although the coefficient of Top_50_MBA is not statistically significant, the sign is negative. This shows that there is still a difference in education quality and not just the type of education. In contrast, the coefficients of Top_50_GRAD, Top_50_LAW, LAW, ACTUARY, and QUANT are statistically significant and negative. This suggests that firms that have CEOs with a top graduate degree, a law degree, actuarial credentials, or a quantitative degree are associated with fewer operational risk events. The results support H2, H1, and H5.

The results of operational risk severity regressions are presented in Table 6. The coefficient of LAW is negative and significant. This means that firms that have a CEO with a LAW degree on average have operational risk losses that are lower than their peers. The coefficient of Tenure is negative and significant meaning that firms with more experienced CEOs tend to have lower cost of operational risk. These results further support H2.

1.6.1. Robustness Checks

1.6.1.1. Alternative Measure of Education Quality

In previous specifications dummy variables were created for various rankings (i.e., Top_50_MBA and Top_50_LAW). As a robustness check, the numerical values of rankings will be used. The rankings in the sample range from 1-184 for undergraduate institutions, and 1-135 for graduate institutions (as shown in Table 1). The best ranked school is ranked 1, and as the ranking value increases, the perceived education quality is lower. Although this approach is not perfect since rankings are not continuous, nevertheless the approach provides another way to measure education quality.

The results of various models with education rankings are presented in Table 7. The coefficients of the undergraduate rankings (USN_UG_Rank) and the graduate rankings (USN_GRAD_Rank) are statistically significant in specifications (2), (4), (6) and (8). The coefficients of USN_UG_Rank and USN_GRAD_Rank are positive in the Poisson models in specifications (2) and (6), which suggests that firms that have CEOs from lower ranked undergraduate and graduate institutions have more frequent operational losses. Similarly, these coefficients are negative in the OLS models in specification (4) and (8), which implies that firms that have CEOs from lower ranked undergraduate and graduate institutions have a lower distance to default and a higher default probability. These results lend further support to H1.

1.6.1.2. Operational Risk Frequency Estimation Revisited

There is a disproportionate amount of zeros in the operational risk frequency variable. Therefore it is necessary to check the previous results which relied on the Poisson regression. The Zero-Inflated Poisson (ZIP) was introduced by Lambert (1992) in order to deal with the problem of excess zeros in count data. I re-estimate the model in equation (1.5) by defining the Operational_Freq variable as:

$$\text{Operational\_Freq}_{it} \sim \begin{cases} 0 & \text{with probability} \quad p_{it} \\ \text{Poisson}(\lambda_{it}) & \text{with probability} \quad 1 - p_{it}. \end{cases} \tag{1.7}$$

This model essentially estimates two equations. The first equation (also known as the "inflation" component) estimates the effect of the determinants of operational risk on whether a firm does not have an operational risk event versus a firm having one or more operational risk events. The second equation estimates the count model for the number of operational risk events, conditional on there being at least one event. Firm age (Firm_Age), and return volatility (σ_{ret}) are used as explanatory variables in the "inflation" component of the ZIP model. Based on the findings in Chernobai et al. (2011), these variables may account for the differences in operational losses and operational risk event occurrences across firms.

The results of the ZIP estimation are given in Table 8. The models with GRAD, Top_50_UG, Top_50_LAW, Top_50_MBA, MBA, and ACTUARY were not presented as the maximum likelihood estimation did not converge in these specifications. This is a common problem when working with non-linear models. The Vuong statistics indicate that the standard Poisson regression should be rejected in favor of the ZIP model. The coefficient of BUSINESS is positive and significant. This is consistent with the standard Poisson estimates from Table 5. These results confirm the previous results that a firm with a CEO that has a business degree is associated with more operational loss occurrences. The coefficients of Top_50_GRAD, LAW, and QUANT are still negative and significant which is also consistent with the previous results. This is a stronger result than in previous Poisson models and it implies that firms with CEOs that attended more selective graduate institutions or firms with CEOs that have a law or quantitative background are associated with less frequent operational loss occurrences. These results provide additional support for H1 and H2.

1.6.1.3. Endogenous Matching

As Graham et al. (2012) point out, endogenous matching is present in any employer-employee matched data set. Based on the literature, a good way to deal with the endogenous matching problem is to include both firm and manager fixed effects (e.g., Bertrand and Schoar, 2003; Graham et al., 2012; Coles and Li, 2013). Various managerial fixed-effects methods such as "spell fixed effects" and the mover dummy variable (MDV) method have been used in the literature. The basic idea of the spell method is to combine firm and manager fixed effects using a dummy variable for each firm-manager combination, which is called a spell. This approach allows researchers to control for firm and manager fixed effects simultaneously. While the spell fixed-effects approach is not able to isolate the relative influence of firm and manager effects, the MDV method was proposed as a way to separately estimate the importance of these effects. The main idea of the MDV approach is to restrict the panel to the sample of only managers that changed firms and to include manager, firm, and year dummies in the model. However, those approaches fail if the primary explanatory variables of interest are time-invariant, such as education or gender (Graham et al., 2012). Since the focus of this study is the impact of education on risk, including manager fixed effects would eliminate the variation in education which is necessary to estimate the relevant coefficients.

While limiting the sample to property-liability insurers mitigates the severity of the endogenous matching problem that plagues the CEO compensation literature, it is a relatively ad-hoc solution. Even within the industry, CEOs may be matched with firms based on covariates such as size, and incentive compensation. Therefore, I use propensity score matching as a way of dealing with the endogenous matching problem.

The main assumption in propensity score matching is the ignorability of treatment (also known as *conditional independence* or *selection on observables*). Intuitively, this assumption means that the assignment to the treatment is random if we observe characteristics of treated and non-treated individuals. The treatment variables used in this study are CEO education credentials. So the treatment group can be defined as firms with CEOs that have a particular credential, and the control group as firms with similar characteristics that do not have a CEO with the particular credential. CEOs do not choose their level of education based on firm risk. Although CEOs with different credentials may choose to work for firms with different characteristics as well as based on the total compensation package. The assumption I make to use propensity score matching is that controlling for observables such as firm size, firm age, and the CEO total incentive compensation, the ignorability of treatment assumption holds in this study.

The conditional independence assumption can be stated more formally using results from Rosenbaum and Rubin (1983) and notation from Dehejia and Wahba (2002). Let T_i be the treatment effect which in the context of the firm is having a CEO with a particular education credential. Let R_{i0} and R_{i1} be the firm risk without treatment, and with treatment respectively. Also, let X be a vector of observable firm characteristics. Let the probability of being assigned to the treatment be defined by $p(X_i) = P(T_i = 1|X_i) = E[T_i|X_i]$. Then,

$$(R_{i1}, R_{i0}) \perp\!\!\!\perp T_i|X_i \Rightarrow (R_{i1}, R_{i0}) \perp\!\!\!\perp T_i|p(X_i). \tag{1.8}$$

The estimates of interest are the average treatment effect (ATE), and the average treatment effect on the treated (ATT). The average treatment effect is defined as:

$$ATE = E[R_{i1} - R_{i0}], \tag{1.9}$$

which in this study is the expected effect of education on risk between firms which were "treated", or had a CEO with a particular credential, and firms that were "not-treated", or did not have a CEO with that credential. The average treatment effect on the treated is defined as

$$ATT = E[R_{i1} - R_{i0}|T_i = 1], \tag{1.10}$$

which can be interpreted as the expected effect of education on firm risk conditional on the firm intending to hire the CEO with that credential in the context of this study. The ATT captures the effect of education on risk more directly.

However, $E[R_{i0}|T_i = 1]$, which is the outcome on risk for firms without the CEO having the specific credential given that the firm has a CEO that actually has the credential is not observed. Also, since the outcomes of firms from the treatment and control would be different even in the absence of treatment this leads to the selection-bias problem. In order to state this problem more precisely the outcome R_i can be written as:

$$R_i = (1 - T_i)R_{i0} + T_i R_{i1}. \tag{1.11}$$

Using (1.11), the average treatment effect on the treated can be estimated by writing the observed difference in R_i among the treatment and control groups as:

$$E[R_i|T_i = 1] - E[R_i|T_i = 0] = E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 0], \tag{1.12}$$

adding and subtracting $E[R_{i0}|T_i = 1]$ on the right hand side we get:

$$\begin{aligned}
&= E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 0] + E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 1] && (1.13)\\
&= \Big(E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 1]\Big) + E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 0] && (1.14)\\
&= \Big(E[R_{i1} - R_{i0}|T_i = 1]\Big) + \Big(E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 0]\Big) && (1.15)\\
&= ATT + \textbf{selection bias}. && (1.16)
\end{aligned}$$

Using the conditional independence assumption allows us to identify ATT. Applying mean conditional independence to (1.12) and (1.15) we get the classic result from

Rosenbaum and Rubin (1983):

$$\begin{aligned}
E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 0] &= \Big(E[R_{i1} - R_{i0}|T_i = 1]\Big) + \Big(E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 0]\Big) \\
E[R_{i1}] - E[R_{i0}] &= ATT + \Big(E[R_{i0}] - E[R_{i0}]\Big) && (1.17) \\
E[R_{i1} - R_{i0}] &= ATT + 0 && (1.18) \\
ATE &= ATT. && (1.19)
\end{aligned}$$

This means that under the conditional independence assumption the average treatment effect is equal to the average treatment effect on the treated. The equality in (1.19) shows the importance of the conditional independence assumption, because otherwise there would be selection bias, and the average treatment effect on the treated would not be identified.

Another assumption that is needed to use propensity score matching is the common support condition (or overlap) which states that:

$$0 < P(T_i = 1|X_i) < 1. \tag{1.20}$$

This means that for any combination of characteristics there are treated and untreated subjects. In the context of this study, it means there are firms with CEOs that have a specific credential and there are firms with CEOs without that credential which have similar characteristics. The conditional independence assumption and the common support condition allows us to estimate the average treatment effect on the treated. Propensity score matching is essentially a weighting scheme which determines what weights are placed on comparison firms when computing the estimated treatment effect:

$$\widehat{ATT} = \frac{1}{|N|}\sum_{i\in N}\Big(R_i - \frac{1}{|J_i|}\sum_{j\in J_i} R_j\Big), \tag{1.21}$$

where N is the treatment group, $|N|$ is the number of firms in the treatment group, J_i is the set of comparison firms matched to treatment i, and $|J_i|$ is the number of comparison units in J_i (Dehejia and Wahba, 2002).

Any probability model can be used to estimate the propensity score $p(X_i)$. I estimate propensity scores using the logistic distribution since it is a standard model to implement:

$$p(X_i) = P(T_i = 1|X_i) = \frac{e^{h(X_i)}}{1 + e^{h(X_i)}}, \tag{1.22}$$

where $h(X_i)$ is a function of the covariates with linear and higher order terms. There are several different types of matching estimators. I use nearest neighbor matching, and caliper matching estimators as in Dehejia and Wahba (2002). I also use kernel estimators for robustness. The covariates, X_i, that I select for matching are: firm size (ln(Assets)), leverage (Leverage), firm age (Firm_Age), and total incentive compensation (ln($TDC1$)). More in depth discussions on treatment effects and propensity score matching can be found in various sources (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002; Wooldridge, 2002, Chapter 18).

Propensity score models based on various matching estimators are presented in Table 9 for each type of risk. The main variable of interest is ATT for the difference (Diff.) between the treatment and control groups. Bias can arise due to failure to match all treated firms and due to the failure to obtain exact matches

Rosenbaum and Rubin (1985). Therefore, the average bias percent (Bias) is estimated in each specification based on Rosenbaum and Rubin (1985). As a rule of thumb, the bias after matching should be less than 5%.

Panel A shows the results of nearest neighbor matching with two neighbors. The ATT for the difference between the treatment and control group is negative and significant for Top_50_MBA and MBA for market risk. This would imply that firms with CEOs that have an MBA have lower market risk. Although the bias on these coefficients is 14.40% and 9.30% respectively. Conversely the ATT coefficients on ACTUARY and QUANT were positive and significant for market risk. The bias on these coefficients was 8.3% and 49.8% respectively. This means that the ATT estimate for market risk for QUANT is unreliable since it is way above the 5% benchmark. The coefficients of GRAD, ACTUARY, and BUSINESS are negative and significant for distance to default. This would suggest that CEOs with a graduate degree, an actuarial degree, or a business degree would decrease distance to default. However, the bias on these estimates is 6.9%, 7%, and 5.7%. These estimates are not only less reliable due to bias, they are also less reliable due to the small sample size, which is roughly half the sample size for the other two risk measures. The coefficients of GRAD, MBA, and BUSINESS are positive and significant with respect to operational risk. The bias on the coefficients is 11.6%, 12.9%, and 14.9%. The coefficient of BUSINESS is consistent with Zero-Inflated Poisson regression estimates in Table 8. These results support H4.

Panel B shows the results of radius matching with a caliper of $\rho = .05$. The ATT estimates for Top_50_UG, Top_50_GRAD, Top_50_MBA, and MBA are negative and significant for market risk, with estimated bias of 3.4%, 9%, 8%, and 6.3% respectively. This suggests that on average firms with CEOs that come from top undergraduate and graduate programs as well as MBA programs have lower market risk than similar firms that have CEOs with other credentials. The ATT estimates for Top_50_UG and LAW were statistically significant and positive for Z-Score, with bias estimates of 0.6% and 4.8% respectively. This is strong evidence that firms with CEOs that have a law background or come from top undergraduate institutions have lower default probability. However, the ATT estimates for ACTUARY and BUSINESS were negative and significant for distance to default, although they had estimated bias of 6.2% and 8.5% respectively. The ATT estimates for GRAD, MBA, and BUSINESS are statistically significant and positive for operational risk. These results support H1 and H4.

Panel C shows the results of kernel matching using the Epanechnikov kernel. The ATT estimates for Top_50_UG, Top_50_GRAD, and Top_50_MBA, are negative and significant for market risk, with estimated bias of 3.1%, 8.9%, and 6.8% respectively. This is consistent with radius matching results in Panel C, except now MBA is not significant. The ATT estimates for Top_50_UG and LAW were statistically significant and positive for Z-Score, with bias estimates of 0.8% and 4.3% respectively. While the ATT estimates for ACTUARY and BUSINESS were negative and significant for distance to default, although they had estimated bias of 7.4% and 8.2% respectively. These results also support H1 and H4.

I also estimate propensity matching models with two outcomes, where Tobin's Q (Q) and total risk (σ_{ret}) are the outcome variables. This allows me to estimate the treatment effect of CEO education on firm value and firm risk simultaneously. The results of matching with both firm value and firm risk are shown in Table 10. The ATT of Top_50_UG is positive and significant for Tobin's Q and negative and significant for total risk, with an average bias that ranges from 3.3%-10.6% across the different matching estimators. This result adds further support to the main hypothesis that firms with CEOs that graduated from top schools have lower risk. In addition, the risk reduction is accompanied by an increase in firm value. The ATT of Top_50_GRAD is negative and significant for total risk in the radius matching specification, and positive but not significant for Tobin's Q. The bias estimates on Top_50_GRAD range from 3.6%-24.1%. This implies that the results for Top_50_GRAD are less reliable than those for Top_50_UG. This could be due to less CEOs with top graduate degrees in the sample than those with top undergraduate degrees, which would make matching more difficult. The ATT for Top_50_MBA is negative and significant for total risk across all specifications, and positive but not significant for Tobin's Q, with average bias ranging from 4%-15.1%.

The ATT for LAW is positive and significant for Tobin's Q and for total risk in the nearest neighbor model with an average bias of 9.4%. The ATT for MBA is negative and significant for total risk in the nearest neighbor model, and positive but not significant for Tobin's Q, with average bias ranging from 1.7%-4.3%. It is surprising that the ATT for those with a CPA license is negative and significant across all specifications with an average bias ranging from 6%-6.5%. The ATT for QUANT is positive and significant for Tobin's Q and positive but not significant for total risk, with an average bias ranging from 4.2%-6.6%. Overall the propensity score results show strong support H1. The results in Table 10 also show that firms with CEOs that have degrees from top schools can benefit from the simultaneous reduction in firm risk and increase in firm value.

There are several advantages to using propensity score matching over OLS. The common support condition allows for the comparison of comparable firms. Also, matching is a non-parametric technique which avoids potential misspecification of the functional form of the conditional expectations needed to estimate treatment effects. Although the methods used in this study are semi-parametric since a logit model is used to estimate the propensity scores in the first stage. Another advantage of propensity score methods is that they do not impose restrictions on the heterogeneity of treatment effects.

Nevertheless, there are a few caveats to propensity score approaches. Both propensity score matching and regression models rely on selection on observables. In other words, both models are only as good as their covariates, X, and missing an important variable would result in omitted variable bias with either approach. Also, in the special case where the treatment effects are homogeneous, regression methods have lower variance.

1.7. Conclusion

This study examined the relationship between CEO ability and firm risk using various education credentials as proxies for ability. I found that various CEO credentials are related to firm risk in different ways. There is empirical support for CEOs with law degrees and CEOs with actuarial credentials being better than their peers at avoiding operational risk events. There is also evidence that CEOs with MBA degrees from market risk better than their peers.

The results are robust to various alternative specifications. Propensity score methods were proposed to estimate the time-invariant effects of CEO education on firm risk. Various propensity score estimators were used to ensure that the results are robust to endogenous matching. Overall the results suggest that the quality of CEO education is related to risk management ability. In addition there is evidence that firms with CEOs from top schools can benefit from a simultaneous risk reduction and increase in firm value. This highlights the importance of including measures of quality to capture ability heterogeneity. An implication of these findings is that studies which only use measures of education level (i.e., undergraduate vs. graduate) or type (i.e., MBA vs. LAW) as proxies for ability without controlling for education quality may be misspecified. Furthermore, the results of this study provide additional support of education as a good proxy for ability, which is otherwise an unobserved variable.

Table 3: CEO Education and the Balance of Return and Risk

Panel A: Firm Fixed-Effects Regressions

Dependent:	ret/σ_{ret}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.332								
	(0.590)								
Top_50_UG		-0.293							
		(0.519)							
Top_50_GRAD			-0.0224						
			(0.973)						
Top_50_MBA				1.669					
				(0.155)					
LAW					-0.260				
					(0.519)				
MBA						0.995			
						(0.161)			
ACTUARY							-0.698		
							(0.672)		
BUSINESS								0.286	
								(0.678)	
QUANT									-0.0502
									(0.930)
CPA	-0.653	-0.622	-0.602	-0.817	-0.607	-0.795			
	(0.274)	(0.276)	(0.320)	(0.157)	(0.300)	(0.185)			
INS_Cert	0.134	0.159	0.0963	-0.0416	0.0344	0.275			
	(0.802)	(0.751)	(0.837)	(0.930)	(0.948)	(0.547)			
ln(Assets)	0.800	0.826	0.843	0.782	0.828	0.785	0.808	0.784	0.815
	(0.140)	(0.132)	(0.120)	(0.145)	(0.125)	(0.139)	(0.120)	(0.128)	(0.127)
Leverage	-12.51***	-12.04***	-12.39***	-12.77***	-12.37***	-12.70***	-11.86***	-11.84***	-11.91***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
ln(TDC1)	-0.629	-0.603	-0.620	-0.614	-0.610	-0.626	-0.558	-0.537	-0.557
	(0.112)	(0.140)	(0.121)	(0.117)	(0.129)	(0.104)	(0.151)	(0.173)	(0.152)
CEO_AGE	0.00284	0.00457	0.00219	0.00596	0.00274	-0.00000804	0.00809	0.00660	0.00616
	(0.919)	(0.877)	(0.937)	(0.826)	(0.924)	(1.000)	(0.761)	(0.802)	(0.817)
Tenure	0.0152	0.0146	0.0135	0.0172	0.0146	0.0180	0.0184	0.0205	0.0198
	(0.509)	(0.501)	(0.555)	(0.438)	(0.505)	(0.433)	(0.423)	(0.403)	(0.393)
LONG_TAIL	0.00543	0.00473	0.00414	0.00294	0.00363	0.00542	0.00336	0.00398	0.00367
	(0.711)	(0.742)	(0.770)	(0.835)	(0.801)	(0.722)	(0.811)	(0.780)	(0.793)
N	361	361	361	361	361	361	361	361	361
adj. R^2	0.008	0.008	0.008	0.013	0.008	0.012	0.012	0.012	0.011

The dependent variable is the ratio of the annual geometric return, ret, to the 12-month return volatility (σ_{ret}). ln(Assets) is the natural log of firm assets. Leverage is the debt to assets ratio. ln(TDC1) is the natural logarithm total incentive compensation. p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 3 – Continued

Panel B: Median Regressions

Dependent:	ret/σ_{ret}									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRAD	0.108 (0.672)									
Top_50_UG		-0.0634 (0.821)								
Top_50_GRAD			-0.104 (0.703)							
Top_50_LAW				-0.505 (0.386)						
Top_50_MBA					-0.0502 (0.882)					
LAW						0.0326 (0.940)				
MBA							0.489* (0.077)			
ACTUARY								0.179 (0.744)		
BUSINESS									0.463* (0.065)	
QUANT										-0.421 (0.309)
CPA	-0.145 (0.674)	-0.155 (0.651)	-0.216 (0.527)	-0.274 (0.427)	-0.232 (0.494)	-0.238 (0.504)	-0.216 (0.533)			
INS_Cert	0.206 (0.607)	0.107 (0.792)	0.0665 (0.868)	0.110 (0.786)	0.122 (0.759)	0.113 (0.785)	0.510 (0.219)			
ln(Assets)	0.135 (0.239)	0.155 (0.186)	0.157 (0.182)	0.157 (0.201)	0.173 (0.134)	0.169 (0.169)	0.147 (0.212)	0.192* (0.096)	0.241** (0.036)	0.197* (0.100)
Leverage	-2.708** (0.035)	-2.644** (0.048)	-2.265* (0.091)	-2.382* (0.072)	-2.498* (0.058)	-2.622* (0.055)	-2.937** (0.025)	-3.217** (0.011)	-3.257*** (0.009)	-3.379*** (0.009)
ln(TDC1)	-0.0934 (0.615)	-0.0920 (0.627)	-0.111 (0.553)	-0.128 (0.499)	-0.131 (0.482)	-0.121 (0.533)	-0.0888 (0.640)	-0.104 (0.572)	-0.102 (0.576)	-0.103 (0.581)
CEO_AGE	0.0317* (0.059)	0.0343** (0.043)	0.0261 (0.121)	0.0268 (0.116)	0.0292* (0.080)	0.0286 (0.100)	0.0202 (0.235)	0.0328** (0.049)	0.0211 (0.198)	0.0318* (0.061)
Tenure	-0.0221* (0.074)	-0.0231* (0.071)	-0.0195 (0.120)	-0.0189 (0.159)	-0.0228* (0.072)	-0.0231* (0.098)	-0.0148 (0.246)	-0.0207* (0.096)	-0.0171 (0.164)	-0.0208 (0.102)
LONG_TAIL	-0.00191 (0.589)	-0.00175 (0.628)	-0.00117 (0.743)	-0.00191 (0.609)	-0.00192 (0.590)	-0.00163 (0.661)	-0.00409 (0.266)	-0.00208 (0.555)	-0.00158 (0.646)	-0.00230 (0.517)
N	361	361	361	361	361	361	361	361	361	361

p-values are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 4: CEO Education and Credit Risk

Panel A: Pooled Probit Regressions

Dependent:	Lower_Grade								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.149 (0.588)								
Top_50_UG		-0.787*** (0.004)							
Top_50_GRAD			-0.378 (0.182)						
Top_50_MBA				0.561** (0.028)					
LAW					3.543*** (0.000)				
MBA						-0.00358 (0.988)			
ACTUARY							-0.808* (0.061)		
BUSINESS								-0.0293 (0.900)	
QUANT									0.129 (0.699)
CPA	-0.391 (0.217)	-0.747** (0.018)	-0.517* (0.093)	-0.389 (0.194)	-0.407 (0.167)	-0.452 (0.135)			
INS_Cert	-0.285 (0.467)	-0.669* (0.088)	-0.483 (0.205)	-0.268 (0.475)	-0.292 (0.440)	-0.371 (0.355)			
ln(Assets)	-0.842*** (0.000)	-0.920*** (0.000)	-0.867*** (0.000)	-0.797*** (0.000)	-0.873*** (0.000)	-0.829*** (0.000)	-0.839*** (0.000)	-0.812*** (0.000)	-0.821*** (0.000)
ROA	-8.937 (0.101)	-8.272 (0.142)	-8.099 (0.140)	-8.873* (0.094)	-7.755 (0.149)	-8.784 (0.105)	-7.940 (0.118)	-6.751 (0.187)	-7.185 (0.170)
Leverage	2.796* (0.059)	4.372*** (0.008)	3.677** (0.030)	1.876 (0.243)	2.811* (0.060)	2.783* (0.063)	2.485* (0.082)	3.410** (0.017)	3.424** (0.013)
ret	0.864* (0.090)	0.872* (0.097)	0.815 (0.109)	0.862* (0.091)	0.722 (0.165)	0.857* (0.094)	0.849* (0.094)	0.786 (0.122)	0.795 (0.121)
ln(TDC1)	0.0726 (0.687)	0.0466 (0.799)	0.0709 (0.688)	0.0924 (0.613)	0.0522 (0.772)	0.0711 (0.690)	0.168 (0.339)	0.131 (0.453)	0.132 (0.448)
CEO_AGE	-0.0221 (0.196)	-0.0132 (0.431)	-0.0291* (0.100)	-0.0223 (0.193)	-0.0233 (0.170)	-0.0225 (0.195)	-0.0215 (0.205)	-0.0220 (0.176)	-0.0209 (0.210)
Tenure	-0.0661*** (0.000)	-0.0908*** (0.000)	-0.0796*** (0.000)	-0.0611*** (0.000)	-0.0644*** (0.000)	-0.0688*** (0.000)	-0.0691*** (0.000)	-0.0608*** (0.000)	-0.0603*** (0.000)
LONG_TAIL	0.0150*** (0.000)	0.0174*** (0.000)	0.0168*** (0.000)	0.0146*** (0.000)	0.0150*** (0.000)	0.0155*** (0.000)	0.0171*** (0.000)	0.0140*** (0.000)	0.0138*** (0.000)
N	202	202	202	202	202	202	202	202	202
pseudo R^2	0.342	0.360	0.346	0.350	0.368	0.341	0.347	0.332	0.333

The dependent variable is Lower_Grade, it is a dummy variable equal to 1 if the firm is rated below A-, and 0 otherwise. *ret* is the annual geometric return. ln(TDC1) is the natural logarithm of total incentive compensation. *p*-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 4 – Continued

Panel B: Average Marginal Effects for Probit Coefficients

Dependent:	Lower_Grade								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.038 (0.586)								
Top_50_UG		-0.194*** (0.003)							
Top_50_GRAD			-0.096 (0.176)						
Top_50_MBA				0.141** (0.023)					
LAW					0.867*** (0.000)				
MBA						-0.001 (0.988)			
ACTUARY							-0.205* (0.053)		
BUSINESS								-0.008 (0.900)	
QUANT									0.033 (0.700)
CPA	-0.099 (0.213)	-0.184** (0.015)	-0.130* (0.085)	-0.098 (0.188)	-0.100 (0.160)	-0.115 (0.129)			
INS_Cert	-0.072 (0.466)	-0.165* (0.084)	-0.122 (0.200)	-0.067 (0.474)	-0.071 (0.439)	-0.095 (0.355)			
ln(Assets)	-0.214*** (0.000)	-0.227*** (0.000)	-0.219*** (0.000)	-0.200*** (0.000)	-0.214*** (0.000)	-0.211*** (0.000)	-0.213*** (0.000)	-0.210*** (0.000)	-0.212*** (0.000)
ROA	-2.273* (0.094)	-2.037 (0.135)	-2.045 (0.134)	-2.231* (0.089)	-1.897 (0.144)	-2.237* (0.099)	-2.015 (0.112)	-1.743 (0.182)	-1.851 (0.167)
Leverage	0.711* (0.060)	1.076*** (0.007)	0.929** (0.027)	0.472 (0.247)	0.688* (0.060)	0.709* (0.064)	0.631* (0.083)	0.880** (0.016)	0.882** (0.011)
ret	0.220* (0.086)	0.215* (0.092)	0.206 (0.105)	0.217* (0.088)	0.177 (0.164)	0.218* (0.090)	0.215* (0.091)	0.203 (0.119)	0.205 (0.118)
ln(TDC1)	0.018 (0.686)	0.011 (0.799)	0.018 (0.688)	0.023 (0.611)	0.013 (0.771)	0.018 (0.689)	0.043 (0.332)	0.034 (0.450)	0.034 (0.445)
CEO_AGE	-0.006 (0.197)	-0.003 (0.431)	-0.007* (0.100)	-0.006 (0.193)	-0.006 (0.170)	-0.006 (0.194)	-0.005 (0.206)	-0.006 (0.176)	-0.005 (0.210)
Tenure	-0.017*** (0.000)	-0.022*** (0.000)	-0.020*** (0.000)	-0.015*** (0.000)	-0.016*** (0.000)	-0.018*** (0.000)	-0.018*** (0.000)	-0.016*** (0.000)	-0.016*** (0.000)
LONG_TAIL	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)

p-values based on delta-method standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 4 – Continued

Panel C: Firm Fixed-Effects Regressions for Distance to Default								
Dependent:	ln(Z)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GRAD	-0.549							
	(0.123)							
Top_50_UG		0.866**						
		(0.047)						
Top_50_GRAD			0.243					
			(0.256)					
LAW				0.580				
				(0.164)				
MBA					-0.679**			
					(0.014)			
ACTUARY						0.0826		
						(0.762)		
BUSINESS							-0.384**	
							(0.030)	
QUANT								-0.548
								(0.287)
CPA	-0.745**	-0.0854	-0.792**	-0.780**	-0.810***			
	(0.014)	(0.876)	(0.010)	(0.011)	(0.010)			
INS_Cert	0.0877	0.167	0.168	0.408	0.0834			
	(0.786)	(0.342)	(0.382)	(0.122)	(0.692)			
ln(Assets)	0.570***	0.548**	0.573***	0.655***	0.634***	0.456**	0.475**	0.443**
	(0.008)	(0.012)	(0.009)	(0.009)	(0.006)	(0.047)	(0.045)	(0.049)
Leverage	-4.438**	-4.822**	-4.552**	-4.791**	-4.975**	-3.195	-3.519	-3.260
	(0.032)	(0.023)	(0.030)	(0.026)	(0.026)	(0.200)	(0.179)	(0.193)
ret	1.044**	1.035**	1.047**	1.009**	1.029**	1.065**	1.078**	1.078**
	(0.031)	(0.033)	(0.030)	(0.033)	(0.031)	(0.033)	(0.030)	(0.032)
ln(TDC1)	-0.360**	-0.379**	-0.389**	-0.431**	-0.397**	-0.284*	-0.314*	-0.282*
	(0.030)	(0.024)	(0.023)	(0.016)	(0.016)	(0.066)	(0.057)	(0.058)
CEO_AGE	-0.00957	-0.00814	-0.0108	-0.0152	-0.0175	0.00562	0.00336	0.00815
	(0.555)	(0.621)	(0.507)	(0.363)	(0.365)	(0.753)	(0.843)	(0.612)
Tenure	0.0336**	0.0128	0.0345**	0.0327**	0.0407**	0.0252	0.0261	0.0226
	(0.024)	(0.542)	(0.026)	(0.033)	(0.020)	(0.139)	(0.119)	(0.153)
LONG_TAIL	-0.00864	-0.00679	-0.00724	-0.00691	-0.00747	-0.0108	-0.0112	-0.0112
	(0.203)	(0.276)	(0.247)	(0.253)	(0.250)	(0.171)	(0.164)	(0.159)
N	197	197	197	197	197	197	197	197
adj. R^2	0.118	0.117	0.107	0.117	0.116	0.086	0.091	0.093

The dependent variable is ln(Z) which is the natural logarithm of Z-score. p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 5: CEO Education and Operational Risk Frequency – Poisson Regressions

Dependent:	Operational_Freq									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRAD	0.689*									
	(0.094)									
Top_50_UG		-0.486								
		(0.269)								
Top_50_GRAD			-1.020**							
			(0.020)							
Top_50_LAW				-12.92***						
				(0.000)						
Top_50_MBA					-0.663					
					(0.280)					
LAW						-14.96***				
						(0.000)				
MBA							1.631***			
							(0.003)			
ACTUARY								-15.07***		
								(0.000)		
BUSINESS									1.279**	
									(0.021)	
QUANT										-1.975*
										(0.068)
CPA	-0.170	-0.496	-0.397	-0.408	-0.356	-0.358	-0.521			
	(0.825)	(0.519)	(0.606)	(0.600)	(0.648)	(0.661)	(0.587)			
INS_Cert	-0.299	-0.855	-0.903	-0.667	-0.718	-0.703	0.0880			
	(0.723)	(0.348)	(0.275)	(0.421)	(0.382)	(0.393)	(0.922)			
ln(Assets)	0.518***	0.472***	0.438***	0.470***	0.465***	0.474***	0.585***	0.485***	0.600***	0.551***
	(0.002)	(0.001)	(0.007)	(0.002)	(0.005)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)
ROA	4.861	4.085	6.731	5.953	5.426	5.169	6.113	6.477	8.198	15.04
	(0.594)	(0.660)	(0.499)	(0.544)	(0.582)	(0.612)	(0.551)	(0.520)	(0.450)	(0.251)
Leverage	-0.538	-0.685	0.496	-0.0505	0.133	-0.264	0.0232	-0.442	-0.160	1.702
	(0.825)	(0.779)	(0.846)	(0.984)	(0.959)	(0.911)	(0.993)	(0.852)	(0.952)	(0.571)
ln(TDC1)	0.456*	0.474*	0.408	0.413	0.391	0.457*	0.542**	0.468**	0.528**	0.387
	(0.087)	(0.068)	(0.156)	(0.111)	(0.184)	(0.090)	(0.026)	(0.048)	(0.024)	(0.121)
CEO_AGE	-0.0000254	0.00152	-0.00250	-0.00147	0.00370	0.00491	-0.0312	-0.000860	-0.0128	0.0000530
	(0.999)	(0.949)	(0.917)	(0.950)	(0.884)	(0.846)	(0.416)	(0.971)	(0.631)	(0.998)
Tenure	-0.0457**	-0.0547***	-0.0647***	-0.0481***	-0.0546***	-0.0253	-0.0393*	-0.0489***	-0.0293	-0.0441***
	(0.015)	(0.000)	(0.000)	(0.004)	(0.001)	(0.348)	(0.066)	(0.003)	(0.173)	(0.007)
LONG_TAIL	-0.00190	0.000861	0.00207	-0.000131	0.000437	-0.000789	0.000342	0.000614	-0.00207	0.000826
	(0.765)	(0.887)	(0.696)	(0.982)	(0.937)	(0.888)	(0.961)	(0.906)	(0.679)	(0.884)
N	411	411	411	411	411	411	411	411	411	411
pseudo R^2	0.181	0.175	0.191	0.171	0.174	0.187	0.240	0.183	0.206	0.193

The dependent variable is the yearly count of operational risk events (Operational_Freq). ln($TDC1$) is the logarithm of total incentive compensation. p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 6: CEO Education and Operational Risk Severity – Firm Fixed-Effects Panels

Dependent:	Operational_Loss								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	-0.0800								
	(0.691)								
Top_50_UG		-0.201							
		(0.305)							
Top_50_GRAD			-0.440						
			(0.186)						
Top_50_MBA				-0.0189					
				(0.868)					
LAW					-0.703**				
					(0.010)				
MBA						0.219			
						(0.204)			
ACTUARY							-0.146		
							(0.194)		
BUSINESS								-0.175	
								(0.185)	
QUANT									-0.0701
									(0.585)
CPA	-0.166	-0.205*	-0.0510	-0.175	-0.173	-0.0650			
	(0.169)	(0.070)	(0.793)	(0.187)	(0.192)	(0.421)			
INS_Cert	0.247*	0.255	0.314*	0.253*	0.117	-0.0425			
	(0.091)	(0.148)	(0.072)	(0.097)	(0.283)	(0.574)			
ln(Assets)	0.0265	0.0237	0.0740	0.0194	-0.00840	0.0912*	0.0147	0.0295	0.0237
	(0.701)	(0.754)	(0.356)	(0.770)	(0.898)	(0.089)	(0.836)	(0.690)	(0.736)
ROA	-0.142	-0.144	0.101	-0.164	-0.646	-0.0882	-0.170	0.185	-0.0805
	(0.901)	(0.898)	(0.926)	(0.886)	(0.580)	(0.919)	(0.884)	(0.878)	(0.944)
Leverage	0.153	0.257	0.303	0.117	0.0378	-0.271	0.246	0.318	0.233
	(0.768)	(0.641)	(0.597)	(0.820)	(0.937)	(0.394)	(0.631)	(0.548)	(0.655)
ln(TDC1)	0.102	0.110	0.107	0.0996	0.127	0.0694	0.105	0.0945	0.105
	(0.247)	(0.252)	(0.253)	(0.260)	(0.189)	(0.190)	(0.202)	(0.266)	(0.202)
CEO_AGE	0.00263	0.00396	-0.000561	0.00280	0.00330	-0.00433	0.00501	0.00451	0.00466
	(0.618)	(0.471)	(0.915)	(0.582)	(0.500)	(0.286)	(0.376)	(0.418)	(0.417)
Tenure	-0.0295**	-0.0283***	-0.0280**	-0.0291**	-0.0254***	-0.00545	-0.0252**	-0.0262**	-0.0248**
	(0.015)	(0.007)	(0.014)	(0.013)	(0.002)	(0.213)	(0.040)	(0.030)	(0.043)
LONG_TAIL	-0.00862	-0.00783	-0.00844	-0.00832	-0.00977	-0.00114	-0.00793	-0.00802	-0.00789
	(0.187)	(0.220)	(0.165)	(0.207)	(0.168)	(0.310)	(0.212)	(0.210)	(0.202)
N	411	411	411	411	411	411	411	411	411
adj. R^2	0.032	0.038	0.045	0.032	0.046	0.043	0.029	0.031	0.029

The dependent variable is the operational loss amount in millions of dollars (Operational_Loss). p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 7: CEO Education Using Rankings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent:	ret/σ_{ret}	Operational_Freq	Lower_Grade	ln(Z)	ret/σ_{ret}	Operational_Freq	Lower_Grade	ln(Z)
Model	OLS	Poisson	Probit	OLS	OLS	Poisson	Probit	OLS
USN_UG_Rank	0.000187	0.0119**	0.00436	-0.0332*				
	(0.982)	(0.015)	(0.504)	(0.059)				
USN_GRAD_Rank					0.00785	0.0291***	0.0105	-0.0162**
					(0.194)	(0.006)	(0.640)	(0.040)
ln(Assets)	-0.434	0.753**	-1.399***	0.794**	0.180	0.845*	-2.308***	0.630
	(0.603)	(0.031)	(0.000)	(0.044)	(0.854)	(0.074)	(0.001)	(0.144)
Leverage	-9.908*	-1.015	31.32***	-8.915***	-8.117	-7.578	43.87***	2.964
	(0.073)	(0.809)	(0.000)	(0.002)	(0.137)	(0.289)	(0.003)	(0.370)
ln(TDC1)	-0.428	0.603*	-0.101	-1.082***	-0.407	0.365	-1.122	-0.640***
	(0.339)	(0.088)	(0.792)	(0.000)	(0.245)	(0.468)	(0.499)	(0.010)
CEO_AGE	0.0146	-0.0201	0.308***	-0.0197	0.0446	-0.0811	0.151	0.0248
	(0.692)	(0.564)	(0.001)	(0.197)	(0.550)	(0.265)	(0.274)	(0.629)
Tenure	-0.0237	-0.0468***	-0.240***	-0.210	0.000919	-0.0731**	-0.294**	-0.0593
	(0.643)	(0.004)	(0.000)	(0.116)	(0.990)	(0.049)	(0.047)	(0.411)
LONG_TAIL	0.0477	-0.00577	0.157***	-0.0290	0.0217	0.0129	0.136	-0.00934
	(0.399)	(0.349)	(0.000)	(0.519)	(0.601)	(0.206)	(0.190)	(0.472)
ROA		19.89	-23.50	12.17		-0.819	-14.64	2.309
		(0.379)	(0.428)	(0.181)		(0.946)	(0.641)	(0.800)
ret			1.755*	0.512			3.902**	1.947**
			(0.073)	(0.329)			(0.032)	(0.011)
N	197	215	96	91	173	189	90	82

The dependent variables are the ROA to 12-month return volatility ratio (ROA/σ_{ret}), operational risk frequency, (Operational_Freq), and Lower_Grade which is a dummy variable equal to 1 if the S&P ranking of the firm is below A-, and 0 otherwise. OLS regressions are estimated in (1) and (4). Poisson regressions are estimated in (2) and (5), and Probit regressions are estimated in (3) and (6). p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 8: CEO Education and Operational Risk Frequency – ZIP Regressions

Dependent:	Operational_Freq			
	(1)	(2)	(3)	(4)
Top_50_GRAD	-1.947***			
	(0.001)			
LAW		-22.28***		
		(0.000)		
BUSINESS			1.278**	
			(0.033)	
QUANT				-2.225**
				(0.029)
CPA	-0.507	-0.133		
	(0.574)	(0.890)		
INS_Cert	-1.652	-1.253		
	(0.162)	(0.293)		
ln(Assets)	0.105	0.366**	0.435**	0.265
	(0.589)	(0.031)	(0.023)	(0.101)
ROA	-4.959	-6.163	-0.0745	8.444
	(0.718)	(0.613)	(0.996)	(0.584)
Leverage	-3.309	-4.590	-2.525	0.126
	(0.337)	(0.166)	(0.372)	(0.968)
ln(TDC1)	0.910***	0.657**	0.533**	0.571**
	(0.004)	(0.022)	(0.049)	(0.033)
CEO_AGE	-0.0628*	-0.0246	-0.0658	-0.0615*
	(0.072)	(0.389)	(0.103)	(0.060)
Tenure	-0.0378*	0.0227	0.00239	-0.0115
	(0.064)	(0.486)	(0.935)	(0.546)
LONG_TAIL	0.00869	-0.00119	-0.00509	-0.00109
	(0.191)	(0.855)	(0.387)	(0.865)
N	291	291	291	291
Vuong Statistic	2.39***	2.25***	1.92**	2.21**

The dependent variable is the yearly count of operational risk events (Operational_Freq). σ_{ret} is the 12-month return volatility. Firm_Age is the age of the firm. p-values are reported in parentheses. High positive values of the Vuong statistic indicate rejection of the standard Poisson regression in favor of the ZIP model. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 9: **CEO Education and Risk – Propensity Score Matching**

Panel A: Nearest Neighbor Matching (2 Neighbors)

		ATT				
		Treat.	Control	**Diff.**	Bias	N
GRAD	σ_{ret}	0.74	0.073	0.001	12.70%	335
	ln(Z)	3.893	4.383	-0.489*	6.90%	175
	Operational_Freq	0.193	0.086	0.107*	11.60%	341
Top_50_UG	σ_{ret}	0.068	0.077	-0.009	8.40%	335
	ln(Z)	4.269	3.826	0.442	5.00%	175
	Operational_Freq	0.157	0.208	-0.051	4.80%	341
Top_50_GRAD	σ_{ret}	0.070	0.081	-0.011	9.20%	335
	ln(Z)	3.879	4.210	-0.331	23.10%	175
	Operational_Freq	0.118	0.125	-0.007	15.70%	341
Top_50_MBA	σ_{ret}	0.065	0.092	-0.027***	14.40%	335
	ln(Z)	4.068	4.077	-0.009	21.30%	175
	Operational_Freq	0.161	0.081	0.081	18.50%	341
LAW	σ_{ret}	0.083	0.069	0.014	10.90%	335
	ln(Z)	4.413	3.855	0.558	15.20%	175
	Operational_Freq	0.069	0.207	-0.138	11.20%	341
MBA	σ_{ret}	0.0651	0.0725	-0.007*	9.30%	335
	ln(Z)	3.950	4.433	-0.482	9.60%	175
	Operational_Freq	0.278	0.044	0.233***	12.90%	341
CPA	σ_{ret}	0.076	0.081	-0.005	10.90%	335
	ln(Z)	4.415	4.412	0.003	50.70%	175
	Operational_Freq	0.085	0.043	0.043	8.30%	341
INS_Cert	σ_{ret}	0.063	0.071	-0.007	10.40%	335
	ln(Z)	4.447	4.949	-0.502	3.90%	175
	Operational_Freq	0.020	0.049	-0.029	6.00%	341
ACTUARY	σ_{ret}	0.072	0.060	0.012**	8.30%	335
	ln(Z)	3.993	4.589	-0.596*	7.00%	175
	Operational_Freq	0	0.192	-0.192	9.70%	341
BUSINESS	σ_{ret}	0.070	0.069	0.002	17.00%	335
	ln(Z)	3.774	4.796	-1.022***	5.70%	175
	Operational_Freq	0.160	0.021	0.138***	14.90%	341
QUANT	σ_{ret}	0.084	0.066	0.018*	49.80%	335
	ln(Z)	3.151	3.232	-0.081	85.60%	175
	Operational_Freq	0.059	0.118	-0.059	52.70%	341

The propensity score is estimated using a logit model of education credentials on: firm size (ln(Assets)), leverage (Leverage), firm age (Firm_Age), and total incentive compensation (ln($TDC1$)). The main variable of interest is ATT for **Diff.** which is the difference between the treatment and control groups. Bias is the estimated average selection bias. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 9 – Continued

Panel B: Radius Matching ($\rho = .05$)

		ATT				
		Treat	Control	**Diff.**	Bias	N
GRAD	σ_{ret}	0.074	0.075	-0.001	10.30%	335
	ln(Z)	3.893	4.188	-0.295	17.20%	175
	Operational_Freq	0.194	0.066	0.129**	10.70%	341
Top_50_UG	σ_{ret}	0.068	0.079	-0.011**	3.40%	335
	ln(Z)	4.269	3.720	0.549*	0.60%	175
	Operational_Freq	0.157	0.190	-0.032	3.20%	341
Top_50_GRAD	σ_{ret}	0.070	0.081	-0.011**	9.00%	335
	ln(Z)	3.879	4.197	-0.317	17.20%	175
	Operational_Freq	0.118	0.108	0.010	7.60%	341
Top_50_MBA	σ_{ret}	0.065	0.093	-0.028***	8.00%	335
	ln(Z)	4.068	4.194	-0.126	27.70%	175
	Operational_Freq	0.161	0.093	0.068	7.00%	341
LAW	σ_{ret}	0.083	0.073	0.010	16.30%	335
	ln(Z)	4.413	3.579	0.833***	4.80%	175
	Operational_Freq	0.069	0.142	-0.073	16.30%	341
MBA	σ_{ret}	0.065	0.073	-0.008*	6.30%	335
	ln(Z)	3.950	4.320	-0.370	3.70%	175
	Operational_Freq	0.278	0.061	0.216***	6.30%	341
CPA	σ_{ret}	0.073	0.076	-0.003	4.00%	335
	ln(Z)	4.415	4.301	0.114	39.70%	175
	Operational_Freq	0.0851	0.0573	0.0278	5.00%	341
INS_Cert	σ_{ret}	0.063	0.072	-0.009	3.40%	335
	ln(Z)	4.447	4.454	-0.007	10.20%	175
	Operational_Freq	0.020	0.095	-0.075	7.30%	341
ACTUARY	σ_{ret}	0.072	0.066	0.006	6.20%	335
	ln(Z)	3.993	4.643	-0.649**	6.20%	175
	Operational_Freq	0.000	0.064	-0.064	5.10%	341
BUSINESS	σ_{ret}	0.070	0.073	-0.003	9.60%	335
	ln(Z)	3.774	4.580	-0.807***	8.50%	175
	Operational_Freq	0.160	0.050	0.109**	12.80%	341
QUANT	σ_{ret}	0.078	0.068	0.010	8.00%	335
	ln(Z)	3.151	3.345	-0.194	16.60%	175
	Operational_Freq	0.065	0.116	-0.050	11.60%	341

The propensity score is estimated using a logit model of education credentials on: firm size (ln(Assets)), leverage (Leverage), firm age (Firm_Age), and total incentive compensation (ln($TDC1$)). The main variable of interest is ATT for **Diff.** which is the difference between the treatment and control groups. Bias is the estimated average selection bias. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 9 – Continued

Panel C: Kernel Matching (Epanechnikov Kernel)						
		ATT				
		Treat	Control	**Diff.**	Bias	N
GRAD	σ_{ret}	0.074	0.075	-0.001	10%	335
	ln(Z)	3.893	4.200	-0.307	15.9%	175
	Operational_Freq	0.193	0.065	0.128**	10.4%	341
Top_50_UG	σ_{ret}	0.068	0.079	-0.011**	3.1%	335
	ln(Z)	4.269	3.716	0.553*	0.8%	175
	Operational_Freq	0.157	0.190	-0.033	3.2%	341
Top_50_GRAD	σ_{ret}	0.070	0.082	-0.011**	8.9%	335
	ln(Z)	3.879	4.196	-0.317	15.7%	175
	Operational_Freq	0.118	0.109	0.008	8.3%	341
Top_50_MBA	σ_{ret}	0.065	0.092	-0.027***	6.8%	335
	ln(Z)	4.068	4.207	-0.138	23.3%	175
	Operational_Freq	0.161	0.095	0.066	6.5%	341
LAW	σ_{ret}	0.083	0.073	0.010	15.1%	335
	ln(Z)	4.413	3.571	0.841***	4.3%	175
	Operational_Freq	0.069	0.145	-0.076	14.4%	341
MBA	σ_{ret}	0.065	0.073	-0.008*	6.1%	335
	ln(Z)	3.950	4.301	-0.351	3.8%	175
	Operational_Freq	0.278	0.063	0.215***	6.3%	341
CPA	σ_{ret}	0.073	0.076	-0.003	4%	335
	ln(Z)	4.415	4.312	0.102	39.3%	175
	Operational_Freq	0.085	0.056	0.029	5.1%	341
INS_Cert	σ_{ret}	0.063	0.072	-0.008	3.2%	335
	ln(Z)	4.447	4.503	-0.056	9.1%	175
	Operational_Freq	0.020	0.095	-0.075	7%	341
ACTUARY	σ_{ret}	0.072	0.066	0.006	5.1%	335
	ln(Z)	3.993	4.649	-0.656**	7.4%	175
	Operational_Freq	0	0.070	-0.070	5%	341
BUSINESS	σ_{ret}	0.070	0.076	-0.003	9.8%	335
	ln(Z)	3.774	4.573	-0.800***	8.2%	175
	Operational_Freq	0.160	0.050	0.109**	13.2%	341
QUANT	σ_{ret}	0.084	0.071	0.013	14.9%	335
	ln(Z)	3.151	3.334	-0.183	15.9%	175
	Operational_Freq	0.060	0.105	-0.045	18.6%	341

The propensity score is estimated using a logit model of education credentials on: firm size (ln(Assets)), leverage (Leverage), firm age (Firm_Age), and total incentive compensation (ln($TDC1$)). The main variable of interest is ATT for **Diff.** which is the difference between the treatment and control groups. Bias is the estimated average selection bias. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 10: Matching with Simultaneous Outcomes – Tobin's Q and Total Risk

		ATT NN, N=2		ATT Radius, $\rho = .05$		ATT Kernel		
		Diff.	Bias	**Diff.**	Bias	**Diff.**	Bias	N
GRAD	Q	-0.011	9.9%	0.009	9.4%	0.010	9.8%	308
	σ_{ret}	-0.003		-0.002		-0.002		
Top_50_UG	Q	0.056**	10.6%	0.054**	3.7%	0.055**	3.3%	308
	σ_{ret}	-0.013**		-0.009*		-0.009*		
Top_50_GRAD	Q	0.043	8.9%	0.029	3.6%	0.041	24.1%	308
	σ_{ret}	-0.008		-0.008*		-0.002		
Top_50_MBA	Q	-0.005	4%	-0.030	15.1%	-0.030	13.7%	308
	σ_{ret}	-0.018*		-0.018***		-0.019***		
LAW	Q	0.061*	9.4%	0.050	14.8%	0.050	14%	308
	σ_{ret}	0.019**		0.011		0.011		
MBA	Q	0.022	4.3%	0.005	1.7%	0.004	1.7%	308
	σ_{ret}	-0.010*		-0.006		-0.006		
CPA	Q	-0.053*	6.5%	-0.051**	6%	-0.052**	6.2%	308
	σ_{ret}	-0.001		-0.001		-0.0002		
INS_Cert	Q	0.014	14.1%	-0.0003	8.9%	0.002	8.9%	308
	σ_{ret}	-0.001		-0.005		-0.005		
ACTUARY	Q	0.008	26.6%	0.009	7%	0.009	5.6%	308
	σ_{ret}	0.003		0.006		0.006		
BUSINESS	Q	-0.040	6.2%	-0.035	9.1%	-0.035	9%	308
	σ_{ret}	-0.005		-0.001		-0.002		
QUANT	Q	0.098**	6.5%	0.098**	6.6%	0.092*	4.2%	308
	σ_{ret}	0.019		0.018		0.020		

Tobin's Q (Q) and total risk (σ_{ret}) are included as simultaneous outcomes in the propensity score model. The propensity score is estimated using a logit model of education credentials on: firm size (ln(Assets)), leverage (Leverage), firm age (Firm_Age), and total incentive compensation (ln($TDC1$)). The main variable of interest is ATT for **Diff.** which is the difference between the treatment and control groups. ATT NN, $N = 2$, denotes the average treatment effect on the treated via nearest neighbor matching with 2 neighbors. ATT Radius, denotes the average treatment effect on the treated via radius matching with a caliper of .05. ATT Kernel denotes the average treatment effect on the treated via kernel matching with the Epanechnikov kernel. Bias is the estimated average selection bias. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

CHAPTER 2

INSTITUTIONAL SHAREHOLDER OWNERSHIP AND FIRM RISK TAKING

2.1. Introduction

Stakeholder monitoring is an important feature of corporate governance. Monitoring by large institutional investors and institutional block holders can help reduce agency problems between managers and stakeholders. This is especially true in the U.S. where institutional investors are the majority owners for most large companies. These investors can exercise their voting rights to incentivize managers to act in the best interests of the shareholders.

However, there are disagreements on the costs and benefits of institutional shareholder monitoring. On the upside, there is evidence of positive impact of institutional ownership on firm performance (Cornett et al., 2007). While, the downside is that block holders may be maximizing their wealth at the expense of other investors (Shleifer and Vishny, 1997). There is even less that is known about the effects of institutional ownership on firm risk taking. Few studies examine the effect of institutional shareholder ownership on firm risk (e.g., Wright et al., 1996; Cheng et al., 2011). This study extends the literature on institutional ownership to analyze the effect of large shareholders on firm risk taking.

In particular, I examine the effect of institutional ownership on market risk and credit risk. Using different risk measures allows me to test both the prudent-man law and the large institutional ownership hypotheses. Another advantage of using multiple risk measures is that the results will not driven by a specific risk measure or measurement error. Furthermore, I investigate the situation when institutional shareholders have majority control. I find support for both the prudent-man law and the large institutional ownership hypotheses.

The remainder of the paper is organized as follows. The literature review and the hypothesis development is presented in Section 2.2. The data, variable selection, and methodology is described in Section 2.3. The results and robustness checks are presented in Section 2.4. Section 2.5 concludes.

2.2. Literature Review and Hypothesis Development

2.2.1. Institutional Ownership, Shareholder Wealth and Firm Value

There is theoretical and empirical evidence on the benefits of large shareholder monitoring of managers. Fama and Jensen (1983) posit that firms with block shareholding should have lower agency costs and superior performance relative to firms with fragmented ownership. Shleifer and Vishny (1986) argue that shareholders which own a greater proportion of shares in a firm have better monitoring incentives. They show that an increase in the proportion of shares held by the institutional owner would decrease the takeover premium and increase market value of the firm.

Agrawal and Mandelker (1990) provide empirical support for the findings in Shleifer and Vishny (1986). Specifically, they find a positive relationship between changes in the wealth of shareholders around announcements of adopt anti-takeover charter amendments (ATCAs) proposals and the proportion of equity owned by institutions. Demiralp et al. (2011) provide evidence that seasoned equity offering announcements are positively related to total and active institutional ownership levels and concentration.

Konijn et al. (2011) find that ownership concentration is positively related with Tobin's Q. Elyasiani and Jia (2010) show that there is a positive relationship between institutional ownership stability and firm performance. In addition, Burns et al. (2010) show that concentrated ownership induces greater monitoring and mitigates the incentives for firms to misreport.

However, Burkart et al. (1997) argue that monitoring and ownership concentration may conflict with performance based incentive schemes. Similarly, Claessens et al. (2002) find that increases in control rights by the largest shareholder are followed by declines in firm value. Maury and Pajuste (2005) find that firm value increases when voting power is distributed more equally among shareholders. While Cornett et al. (2007) provide evidence that the percent of institutional stock ownership is positively related to operating cash-flow returns, although this relationship only holds for investors that have no business relation with the firm. In contrast, Thomsen et al. (2006) find no effect of blockholder ownership on firm value in the US and UK.

2.2.2. Institutional Ownership and Risk Taking

There have been few prior studies that examined the relationship between institutional ownership and risk taking. Using the standard deviation of analyst's forecasts as a risk measure, Wright et al. (1996) find that institutional ownership positively influences corporate risk taking for firms with growth opportunities. In addition, they highlight the importance of further research on institutional ownership and corporate risk taking. Cheng et al. (2011) examine institutional ownership stability and risk taking in the life-health insurance industry. They find that stable ownership is associated with lower total risk of life-health insurers, and that large institutional owners do not raise the riskiness of firms. Similarly, Eling and Marek (2013) find that the number of blockholders is negatively associated with firm risk taking in European insurance companies.

2.2.3. Hypothesis Development

I consider two hypotheses proposed in the literature, as in Cheng et al. (2011): (1) the prudent-man law hypothesis, and (2) the large shareholder hypothesis. The prudent-man law hypothesis is based on the fact that institutional portfolio managers have fiduciary responsibility to their clients for making sound investments. By law, investments by institutions are required to be individually prudent, so total risk has to be considered as a cross-sectional determinant of institutional ownership patterns (Badrinath et al., 1989). In order to protect themselves from potential shareholder litigation, institutional managers tend to tilt their portfolios toward high quality stocks, which can be defended as prudent investments in court (Badrinath et al., 1989; Del Guercio, 1996; Cheng et al., 2011).

Badrinath et al. (1989) find a positive relationship between the level of institutional ownership and the quality of a firm's S&P rankings. Del Guercio (1996) also find evidence of portfolio tilting towards high quality stocks for bank managers. Elyasiani and Jia (2010) also find a negative relationship between institutional ownership stability and total risk in the life-health insurance industry. Based on this evidence, I expect that institutional ownership percentage with be negatively related to firm risk.

The large shareholder hypothesis can be stated as follows: ownership of firms by institutional investors holding a large proportion of the company in a steady manner is associated with higher, rather than lower risk (Cheng et al., 2011). Shareholders may have an incentive to increase the value of their investment by increasing firm risk (Eling and Marek, 2013). Large institutional investors would have the biggest incentives to increase firm value by forcing the firm to adopt risky strategies (Shleifer and Vishny, 1986; Wright et al., 1996; Cheng et al., 2011). However, when the wealth of the large shareholders is concentrated, they have incentives to limit firm risk in order to prevent a great loss to their portfolio at a given point in time (Cheng et al., 2011).

Cheng et al. (2011) find that large institutional owners, such as blockholders do not increase firm risk. While Eling and Marek (2013) show that more blockholders are associated with lower risk taking. Based on these findings I expect that dispersed ownership by large institutional investors to be negatively related to firm risk. Although Cheng et al. (2011) and Eling and Marek (2013) find no support for the large shareholder hypothesis, the relationship between ownership concentration and firm risk is still ambiguous. Furthermore, Cheng et al. (2011) point out that the net effect of large institutional investors is indeterminate, and they let the data determine whether to accept or reject the large institutional shareholder hypothesis.

2.3. Data and Methodology

The firm level accounting and return data comes from Compustat and CRSP. Institutional shareholder ownership data comes from the Thomson Reuters 13F database. This data comes from the Securities and Exchange Commission (SEC) 13F filings. The SEC requires institutional investment managers located in the U.S. and exercising discretion over $100 million or more in Section 13(f) securities to report their holdings on Form 13F. Securities listed in form 13(f) generally include securities that trade on an exchange, and include options[1].

The data was screened for outliers in several ways. Observations with negative net income, and negative shareholders equity were dropped. Additionally, institutional ownership variables that had a ratio to total shares outstanding of more than one were dropped. Following the literature, I also excluded financial institutions (SIC 6000-6999) and regulated utilities (SIC 4900-4999) due to their unique asset composition, high leverage and stricter government regulation (e.g., Claessens et al., 2002; Elyasiani and Jia, 2010). After merging the Thomson Reuters 13F data with the CRSP, Compustat, and screening for outliers, the sample yielded 9,745 firm-year observations from 1992-2013 in an unbalanced panel.

[1]For the current list of 13(f) securities see: http://www.sec.gov/divisions/investment/13flists.htm

2.3.1. Measures of Institutional Ownership

Several institutional ownership measures are used based on the literature (e.g., Parrino et al., 2003; Burns et al., 2010). Blockholders are shareholders that own at least 5% of a company's total shares outstanding. Block ownership is measured by the ratio of the total number of shares held by blockholders to the total number of shares outstanding (BLOCK_OWN). The ratio of shares owned by institutional investors to the total number of shares outstanding is measured by (INSTOWN).

It is also important to measure institutional ownership concentration, because institutional investors would be expected to have more influence when they are large shareholders (e.g., Shleifer and Vishny, 1986; Hartzell and Starks, 2003). Various ownership concentration measures are used. The ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding (top5), and the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding (top10), capture ownership concentration to some extent. The Herfindahl–Hirschman Index (HHI) based on institutional ownership is used as the primary ownership concentration measure (INSTOWN_HHI).

2.3.2. Risk Measures

Three risk measures are used to control for the effects of different types of risks. The 12-month return volatility (σ_{ret}) is used as a measure of market risk or total risk. The Altman Z-Score (Z_SCORE) with updated Altman (2000) coefficients is used as a measure of distance-to-default. The Z_SCORE variable is winsorised at the 1% and 99% percentiles in order for estimation using Z_SCORE to be robust to outliers.

Also, an ordinal variable is constructed based on firm S&P Quality Rankings (SPQ), which is used as an alternate measure to the distance-to-default measure.

2.3.3. Control Variables

The natural logarithm of firm assets (ln(ASSETS)) is used to control for firm size (e.g., Claessens et al., 2002; Cheng et al., 2011). The debt to assets ratio (LEVERAGE) is also computed as in Bushee (2001). Industry adjusted return on assets (IND_ROA) is constructed by subtracting the industry median ROA from the firm's ROA. This allows for a meaningful measure of firm performance at that can be used across industries.

2.3.4. Descriptive Statistics

The descriptive statistics are presented in Table 11. The mean leverage, LEVERAGE, is 0.471, which indicates that most firms in the sample are largely equity financed. The mean industry-adjusted ROA, IND_ROA, is 0.086, which means that on average the firms in the sample outperform the median firm in their industry. The mean Z_SCORE is 2.714, with a standard deviation of 1.625, which suggests that there is a lot of variability in the distance to default in the sample. The average institutional ownership as a ratio of total shares outstanding, INSTOWN, is 43.5%, which suggests that institutional investors as a group have large ownership stakes across firms. The mean institutional ownership concentration, as given by the Herfindahl-Hirschman Index (HHI), INSTOWN_HHI, is 0.221, which implies that on average ownership is dispersed among various stakeholders.

Table 11: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Firm Characteristics					
ln(ASSETS)	8709	5.542	2.180	0.000	12.627
LEVERAGE	8688	0.471	0.220	0.000	1
IND_ROA	8624	0.086	0.283	-0.097	14.293
Risk Measures					
σ_{ret}	2630	0.146	0.128	0.001	2.746
Z_SCORE	7780	2.714	1.625	-1.628	9.129
SPQ	4648	1.827	0.599	1	3
Institutional Ownership Measures					
top5	9745	0.242	0.123	0.000	0.998
top10	9745	0.309	0.155	0.000	0.998
BLOCK_OWN	9745	0.176	0.130	0.000	0.998
INSTOWN_HHI	9745	0.221	0.236	0.019	1.000
INSTOWN	9745	0.435	0.257	0.016	0.999

ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. σ_{ret} is the 12-month return volatility. Z_SCORE is the Altman Z-Score with updated Altman (2000) coefficients. SPQ is constructed based on firm S&P Quality Rankings where quality is increasing from 1 to 3 (lowest ranked to highest ranked). top5 is the ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding. top10 is the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding. BLOCK_OWN is the ratio of the total number of shares held by blockholders to the total number of shares outstanding. INSTOWN_HHI is the Herfindahl–Hirschman Index (HHI) of institutional ownership concentration. INSTOWN is the ratio of shares owned by institutional investors to the total number of shares outstanding.

2.3.5. Empirical Models

2.3.5.1. Institutional Ownership and Market Risk

In order to test the large shareholder hypotheses we need to estimate the effect of institutional ownership on market risk. The 12-month return volatility (σ_{ret}) is used as a measure of market risk or total risk of the firm. Using this measure allows me to estimate fixed-effects panels of the form:

$$\begin{aligned}(\sigma_{ret})_{it} &= \alpha_i + \beta_1 \text{Institutional\_Ownership}_{it} + \beta_2 \ln(\text{ASSETS})_{it} + \beta_3 \text{LEVERAGE}_{it} \\ &+ \beta_4 \text{IND\_ROA}_{it} + \varepsilon_{it}, \qquad (2.1)\end{aligned}$$

where α_i denote firm fixed-effects, Institutional_Ownership takes the values of top5, top10, BLOCK_OWN, INSTOWN_HHI, and INSTOWN variables, and ε_{it} denotes heteroskedasticity corrected standard errors.

2.3.5.2. Institutional Ownership and Credit Risk

One way to model credit risk is by using a distance-to-default measure. The Altman Z-Score provides a distance-to-default measure that can be constructed from firm financial statements. As the original Altman Z-Score measure is out-dated, I use the revised Z-Score measure as in Altman (2000):

$$\text{Z\_SCORE} = 0.717(X_1) + 0.847(X_2) + 3.107(X_3) + 0.420(X_4) + 0.998(X_5), \qquad (2.2)$$

where X_1 is working capital to total assets, X_2 is retained earnings to total assets, X_3 is earnings before interest and taxes to total assets, X_4 market value of equity to book value of total liabilities, and X_5 is sales to total assets. Altman (2000) recommends substituting book values of equity for the market value of equity in X_4. This is the approach followed in this study. The higher the Z_SCORE value, the higher the distance-to-default, and the lower the default probability. Similarly, lower values of Z_SCORE indicate a shorter distance-to-default, and a higher default probability.

Using the Z_SCORE measure allows us to estimate the effect of institutional ownership on credit risk with the following model:

$$\begin{aligned} \text{Z\_SCORE}_{it} &= \alpha_i + \beta_1 \text{Institutional\_Ownership}_{it} + \beta_2 \ln(\text{ASSETS})_{it} + \beta_3 \text{LEVERAGE}_{it} \\ &+ \beta_4 \text{IND\_ROA}_{it} + \eta_{it}. \end{aligned} \tag{2.3}$$

An alternative way to model credit risk is by using measures of firm credit quality as determined by various credit rating agencies. The downside to using these measures is that the methodology is not transparent and the ratings are usually stable over time. This is in contrast to the Z_SCORE measure which is transparent and has more time variation. However, the advantage of using credit ratings is that they are widely used by institutional investors as institutional shareholders have to make sure that their investments are investment grade securities in order to avoid potential litigation.

Following Badrinath et al. (1989) and Del Guercio (1996), I use Standard and Poor's (S&P) Earnings and Dividend rankings, also known as Quality Rankings. These rankings measure long-term growth and stability of a company's earnings and dividends. There is evidence that fundamental risk is lower in portfolios of stocks with high quality rankings (Kallu and Tortoriello, 2012). In addition, portfolios of stocks with high quality rankings provided investors downside protection as these stocks significantly outperformed both the S&P 500 index and portfolios with low quality rankings over the 1987-2010 period in times of earnings deceleration, credit risk, and investor uncertainty (Kallu and Tortoriello, 2012).

The distribution of S&P Quality Rankings are given in Table 14. The sample consists of 4,648 firm-year observations with S&P quality ratings. Of these observations, 10.8% are rated 'A−' to 'A+', 61.15% are rated 'B−' to 'B', and 28.06% are ranked 'C' and below. Using the S&P Rankings allows me to construct a discrete variable SPQ, which ranges from 1 to 3, where 1 reflects the lowest ranked firms and 3 reflects the highest rated firms. The variable is constructed in the following way: 1) 3 includes high quality investments ('A−' to 'A+'), 2) 2 includes average investments ('B−' to 'B+'), and 3) 1 includes investments below 'B−'.

Using the SPQ variable allows me to estimate ordered-probit models of institutional ownership and credit risk. Let y^*_{it} be the unobserved firm earnings and dividend stability. In order to control for the effect of institutional investors endogenously selecting into firms with certain S&P Quality Rankings, I lag institutional ownership and firm characteristics variables by one period (denoted by the $t-1$ subscript). Then the model can be written as follows:

$$\begin{aligned} y^*_{it} &= \alpha_i + \beta_1 \text{Institutional\_Ownership}_{it-1} + \beta_2 \ln(\text{ASSETS})_{it-1} + \beta_3 \text{LEVERAGE}_{it-1} \\ &+ \beta_4 \text{IND\_ROA}_{it-1} + u_{it}, \end{aligned} \tag{2.4}$$

where there is a set of thresholds $\alpha_1 < \alpha_2$ that are additional unknown parameters of the model which satisfy:

$$\begin{aligned} P(\mathrm{SPQ}_{it} = 1) &= P(y^*_{it} \leq \alpha_1) \\ P(\mathrm{SPQ}_{it} = 2) &= P(\alpha_1 < y^*_{it} \leq \alpha_2) \\ P(\mathrm{SPQ}_{it} = 3) &= P(y^*_{it} > \alpha_2). \end{aligned} \tag{2.5}$$

2.3.5.3. When Institutional Investors Have Majority Control

When institutional investors control more than 50% of shares in a firm they have better monitoring incentives (Shleifer and Vishny, 1986). Through increased control institutional shareholders can have a stronger impact on major corporate decisions such as mergers and acquisitions (M&As), seasoned equity offerings (SEOs) as well as corporate governance mechanisms such as anti-takeover provisions (Shleifer and Vishny, 1986; Agrawal and Mandelker, 1990; Demiralp et al., 2011). Furthermore, these monitoring effects can be reflected in firm risk, because when the wealth of the large shareholders is concentrated, they have incentives to limit firm risk (Cheng et al., 2011).

The natural 50% ownership threshold can be exploited to estimate the effect of institutional ownership on risk taking via a quasi-experimental design. I construct dummy variables top5_50, top10_50, block50, and inst50 which are equal to 1 if there the ownership level is 50% or more for top5 ownership, top10 ownership, block ownership, and institutional ownership percentage levels respectively, and 0 otherwise. I also construct the variable insthhi50 which is equal to 1 if there is more than 50%

ownership concentration, and 0 otherwise. This allows me to have treatment groups of greater than 50% ownership or concentration and control groups with ownership or concentration levels below 50%.

Let $T_i \in \{0, 1\}$ be the treatment effect dummy variable denoting ownership level above or below the 50% threshold. Also let R_{i0} and R_{i1} denote the firm risk outcomes without treatment and with treatment respectively. In the context of this study R_{i0} is the risk of firm i with institutional ownership below the 50% threshold and R_{i1} is the risk of firm i with institutional ownership above the 50% threshold. Then we can estimate the average treatment effect on the treated (ATT) as follows:

$$ATT = E[R_{i1} - R_{i0}|T_i = 1], \tag{2.6}$$

which would directly capture the effect of institutional investors with majority control on firm risk.

Propensity score methods are used to estimate ATT. If we let X be the vector of firm characteristics, then we can define the probability of being assigned to the treatment as:

$$p(X_i) = P(T_i = 1|X_i) = E[T_i|X_i]. \tag{2.7}$$

While any probability model can be used to estimate the propensity score, I use the logit model given by:

$$p(X_i) = P(T_i = 1|X_i) = \frac{e^{h(X_i)}}{1 + e^{h(X_i)}}, \tag{2.8}$$

where $h(X_i)$ is a function of the covariates with linear and higher order terms.

2.4. Results

The results of the market risk regressions are presented in Table 12. Fixed-effects models are presented in Panel A. The coefficient of top5 is statistically significant at the 10% level. The sign of top5 is positive. This means that when ownership is concentrated among the five largest shareholders there is higher risk taking. However, the other institutional ownership variables were not statistically significant. This lends weak support to the large shareholder hypothesis.

Since return volatility distributions are skewed, median regressions are estimated to ensure that the results are robust to outliers. The results of median regressions are presented in Panel B. This time INSTOWN_HHI is the only statistically significant institutional ownership variable with significance at the 5% level. The sign of INSTOWN_HHI is positive. This is consistent with the results in Panel A, and shows that institutional ownership concentration as measured by the HHI index induces risk taking. This provides additional support for the large shareholder hypothesis.

The results of the distance-to-default regressions are presented in Table 13. Institutional ownership concentration, INSTOWN_HHI, is the only statistically significant institutional ownership variable. The sign of INSTOWN_HHI is negative. This means that as the aggregate institutional ownership increases the distance to default increases. An implication of this finding is that institutional ownership concentration is negatively related to distance-to-default and positively related to the probability of default. This provides further support for the large shareholder hypothesis, which is consistent with Table 12 results.

The results of ordered Probit regressions of institutional ownership and S&P ranking quality are presented in Table 15. The marginal effects in all the specifications are estimated at SPQ$=1$, which means that the marginal effects will have the opposite sign of the coefficients. The coefficient of ownership among the ten largest shareholders, top10, is positive and significant at the 10% level with a marginal effect of -0.07. This means as ownership among the top 10 largest shareholders increases, the firm is more likely to have a higher quality S&P ranking and lower downside risk. The coefficient of ownership concentration, INSTOWN_HHI, is negative and significant at the 5% level with a marginal effect of 0.055. This means as ownership concentration increases, the firm is less likely to have a higher quality S&P ranking and would have greater downside risk. The coefficient of ownership by institutional investors as a fraction of total shares outstanding, INSTOWN, is positive and significant at the 1% level with a marginal effect of -0.074. This means as the proportion of shares held by institutional investors to the total shares outstanding increases, the firm is more likely to have a higher quality S&P ranking and lower downside risk. These results provide support for both the large shareholder and the prudent-man law hypotheses.

The results of propensity score estimation are given in Table 16. The average treatment effects on majority ownership among top ten shareholders, top10_50 and on majority ownership among all shareholders, inst50, with respect to return volatility, σ_{ret}, are negative and significant. This shows that when institutional shareholders have majority control they induce lower risk taking. This is consistent with the prudent-man law hypothesis.

The average treatment effect greater than 50% institutional ownership concentration, insthhi50, with respect to Z_SCORE, is negative and significant. This shows that when ownership concentration is above 50%, there is a negative effect on distance-to-default, and increased likelihood of default. This is consistent with the large shareholder hypothesis. Overall these results show that by having majority control, institutional investors can be effective monitors and curb firm risk taking. In contrast, the positive effect of majority control may be offset by concentrated ownership. This implies that institutional monitoring may be more effective when there is dispersed ownership.

2.4.1. Robustness Checks

2.4.1.1. Endogeneity

A potential concern is endogeneity arising from sample selection. The decision of institutional shareholders' to purchase firm shares is jointly correlated with risk. To address this endogeneity problem I use a two-stage treatment effects model to jointly estimate the effects of majority control by institutional investors and firm risk.

The treatment effects model estimates the effect of majority control by institutional shareholders, MAJORITY_OWN, in period $t-1$ on firm risk, RISK, in period t in the following way:

$$\mathrm{RISK}_{it} = \beta' X_{it} + \delta \mathrm{MAJORITY\_OWN}_{it-1} + \varepsilon_{it}, \tag{2.9}$$

where RISK can be either σ_{ret} or Z_SCORE, and X_{it} is a vector of firm characteristics. $\mathrm{MAJORITY\_OWN}_{it-1}$ is the decision by institutional shareholders to hold more than 50% or more shares in a firm in year $t-1$ (or to get the treatment), which is modeled as an unobserved latent variable $\mathrm{MAJORITY\_OWN}^*_{it-1}$. MAJORITY_OWN is the inst50 dummy variable as defined earlier. It is assumed that $\text{MAJORITY\_OWN}^*_{it-1}$ is a linear function of the coefficient vector w_{it-1} that is composed of hypothesized determinants of institutional shareholder investment:

$$\text{MAJORITY\_OWN}^*_{it-1} = w_{it-1}\gamma + u_{it}, \tag{2.10}$$

where w_{it-1} includes lagged firm characteristics as well as a lagged S&P quality ranking dummy variable, sp_low_quality, which is equal to 1 if the firm is ranked 'C', 'D', or 'LIQ', and 0 otherwise, lagged cash flow, and a CRISIS dummy variable which is equal to 1 for years 2007-2009 and 0 otherwise. The CRISIS dummy variable will control for the effects of the financial crisis. The observed decision to own firm shares by investors is:

$$\text{MAJORITY\_OWN}_{it-1} = \begin{cases} 1, \quad \text{if} & \text{MAJORITY\_OWN}^*_{it-1} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2.11}$$

where ε_{it} and u_{it} are bivariate normal with mean zero and covariance matrix

$$\Sigma = \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix}. \tag{2.12}$$

The results of the treatment effects models are given in Table 17. The first specification has return volatility, σ_{ret}, as the risk in the second stage, while the second specification has distance to default, Z_SCORE, as the risk in the second stage. The Wald χ^2 test for $\rho = 0$ is statistically significant in both specifications at the 5% and 1% levels respectively. This means that there is support in favor of the alternative hypothesis that $\rho \neq 0$. This suggests that the errors are correlated across equations, which makes this model appropriate. The lagged majority control term, inst50_{t-1} is statistically significant and negative with respect to return volatility, and it is statistically significant and positive for distance to default. This means that even when controlling for majority control decision, majority shareholders on average can reduce firm total risk and increase distance to default. This suggests that institutional monitoring can curb risk taking. This is consistent with the prudent-man law hypothesis.

2.4.1.2. Doubly Robust Estimation

There are many advantages to estimating treatment effects via doubly robust estimators. Doubly robust estimators allow one to combine modeling the outcome and the treatment using different strategies. These estimators have a unique feature where only one of the models needs to be properly specified. This means that if the treatment model was misspecified while the outcome model was correctly specified, then the treatment effect estimates will still be consistent. Similarly, if the outcome model was misspecified while the treatment model was correctly specified, the treatment effect estimates will also be consistent.

In particular, I use the Inverse-Probability-Weighted Regression Adjustment (IPWRA) estimator in order to model institutional ownership and firm risk. The IPWRA estimator uses the reciprocals of estimated treatment probabilities from the treatment model as weights in the outcome model to compute missing data-corrected regression coefficients. Once the corrected regression coefficients are estimated in the outcome model, the means of treatment specific outcomes can be computed. The average treatment effect on the treated can be calculated by restricting the means to the subset of treated subjects.

Using prior notation, let R_i be the risk outcome, and T_i be the treatment which represents institutional ownership majority control. Also let X_i be the covariates for the risk model (outcome model), and Z_i be the covariates of the institutional ownership model (treatment model). Then the probability of having greater than 50% ownership or receiving the treatment conditional on the covariates Z_i can be modeled by a Logit regression:

$$p_i = p(Z_i, T_i) = P(T_i|Z_i) = \frac{e^{Z_i'\gamma}}{1 + e^{Z_i'\gamma}}, \tag{2.13}$$

where the covariates in Z_i are the same as the covariates defined in w_{it-1} from equation (2.10). The risk model conditional on treatment, T_i, can be written as:

$$R_i = E[R_i|X_i, T_i] = X_i'\beta_{T_i}, \tag{2.14}$$

where X_i is the vector of firm characteristics and β_{T_i} are the parameters of the model given majority control, or treatment, T_i. Once the treatment model is estimated, the outcome model parameters can be estimated by weighting the moment conditions by the inverse probabilities. This can be written as in Awel and Azomahou (2014):

$$\sum_{i=1}^{N} \frac{(R_i - X_i'\beta_1)}{\widehat{p}_i} = 0 \qquad \text{if} \quad T_i = 1 \tag{2.15}$$

$$\sum_{i=1}^{N} \frac{(R_i - X_i'\beta_0)}{1 - \widehat{p}_i} = 0 \qquad \text{if} \quad T_i = 0. \tag{2.16}$$

Following Awel and Azomahou (2014) we can compute the average treatment effect on the treated, ATT_{IPWRA}, by taking the difference between the predicted risk values conditional on majority control as follows:

$$ATT_{IPWRA} = \frac{1}{N_T}\sum_{i=1}^{N_T}\left(\widehat{R_{i1}} - \widehat{R_{i0}}\right), \tag{2.17}$$

where $\widehat{R_{i1}}$ and $\widehat{R_{i0}}$ are estimated firm risk levels for $T_i = 1$ and $T_i = 0$ respectively, and N_T is the number of treated firms, or firms with majority control. For a more extensive discussion of the IPWRA estimator see Wooldridge (2007).

The results of IPWRA estimation are given in Table 18. The ATT of all treatments except for the HHI concentration, insthhi50, are negative and significant for return volatility and positive and significant for distance to default. This is consistent with propensity score estimates in Table 16 and treatment effect estimates in Table 17. These findings provide further support for the prudent-man law hypothesis. In addition, the positive and significant effect of institutional ownership HHI on total risk provides further support for the large shareholder hypothesis.

2.5. Conclusion

This study investigated the relationship between institutional ownership and firm risk taking. One of the main findings is that aggregate institutional ownership induces lower risk taking, consistent with the prudent-man law hypothesis. In addition, high ownership concentration induces high risk taking, which is consistent with the large shareholder hypothesis. The results hold for market risk, and credit risk. The effects of institutional shareholder ownership are even stronger when institutional shareholders have majority control. Finally, the results are robust to quasi-experimental approaches including propensity score matching and doubly robust estimation.

Table 12: Institutional Ownership and Market Risk

Panel A: Fixed-Effects Panels

Dependent:	σ_{ret}				
	(1)	(2)	(3)	(4)	(5)
top5	0.0515*				
	(0.064)				
top10		0.0313			
		(0.235)			
BLOCK_OWN			0.0282		
			(0.214)		
INSTOWN_HHI				0.0376	
				(0.389)	
INSTOWN					0.00960
					(0.703)
ln(ASSETS)	0.00839***	0.00843***	0.00849***	0.00894***	0.00856**
	(0.008)	(0.009)	(0.008)	(0.005)	(0.012)
LEVERAGE	-0.00159	-0.00204	-0.00159	-0.00177	-0.00219
	(0.921)	(0.899)	(0.922)	(0.912)	(0.894)
IND_ROA	0.0672**	0.0671**	0.0670**	0.0692**	0.0672**
	(0.025)	(0.026)	(0.028)	(0.024)	(0.028)
Firm Fixed-Effects	YES	YES	YES	YES	YES
N	2333	2333	2333	2333	2333
adj. R-sq	0.004	0.003	0.003	0.003	0.002

The dependent variable is σ_{ret}, which is the 12-month return volatility. top5 is the ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding. top10 is the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding. BLOCK_OWN is the ratio of the total number of shares held by blockholders to the total number of shares outstanding. INSTOWN_HHI is the Herfindahl–Hirschman Index (HHI) of institutional ownership concentration. INSTOWN is the ratio of shares owned by institutional investors to the total number of shares outstanding. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. p-values based on robust standard errors are reported in parentheses. Standard errors are clustered by SIC 2-digit industry codes. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Panel B: Median Regressions					
Dependent:	σ_{ret}				
	(1)	(2)	(3)	(4)	(5)
top5	0.00619				
	(0.734)				
top10		0.000770			
		(0.958)			
BLOCK_OWN			0.00982		
			(0.568)		
INSTOWN_HHI				0.0202**	
				(0.047)	
INSTOWN					-0.00663
					(0.472)
ln(ASSETS)	0.00288**	0.00297**	0.00293**	0.00317***	0.00330***
	(0.012)	(0.010)	(0.010)	(0.007)	(0.005)
LEVERAGE	0.00542	0.00451	0.00375	0.00465	0.00311
	(0.618)	(0.681)	(0.729)	(0.677)	(0.778)
IND_ROA	0.0189***	0.0190***	0.0190***	0.0194***	0.0193***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	2333	2333	2333	2333	2333
pseudo R^2	0.003	0.003	0.003	0.004	0.003

p-values based on robust standard errors are reported in parentheses. Standard errors are clustered by SIC 2-digit industry codes. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 13: Institutional Ownership and Distance to Default

Dependent:	Z_SCORE				
	(1)	(2)	(3)	(4)	(5)
top5	-0.217				
	(0.123)				
top10		-0.106			
		(0.391)			
BLOCK_OWN			-0.207		
			(0.130)		
INSTOWN_HHI				-0.223*	
				(0.089)	
INSTOWN					-0.0289
					(0.755)
ln(ASSETS)	-0.160***	-0.160***	-0.159***	-0.163***	-0.161***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LEVERAGE	-4.414***	-4.416***	-4.415***	-4.417***	-4.418***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IND_ROA	0.824***	0.824***	0.825***	0.823***	0.825***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes
N	7780	7780	7780	7780	7780
adj. R^2	0.371	0.371	0.371	0.371	0.371

The dependent variable is Z_SCORE, which is the Altman Z-Score with updated Altman (2000) coefficients. top5 is the ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding. top10 is the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding. BLOCK_OWN is the ratio of the total number of shares held by blockholders to the total number of shares outstanding. INSTOWN_HHI is the Herfindahl–Hirschman Index (HHI) of institutional ownership concentration. INSTOWN is the ratio of shares owned by institutional investors to the total number of shares outstanding. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. p-values based on robust standard errors are reported in parentheses. Standard errors are clustered by SIC 2-digit industry codes. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 14: Distribution of S&P Quality Rankings

Rating	Frequency	Percent
A+	81	1.74
A	177	3.81
A−	244	5.25
B+	685	14.74
B	1,004	21.6
B−	1,153	24.81
C	977	21.02
D	323	6.95
LIQ	4	0.09
Total	4,648	100

Standard and Poor's Quality Rankings. The rankings measure long-term growth and stability of a company's earnings and dividends. Ratings as defined by Standard and Poor's: 'A+' – Highest Rating. 'A' – High Rating. 'A−' – Above Average. 'B+' – Average. 'B' – Below Average. 'B−' –Lower Rating. 'C' – Lowest Rating. 'D' – In Reorganization. 'LIQ' – Liquidation. See `http://us.spindices.com/documents/methodologies/methodology-sp-500-quality-ranks-index.pdf` for more information on S&P Quality Rankings.

Table 15: Institutional Ownership and S&P Quality Rankings

Dependent:	SPQ									
	(1)		(2)		(3)		(4)		(5)	
	coefficient	dy/dx	coefficient	dy/dx	coefficient	dy/dx	coefficient	dy/dx	coefficient	dy/dx
$top5_{t-1}$	0.151	-0.040								
	(0.368)	(0.369)								
$top10_{t-1}$			0.262*	-0.070*						
			(0.057)	(0.057)						
$BLOCK\_OWN_{t-1}$					0.0402	-0.011				
					(0.791)	(0.791)				
$INSTOWN\_HHI_{t-1}$							-0.206**	0.055**		
							(0.044)	(0.044)		
$INSTOWN_{t-1}$									0.277***	-0.074***
									(0.002)	(0.002)
$ln(ASSETS)_{t-1}$	0.266***	-0.071***	0.265***	-0.071***	0.266***	-0.071***	0.266***	-0.071***	0.264***	-0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$LEVERAGE_{t-1}$	-0.468***	0.125***	-0.469***	0.125***	-0.470***	0.125***	-0.490***	0.130***	-0.476***	0.127***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IND_ROA_{t-1}	0.194	-0.052	0.189	-0.050	0.196	-0.052	0.187	-0.050	0.178	-0.047
	(0.506)	(0.506)	(0.510)	(0.510)	(0.504)	(0.504)	(0.518)	(0.518)	(0.524)	(0.524)
Thresholds										
α_1	0.559***		0.598***		0.530***		0.471***		0.630***	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
α_2	2.682***		2.723***		2.653***		2.595***		2.758***	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
N	2942		2942		2942		2942		2942	
pseudo R^2	0.109		0.110		0.109		0.110		0.111	

The dependent variable is SPQ, which is constructed based on firm S&P Quality Rankings SPQ where quality is increasing from 1 to 3 (lowest ranked to highest ranked). top5 is the ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding. top10 is the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding. BLOCK_OWN is the ratio of the total number of shares held by blockholders to the total number of shares outstanding. INSTOWN_HHI is the Herfindahl–Hirschman Index (HHI) of institutional ownership concentration. INSTOWN is the ratio of shares owned by institutional investors to the total number of shares outstanding. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 16: Institutional Ownership and Risk – Propensity Score Matching

Treatment	Outcome	ATT (1 vs. 0)	p-value	mean bias	N
top5_50	σ_{ret}	0.001	0.937	4.50%	2333
	Z_SCORE	0.147	0.189	2.30%	7780
top10_50	σ_{ret}	-0.020***	0.004	0.70%	2333
	Z_SCORE	0.134**	0.035	3.90%	7780
block50	σ_{ret}	0.011	0.496	8.80%	2333
	Z_SCORE	0.263**	0.024	2.70%	7780
insthhi50	σ_{ret}	0.0003	0.977	3.80%	2333
	Z_SCORE	-0.163***	0.003	1.20%	7780
inst50	σ_{ret}	-0.011*	0.051	2.80%	2333
	Z_SCORE	0.089**	0.016	1.40%	7780

σ_{ret} is the 12-month return volatility. Z_SCORE is the Altman Z-Score with updated Altman (2000) coefficients is used as a measure of distance-to-default. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. top5_50, top10_50, block50, and inst50 are dummy variables which are equal to 1 if there the ownership level is 50% or more for top5 ownership, top10 ownership, block ownership, and institutional ownership percentage levels respectively, and 0 otherwise. insthhi50 is a dummy variable which is equal to 1 if there is more than 50% ownership concentration, and 0 otherwise. ATT is the average treatment effect on the treated. mean bias is the estimated average selection bias. The propensity scores are estimated via nearest-neighbor matching with $N = 3$ neighbors. p-values based on Abadie and Imbens (2012) robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 17: Majority Ownership and Risk – Treatment Effects

	(1)				(2)		
	1st Stage		2nd Stage		1st Stage		2nd Stage
Dependent:	$inst50_{t-1}$		σ_{ret}		$inst50_{t-1}$		Z_SCORE
$ln(ASSETS)_{t-1}$	-0.014	ln(ASSETS)	0.00192	$ln(ASSETS)_{t-1}$	0.005	ln(ASSETS)	-0.0574**
	(0.593)		(0.581)		(0.705)		(0.019)
$LEVERAGE_{t-1}$	0.459**	LEVERAGE	0.0163	$LEVERAGE_{t-1}$	0.120	LEVERAGE	-4.271***
	(0.041)		(0.550)		(0.346)		(0.000)
IND_ROA_{t-1}	0.479	IND_ROA	0.0692	IND_ROA_{t-1}	0.081	IND_ROA	0.229
	(0.236)		(0.200)		(0.65)		(0.718)
$sp\_low\_quality_{t-1}$	-0.123	**$inst50_{t-1}$**	-0.0418***	$sp\_low\_quality_{t-1}$	-0.110*	**$inst50_{t-1}$**	1.331***
	(0.291)		(0.010)		(0.072)		(0.000)
$CASH\_FLOW_{t-1}$	0.00004**			$CASH\_FLOW_{t-1}$	0.00008***		
	(0.04)				(0.000)		
CRISIS	0.342**			CRISIS	0.225***		
	(0.019)				(0.003)		
N	847				2642		
Wald χ^2-test of $\rho = 0$	4.45**				13.05***		

σ_{ret} is the 12-month return volatility. Z_SCORE is the Altman Z-Score with updated Altman (2000) coefficients. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. sp_low_quality is a dummy variable which is equal to 1 if the firm is ranked 'C', 'D', or 'LIQ', and 0 otherwise. CASH_FLOW is income before extraordinary items plus depreciation and amortization. CRISIS is a dummy variable which is equal to 1 for years 2007-2009, and 0 otherwise. inst50 is a dummy variable which is equal to 1 if the institutional ownership level is 50% or more as a fraction of total shares outstanding, and 0 otherwise. The models are estimated via MLE estimation. p-values based on robust standard errors are reported in parentheses. Standard errors are clustered by SIC 2-digit industry codes. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

Table 18: Institutional Ownership and Risk – Inverse Probability Weighted Regression Adjustment

Treatment	Outcome	ATT (1 vs. 0)	p-value	N
top5_50$_{t-1}$	σ_{ret}	-0.028**	0.046	847
	Z_SCORE	0.428**	0.000	2642
top10_50$_{t-1}$	σ_{ret}	-0.036***	0.000	847
	Z_SCORE	0.331**	0.000	2642
block50$_{t-1}$	σ_{ret}	-0.046***	0.000	847
	Z_SCORE	0.388**	0.002	2642
insthhi50$_{t-1}$	σ_{ret}	0.047**	0.022	847
	Z_SCORE	-0.045	0.519	2642
inst50$_{t-1}$	σ_{ret}	-0.023**	0.016	847
	Z_SCORE	0.113**	0.012	2642

σ_{ret} is the 12-month return volatility. Z_SCORE is the Altman Z-Score with updated Altman (2000) coefficients is used as a measure of distance-to-default. ln(ASSETS) is the natural logarithm of firm assets. LEVERAGE is the debt to assets ratio. IND_ROA is industry adjusted return on assets. top5_50, top10_50, block50, and inst50 are dummy variables which are equal to 1 if there the ownership level is 50% or more for top5 ownership, top10 ownership, block ownership, and institutional ownership percentage levels respectively, and 0 otherwise. insthhi50 is a dummy variable which is equal to 1 if there is more than 50% ownership concentration, and 0 otherwise. ATT is the average treatment effect on the treated. p-values based on robust standard errors are reported in parentheses. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively.

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APPENDICES

APPENDIX A

VARIABLE DEFINITIONS

Firm Characteristics

Q – Tobin's Q. I calculate Tobin's Q as in Gompers et al. (2003).

ln(Assets) – the natural logarithm of total assets.

Leverage – debt to assets ratio.

ROA – return on assets.

IND_ROA – industry adjusted return on assets. Constructed by subtracting the industry median ROA from the firm's ROA.

ret – the annualized 12-month geometric average return. The geometric average is used since it is a more conservative estimate than the arithmetic average which is biased upward.

Firm Risk

Operational_Freq – is the yearly count of operational risk events. Data is collected from the Algorithmics Algo OpData database.

Operational_Loss – is the natural logarithm of the total operational loss during the year in millions of U.S. dollars. Data is collected from the Algorithmics Algo OpData database.

σ_{ret} – the 12-month stock return volatility. It is a measure of market risk.

Lower_Grade – dummy variable equal to 1 if the firm has a Standard and Poor's rating below A-, 0 otherwise.

SPQ – constructed based on firm S&P Quality Rankings where quality is increasing from 1 to 3 (lowest ranked to highest ranked)

ln(Z) – the natural logarithm of Z-score which is a measure of distance to default. Z-score is calculated in the following way:

$$Z = \frac{(\mathrm{ROA} + \mathrm{CAR})}{\sigma(\mathrm{ROA})}, \tag{2.18}$$

where CAR is the Capital to Assets ratio, and σ(ROA) is the quarterly standard deviation of ROA.

Z_SCORE – the Altman Z-Score with updated Altman (2000) coefficients.

CEO Characteristics

TDC1 – total incentive compensation from Execucomp: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Total Value of Stock Options Granted (using Black-Scholes), Long-Term Incentive Payouts, and All Other Total.

CEO_AGE – the age of the CEO.

Tenure – the number of years the CEO held office.

GRAD – dummy variable equal to 1 if the CEO has a graduate degree, and zero otherwise.

Top_50_UG – dummy variable equal to 1 if the CEO has an undergraduate degree from a Top 50 U.S. national university according to U.S. News and World Report, and zero otherwise.

Top_50_GRAD – dummy variable equal to 1 if the CEO has a graduate degree from a Top 50 U.S. national university according to U.S. News and World Report, and zero otherwise.

Top_50_LAW – dummy variable equal to 1 if the CEO has a law degree from a Top 50 U.S. law school according to U.S. News and World Report, and zero otherwise.

Top_50_MBA – dummy variable equal to 1 if the CEO has an MBA degree from a Top 50 U.S. business school according to U.S. News and World Report, and zero otherwise.

LAW – dummy variable equal to 1 if the CEO has a law degree. MBA is a dummy variable equal to 1 if the CEO has an MBA degree.

ACTUARY – dummy variable equal to 1 if the CEO has an undergraduate actuarial degree, or a graduate actuarial degree, or has the Fellow of the Casualty Actuarial Society (FCAS) credential, or is a member of the American Academy of Actuaries (AAA), or has the Fellow of the Society of Actuaries (FSA) credential, or has the

Fellow of the Canadian Institute of Actuaries (FCIA) credential. MBA is a dummy variable equal to 1 if the CEO has an MBA degree.

BUSINESS – dummy variable equal to 1 if the CEO has an undergraduate or graduate degree in any of the following majors: business, economics, accounting, finance, insurance, and zero otherwise.

QUANT – dummy variable equal to 1 if the CEO has an undergraduate or graduate degree in any of the following majors: mathematics, biology, engineering, actuarial science, and zero otherwise.

CPA – dummy variable equal to 1 if the CEO has a CPA license, and zero otherwise.

INS_Cert – dummy variable equal to 1 if the CEO has any of the following insurance certifications: Chartered Property Casualty Underwriter (CPCU), Fellow of the Casualty Actuarial Society (FCAS), Chartered Life Underwriter (CLU), Member of the American Academy of Actuaries (MAAA), Fellow of the Canadian Institute of Actuaries (FCIA), and 0 otherwise.

USN_UG_Rank – the ranking of the undergraduate institution attended by the CEO according to the U.S. News and World Report ranking of national universities.

USN_GRAD_Rank – the ranking of the graduate institution attended by the CEO according to the U.S. News and World Report ranking of graduate schools by specialty.

Institutional Ownership Measures

top5 – the ratio of the number of shares owned by the top five institutional investors to the total number of shares outstanding.

top10 – the ratio of the number of shares owned by the top ten institutional investors to the total number of shares outstanding.

BLOCK_OWN – the ratio of the total number of shares held by blockholders to the total number of shares outstanding.

INSTOWN_HHI – the Herfindahl–Hirschman Index (HHI) of institutional ownership concentration. INSTOWN is the ratio of shares owned by institutional investors to the total number of shares outstanding.

APPENDIX B

SAMPLE OF PROPERTY-LIABILITY INSURERS

ALLIED GROUP INC
ALLSTATE CORP
AMERICAN FINANCIAL GROUP INC
AMERICAN INTERNATIONAL GROUP
AMERISAFE INC
BERKLEY (W R) CORP
CNA FINANCIAL CORP
CHUBB CORP
CINCINNATI FINANCIAL CORP
COMMERCE GROUP INC/MA
CONTINENTAL CORP
EMPLOYERS HOLDINGS INC
FRONTIER INSURANCE GROUP INC
GENERAL RE CORP
HCC INSURANCE HOLDINGS INC
HSB GROUP INC
HANOVER INSURANCE GROUP INC
HARTFORD FINANCIAL SERVICES
HORACE MANN EDUCATORS CORP
INFINITY PROPERTY & CAS CORP
INTEGON CORP/DE
LOEWS CORP
MEADOWBROOK INS GROUP INC
MERCURY GENERAL CORP
MUTUAL RISK MANAGEMENT LTD
NAC RE CORP
NATIONAL RE CORP
NAVIGATORS GROUP INC
OHIO CASUALTY CORP
OLD REPUBLIC INTL CORP
ORION CAPITAL CORP
PHILADELPHIA CONS HLDG CORP
PROGRESSIVE CORP-OHIO
RLI CORP
SAFECO CORP
SAFETY INSURANCE GROUP INC
ST PAUL COS
SELECTIVE INS GROUP INC
TRANSATLANTIC HOLDINGS INC
TRAVELERS COS INC
USF&G CORP
UNITED FIRE GROUP INC
ZENITH NATIONAL INSURANCE CP
ARCH CAPITAL GROUP LTD
ASPEN INSURANCE HOLDINGS LTD
AXIS CAPITAL HOLDINGS LTD
ENDURANCE SPECIALTY HOLDINGS
EVEREST RE GROUP LTD
MONTPELIER RE HOLDINGS
PLATINUM UNDERWRITERS HLDG
TOWER GROUP INTL LTD
TRENWICK GROUP LTD
ACE LTD