Is CEO Education Linked With Risk Management Ability?*

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This Version: January 23, 2014

ABSTRACT

This study 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 are associated with fewer operational risk events. While firms with CEOs that have MBA degrees from top business schools are able to manage credit 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.

Keywords: Endogenous Matching, CEO Ability, Corporate Risk Management

JEL Classification: G20, G32

*I would like to thank David Cummins, Mary Weiss, Krupa Viswanathan, and Jacqueline Volkman Wise, Wei Cen, and participants at the 26th Australasian Finance & Banking Conference for helpful comments and suggestions. All remaining errors are my own.

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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 2. Hypotheses about CEO credentials and risk are developed in Section 3. The data and variable selection is described in Section 4. The methodology is described in

Section 5. The results and robustness checks are presented in Section 6. Section 7 concludes.

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.

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.

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.

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

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

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 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.*

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 obtained. Insurance-specific certifications such as CPCU, and FCAS are

[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 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. 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 over-valued. 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.

Pearson correlations are presented in Table 2. There are no signs of multicollinearity with the exception of some of the CEO credentials variables. The high correlations between CEO education variables are expected. For example, the correlation between having a law degree (LAW) and having a law degree from a top 50 school (Top_50_LAW) is .70, which is not surprising since having a law degree already includes those that have a top 50 law degree. In order to address this problem, CEO education variables are included as explanatory variables in separate specifications.

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
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

Table 2: Pearson Correlation Matrix

	A	ROA	*ret*	L	Q	FA	TDC1	CA	T	OL	OF
ln(Assets) (A)	1										
ROA	-0.217	1									
ret	0.018	0.227	1								
Leverage (L)	0.432	-0.579	-0.028	1							
Q	-0.263	0.278	0.016	-0.078	1						
Firm_Age (FA)	0.615	-0.241	0.006	0.468	-0.028	1					
ln(TDC1) (TDC1)	0.635	0.115	-0.039	0.125	-0.078	0.293	1				
CEO_AGE (CA)	0.154	-0.019	0.033	0.008	-0.131	0.175	0.04	1			
Tenure (T)	0.057	-0.059	0.003	0.077	-0.018	0.105	0.078	0.406	1		
ln(Operational_Loss) (OL)	0.225	-0.011	-0.01	0.085	-0.018	0.065	0.159	-0.029	-0.016	1	
Operational_Freq (OF)	0.236	-0.031	-0.007	0.105	-0.025	0.065	0.152	-0.012	-0.003	0.914	1
σ_{ret}	-0.01	-0.397	-0.248	0.276	-0.062	0.225	-0.09	-0.054	-0.026	-0.061	-0.053
Lower_Grade (LG)	-0.466	-0.008	0.024	-0.11	-0.253	-0.362	-0.245	-0.219	-0.223	-0.227	-0.223
ln_Z (Z)	-0.276	0.277	0.144	-0.441	-0.091	-0.459	-0.166	0.101	0.02	-0.108	-0.131
LAW	-0.121	-0.104	0.024	0.154	0.001	0.078	-0.03	0.058	0.395	-0.054	-0.058
GRAD	0.111	-0.044	-0.017	0.152	0.04	0.172	0.166	-0.131	-0.035	0.081	0.119
MBA	0.153	-0.01	-0.012	0.101	0.089	-0.143	0.105	-0.054	-0.071	0.146	0.186
CPA	-0.128	-0.066	-0.021	-0.008	0.069	-0.041	-0.225	-0.159	-0.146	-0.019	-0.026
INS_Cert (IC)	-0.055	-0.009	0.007	-0.199	-0.141	-0.191	-0.117	0.009	-0.071	-0.06	-0.028
Top_50_UG (TUG)	0.226	-0.068	-0.009	0.249	-0.092	0.069	0.21	0.162	0.209	0.026	0.037
Top_50_MBA (TMBA)	0.146	-0.122	-0.003	0.228	-0.03	0.029	0.023	-0.03	-0.123	-0.015	0.013
Top_50_GRAD (TGRAD)	0.028	-0.091	-0.001	0.253	-0.037	0.134	0.033	-0.1	-0.06	-0.033	-0.011
Top_50_LAW (TLAW)	-0.284	-0.006	0.015	0.045	0.065	-0.086	-0.133	-0.002	0.252	-0.06	-0.064
ACTUARY (ACT)	-0.036	0.054	0.015	-0.209	.	-0.2	0.063	-0.101	-0.119	-0.056	-0.035
BUSINESS (BUS)	-0.063	-0.11	-0.012	0.138	0.066	-0.098	-0.153	0.007	0.006	0.064	0.09
QUANT	0.203	0.08	-0.006	-0.056	-0.013	0.254	0.222	-0.01	0.009	-0.037	-0.006
USN_UG_Rank (UGR)	-0.104	-0.103	0.051	-0.083	-0.067	-0.208	-0.121	0.051	-0.078	0.024	0.034
USN_GRAD_Rank (GR)	0.267	-0.03	0.022	0.103	0.076	0.18	0.272	0.174	0.399	0.134	0.109

Table 2 – Continued

	σ_{ret}	LG	Z	LAW	GRAD	MBA	CPA	IC	TUG	TMBA	TGRAD	TLAW	ACT	BUS	QUANT	UGR	GR
σ_{ret}	1																
Lower_Grade (LG)	0.018	1															
ln(Z) (Z)	-0.168	0.205	1														
LAW	0.145	0.007	0.018	1													
GRAD	0.074	-0.082	-0.199	0.165	1												
MBA	-0.058	-0.008	0.006	-0.212	0.623	1											
CPA	0.005	0.183	0.098	-0.147	-0.166	0.028	1										
INS_Cert (IC)	-0.061	0.021	0.133	-0.15	-0.122	-0.156	-0.092	1									
Top_50_UG (TUG)	-0.05	-0.062	0.094	0.198	0.236	0.241	-0.108	-0.179	1								
Top_50_MBA (TMBA)	-0.013	0.166	0.037	-0.142	0.418	0.671	0.072	-0.039	0.33	1							
Top_50_GRAD (TGRAD)	-0.008	0.074	-0.06	0.161	0.544	0.254	0.017	-0.067	0.411	0.568	1						
Top_50_LAW (TLAW)	0.051	.	0.017	0.702	0.26	-0.149	-0.093	-0.095	0.209	-0.1	0.375	1					
ACTUARY (ACT)	-0.056	0.083	0.028	-0.109	-0.05	-0.14	-0.133	0.657	-0.211	-0.074	-0.082	-0.076	1				
BUSINESS (BUS)	0.011	0.059	-0.04	-0.05	0.355	0.531	0.18	-0.164	0.189	0.357	0.261	0.106	-0.296	1			
QUANT	0.049	-0.031	-0.28	-0.094	0.19	-0.152	-0.16	0.194	-0.1	-0.104	-0.011	-0.092	0.316	-0.343	1		
USN_UG_Rank (UGR)	0.081	0.01	-0.263	-0.017	-0.084	-0.024	-0.086	-0.027	-0.846	-0.371	-0.49	-0.163	.	0.17	-0.065	1	
USN_GRAD_Rank (GR)	0.124	-0.509	-0.147	0.464	-0.294	-0.222	-0.189	-0.221	-0.206	-0.435	-0.873	-0.131	-0.113	-0.385	0.117	0.439	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.

5.1. CEO Credentials and the Balance Between Performance and Risk

In order to take into account the risk-return tradeoff, I scale the return on assets, ROA, by the 12-month return volatility σ_{ret}. This allows me to estimate the relationship between CEO education and firm performance for each additional unit of risk. I estimate the relationship between CEO education and the balance between performance and risk in the following way:

$$\begin{aligned} \frac{\mathrm{ROA}_{it}}{(\sigma_{ret})_{it}} &= \alpha_i + \xi_t + \beta_1 \mathrm{Education}_{it} + \beta_2 \mathrm{CPA}_{it} + \beta_3 \mathrm{INS\_Cert}_{it} \\ &+ \beta_4 \ln(\mathrm{Assets})_{it} + \beta_5 \mathrm{Leverage}_{it} + \beta_6 \ln(\mathrm{TDC1}_{it}) \\ &+ \beta_7 \mathrm{CEO\_AGE}_{it} + \beta_8 \mathrm{Tenure}_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where $\mathrm{Education}_{it}$ 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}.

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 3. 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.

Table 3: 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

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 estimate a Probit model with Lower_Grade as the dependent variable:

$$\begin{aligned} \Phi^{-1}\Big(P(\text{Lower\_Grade}_{it}=1)\Big) &= \beta_1\text{Education}_{it} + \beta_2\text{CPA}_{it} + \beta_3\text{INS\_Cert}_{it} + \beta_4\ln(\text{Assets})_{it} \\ &+ \beta_5\text{ROA}_{it} + \beta_6\text{Leverage}_{it} + \beta_7 ret_{it} + \beta_8\ln(\text{TDC1}_{it}) \qquad (2) \\ &+ \beta_9\text{CEO\_AGE}_{it} + \beta_{10}\text{Tenure}_{it} + \nu_{it}, \end{aligned}$$

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:

$$\mathrm{Z} = \frac{(\mathrm{ROA} + \mathrm{CAR})}{\sigma(\mathrm{ROA})}, \tag{3}$$

where $\sigma(\mathrm{ROA})$ 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:

$$\begin{aligned} \ln(\mathrm{Z}_{it}) &= \alpha_i + \xi_t + \beta_1 \mathrm{Education}_{it} + \beta_2 \mathrm{CPA}_{it} + \beta_3 \mathrm{INS\_Cert}_{it} \\ &+ \beta_4 \ln(\mathrm{Assets})_{it} + \beta_5 \mathrm{ROA}_{it} + \beta_6 \mathrm{Leverage}_{it} + \beta_7 ret_{it} \\ &+ \beta_8 \ln(\mathrm{TDC1})_{it} + \beta_9 \mathrm{CEO\_AGE}_{it} + \beta_{10} \mathrm{Tenure}_{it} + \nu_{it}. \end{aligned} \tag{4}$$

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:

$$
\begin{aligned}
\text{Operational\_Freq}_{it} &= \exp\Big(\beta_1 \text{Education}_{it} + \beta_2 \text{CPA}_{it} + \beta_3 \text{INS\_Cert}_{it} \\
&+ \beta_4 \ln(\text{Assets})_{it} + \beta_5 \text{ROA}_{it} + \beta_6 \text{Leverage}_{it} + \beta_7 \ln(\text{TDC1}_{it}) \qquad (5) \\
&+ \beta_8 \text{CEO\_AGE}_{it} + \beta_9 \text{Tenure}_{it} + \eta_{it}\Big).
\end{aligned}
$$

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

$$
\begin{aligned}
\text{Operational\_Loss}_{it} &= \alpha_i + \xi_t + \beta_1 \text{Education}_{it} + \beta_2 \text{CPA}_{it} + \beta_3 \text{INS\_Cert}_{it} \\
&+ \beta_4 \ln(\text{Assets})_{it} + \beta_5 \text{ROA}_{it} + \beta_5 \text{Leverage}_{it} \qquad (6) \\
&+ \beta_6 \ln(\text{TDC1}_{it}) + \beta_7 \text{CEO\_AGE}_{it} + \beta_8 \text{Tenure}_{it} + \kappa_{it}.
\end{aligned}
$$

6. Results

The results for the balance between performance and risk are presented in Table 4. Panel A shows the OLS regression estimates. The specification with Top_50_LAW was not estimated due to collinearity. The only significant credential was GRAD. The coefficient of GRAD is statistically significant and positive, which suggests that CEOs with a graduate degree are associated with increased performance relative to risk. The rest of the education credentials are not statistically significant. Two control variables are statistically significant. Leverage is statistically significant and negative, which implies that each extra unit of debt corresponds decreased performance and increased risk. Meanwhile the coefficient on total compensation is statistically significant and positive, which suggests that increased incentives correspond to increased performance per unit of risk.

Median regressions are estimated in Panel B of Table 4. The median regression is more robust than OLS since it is a non-parametric model. Therefore, it is worthwhile comparing the OLS results to the median regression results. The coefficient of GRAD is not significant anymore in the median regressions. It is interesting that the coefficient of CPA is negative and significant in most specifications. This suggests that firms that have CEOs with CPA degrees have lower return per unit of risk. While the coefficient of QUANT is positive and significant. This implies that firms that have CEOs with a quantitative undergraduate degree such as a science degree or a mathematics degree have higher return per unit of risk. However, there is no support for any of the hypotheses in these panels.

The results of the credit risk models are presented in Table 5. 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 Probit coefficients, while Panel B shows the average marginal effects. The coefficient of Top_50_UG is negative and significant. The marginal effect of Top_50_UG is also statistically significant, with a coefficient of $-.298$. This means that firms with CEOs that attended selective undergraduate institutions are 30% less likely to be rated below A-. However, the Top_50_GRAD is positive and significant, with a significant marginal effect coefficient of .178. This implies that firms with CEOs that attended top graduate institutions are 18% more likely to have credit ratings below A-.

The results of the Distance-to-Default models are presented in Panel C of Table 5. These results should have more statistical power than the results in Panels A and B since there are more observations. The coefficients of Top_50_UG, Top_50_GRAD, and Top_50_MBA are positive and statistically significant. This suggests that firms with CEOs that attended more selective undergraduate or graduate 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 not that while the coefficient of Top_50_MBA was positive, the coefficient of MBA was negative. This shows that the quality the CEO's MBA training can make a big difference with respect to credit risk. Overall the results of the credit risk models support H1 as well as H3.

The results of the pooled Poisson regression are presented in Table 6. 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, and 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 coefficient of Top_50_LAW is statistically significant and negative. This suggests that firms that have CEOs with a top law degree are associated with fewer operational risk events. The result makes sense since legal risk is part of operational risk. Operational risk events also involve things such as products liability, antitrust, and fiduciary breaches, which are a part of standard legal training. The results support H2 and H1.

The results of operational risk severity regressions are presented in Table 7. 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 half a million 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.

6.1. Robustness Checks

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 8. The coefficient of the undergraduate ranking (USN_UG_Rank) is statistically significant across all models. This coefficient is negative in the OLS model in specification (1), which means that the lower the rank of the undergraduate institution attended by the CEO, the lower the firm performance relative to risk. The same coefficient is positive in the Poisson model in specification (2) which suggests that firms that have CEOs from lower ranked undergraduate institutions have more frequent operational losses. Similarly the coefficient is positive in the

Probit model in specification (3), which implies that firms that have CEOs from lower ranked undergraduate institutions are more likely to be rated below A-. Meanwhile, the coefficient of the graduate ranking is not significant across specifications. These results lend further support to H1.

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 (3) by defining the Operational_Freq variable as:

$$\text{Operational\_Freq}_{it} \sim \begin{cases} 0 & \text{with probability} \quad p_{it} \\ \text{Poisson}(\lambda_{it}) & \text{with probability} \quad 1 - p_{it}. \end{cases} \tag{7}$$

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 9. The Vuong statistics indicate that the standard Poisson regression should be rejected in favor of the ZIP model. The specification with the GRAD dummy was not reported since the model did not converge. The coefficients of MBA and BUSINESS are positive and significant. This is consistent with the standard Poisson estimates from Table 6. These results confirm the previous results that a firm with a CEO that has an MBA or other business degree is associated with more operational loss occurrences. The coefficient of LAW is still negative and significant which is also consistent with the previous results, however the Top_50_LAW dummy is not significant in this model. The coefficients of Top_50_GRAD and QUANT are statistically significant and negative. 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 quantitative background are associated with less frequent operational loss occurrences. These results provide additional support for H1 and H2.

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 estiamte 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,

$$(R_{i1}, R_{i0}) \perp\!\!\!\perp T_i|X_i \Rightarrow (R_{i1}, R_{i0}) \perp\!\!\!\perp T_i|p(X_i). \tag{8}$$

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:

$$ATE = E[R_{i1} - R_{i0}], \tag{9}$$

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

$$ATT = E[R_{i1} - R_{i0}|T_i = 1], \tag{10}$$

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:

$$R_i = (1 - T_i)R_{i0} + T_i R_{i1}. \tag{11}$$

Using (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:

$$E[R_i|T_i = 1] - E[R_i|T_i = 0] = E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 0], \tag{12}$$

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

$$\begin{aligned}
&= E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 0] + E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 1] && (13)\\
&= \Big(E[R_{i1}|T_i = 1] - E[R_{i0}|T_i = 1]\Big) + E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 0] && (14)\\
&= \Big(E[R_{i1} - R_{i0}|T_i = 1]\Big) + \Big(E[R_{i0}|T_i = 1] - E[R_{i0}|T_i = 0]\Big) && (15)\\
&= ATT + \textbf{selection bias}. && (16)
\end{aligned}$$

Using the conditional independence assumption allows us to identify ATT. Applying mean conditional independence to (12) and (15) we get the classic result from Rosenbaum and Rubin

(1983):

$$
\begin{aligned}
E[R_{i1}|T_i=1]-E[R_{i0}|T_i=0] &= \Big(E[R_{i1}-R_{i0}|T_i=1]\Big)+\Big(E[R_{i0}|T_i=1]-E[R_{i0}|T_i=0]\Big) \\
E[R_{i1}]-E[R_{i0}] &= ATT+\Big(E[R_{i0}]-E[R_{i0}]\Big) && (17) \\
E[R_{i1}-R_{i0}] &= ATT+0 && (18) \\
ATE &= ATT. && (19)
\end{aligned}
$$

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 (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:

$$0 < P(T_i = 1|X_i) < 1. \tag{20}$$

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:

$$\widehat{ATT} = \frac{1}{|N|} \sum_{i \in N} \Big(R_i - \frac{1}{|J_i|} \sum_{j \in J_i} R_j \Big), \tag{21}$$

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:

$$p(X_i) = P(T_i = 1|X_i) = \frac{e^{h(X_i)}}{1 + e^{h(X_i)}}, \tag{22}$$

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 10 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 coefficients for BUSINESS and MBA are consistent with Zero-Inflated Poisson regression estimates in Table 9. 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, which is consistent with Table 9 results. 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. The ATT estimates for GRAD, MBA, and BUSINESS are statistically significant and positive for operational risk, which is consistent with Panel B, as well as Table 9 results. 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 11. 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 11 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.

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 a law degree being better than their peers at avoiding operational risk events. There is also evidence that CEOs with MBA degrees from top business schools are able to manage credit risk and 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 4: CEO Education and the Balance of Performance and Risk

Panel A: OLS Regressions

Dependent:	ROA/σ_{ret}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.114*								
	(0.092)								
Top_50_UG		0.0246							
		(0.721)							
Top_50_GRAD			0.0982						
			(0.137)						
Top_50_MBA				0.0796					
				(0.349)					
LAW					0.0600				
					(0.460)				
MBA						0.107			
						(0.208)			
ACTUARY							-0.0554		
							(0.704)		
BUSINESS								0.140	
								(0.155)	
QUANT									0.0955
									(0.396)
CPA	-0.0949	-0.0779	-0.113	-0.0881	-0.0772	-0.100			
	(0.209)	(0.357)	(0.148)	(0.247)	(0.386)	(0.181)			
INS_Cert	0.0667	0.0609	0.0415	0.0581	0.0718	0.0783			
	(0.383)	(0.369)	(0.544)	(0.388)	(0.318)	(0.263)			
ln(Assets)	0.103	0.108	0.102	0.104	0.115	0.105	0.103	0.0858	0.0972
	(0.283)	(0.280)	(0.287)	(0.305)	(0.257)	(0.286)	(0.307)	(0.409)	(0.328)
Leverage	-3.399***	-3.374***	-3.361***	-3.351**	-3.387***	-3.365***	-3.313***	-3.268***	-3.292***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
ln(TDC1)	0.150**	0.151**	0.152**	0.155**	0.150**	0.154**	0.158***	0.173***	0.163***
	(0.012)	(0.011)	(0.012)	(0.010)	(0.014)	(0.012)	(0.009)	(0.009)	(0.009)
CEO_AGE	-0.00421	-0.00492	-0.00386	-0.00452	-0.00471	-0.00485	-0.00374	-0.00341	-0.00360
	(0.334)	(0.306)	(0.370)	(0.345)	(0.322)	(0.303)	(0.410)	(0.446)	(0.418)
Tenure	0.00484	0.00448	0.00412	0.00472	0.00434	0.00488	0.00532	0.00547	0.00440
	(0.227)	(0.292)	(0.298)	(0.261)	(0.294)	(0.248)	(0.214)	(0.190)	(0.266)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	474	474	474	474	474	474	474	474	474
adj. R^2	0.423	0.419	0.422	0.420	0.420	0.422	0.420	0.425	0.421

The dependent variable is the ratio of return on assets (ROA) to 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 4 – Continued

Panel B: Median Regressions

Dependent:	ROA/σ_{ret}									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRAD	-0.000794									
	(0.977)									
Top_50_UG		0.0190								
		(0.503)								
Top_50_GRAD			-0.0102							
			(0.721)							
Top_50_LAW				0.0180						
				(0.769)						
Top_50_MBA					-0.0194					
					(0.523)					
LAW						-0.0197				
						(0.697)				
MBA							-0.0318			
							(0.237)			
ACTUARY								-0.0345		
								(0.494)		
BUSINESS									-0.0414	
									(0.116)	
QUANT										0.133***
										(0.010)
CPA	-0.0715*	-0.0589*	-0.0699*	-0.0601	-0.0686**	-0.0751*	-0.0542			
	(0.056)	(0.096)	(0.054)	(0.129)	(0.018)	(0.076)	(0.102)			
INS_Cert	-0.0455	-0.0277	-0.0385	-0.0458	-0.0380	-0.0407	-0.0442			
	(0.209)	(0.429)	(0.277)	(0.235)	(0.185)	(0.324)	(0.177)			
ln(Assets)	-0.0226*	-0.0175	-0.0231*	-0.0196	-0.0224**	-0.0251*	-0.0248**	-0.0270**	-0.0288**	-0.0306**
	(0.069)	(0.146)	(0.063)	(0.162)	(0.026)	(0.086)	(0.028)	(0.040)	(0.020)	(0.050)
Leverage	-2.477***	-2.526***	-2.465***	-2.529***	-2.467***	-2.430***	-2.444***	-2.413***	-2.405***	-2.418***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(TDC1)	0.0825***	0.0794***	0.0823***	0.0834***	0.0805***	0.0867***	0.0856***	0.0974***	0.0881***	0.0856***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CEO_AGE	-0.0000892	-0.000507	-0.000183	0.000413	0.000464	-0.000511	0.000952	0.000176	0.000137	0.00130
	(0.960)	(0.764)	(0.915)	(0.826)	(0.741)	(0.800)	(0.549)	(0.924)	(0.936)	(0.546)
Tenure	0.000294	0.000489	0.000190	0.000135	0.000126	0.000743	-0.000143	0.000407	0.000570	0.000800
	(0.818)	(0.692)	(0.879)	(0.924)	(0.904)	(0.635)	(0.901)	(0.763)	(0.653)	(0.609)
N	474	474	474	474	474	474	474	474	474	474
pseudo R^2	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.25

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

Table 5: CEO Education and Credit Risk

Panel A: Raw Population Averaged Probit Regressions

Dependent:	Lower_Grade								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.218								
	(0.619)								
Top_50_UG		-0.941**							
		(0.036)							
Top_50_GRAD			0.561*						
			(0.092)						
Top_50_MBA				0.352					
				(0.546)					
LAW					0.271				
					(0.759)				
MBA						0.321			
						(0.298)			
ACTUARY							-0.0910		
							(0.748)		
BUSINESS								-0.146	
								(0.447)	
QUANT									0.102
									(0.759)
CPA	0.113	-0.649	0.126	0.122	0.147	0.0766			
	(0.851)	(0.357)	(0.849)	(0.832)	(0.795)	(0.894)			
INS_Cert	-0.558	-0.662	-0.609	-0.621	-0.602	-0.501			
	(0.345)	(0.307)	(0.437)	(0.361)	(0.411)	(0.377)			
ln(Assets)	-0.405	-0.585**	-0.423*	-0.328	-0.301	-0.362	-0.413*	-0.393	-0.440*
	(0.105)	(0.013)	(0.066)	(0.159)	(0.187)	(0.118)	(0.095)	(0.131)	(0.082)
ROA	-0.583	0.733	-0.209	-0.672	-0.372	-0.957	-0.770	-0.677	-0.824
	(0.764)	(0.750)	(0.916)	(0.729)	(0.834)	(0.577)	(0.745)	(0.782)	(0.732)
Leverage	1.880	4.051	1.886	1.505	1.813	1.630	2.253	2.211	2.409
	(0.388)	(0.170)	(0.389)	(0.507)	(0.390)	(0.428)	(0.408)	(0.433)	(0.400)
ret	0.194	0.219	0.201	0.180	0.164	0.191	0.239	0.240	0.251
	(0.320)	(0.306)	(0.380)	(0.373)	(0.367)	(0.333)	(0.214)	(0.212)	(0.175)
ln(TDC1)	-0.0659	-0.0762	-0.104	-0.0582	-0.0679	-0.0467	0.0207	0.0188	0.0178
	(0.790)	(0.760)	(0.704)	(0.812)	(0.779)	(0.848)	(0.928)	(0.935)	(0.939)
CEO_AGE	0.0135	0.0353*	0.0241	0.0135	0.0131	0.00990	0.00899	0.00913	0.00933
	(0.494)	(0.098)	(0.320)	(0.523)	(0.530)	(0.609)	(0.643)	(0.624)	(0.594)
Tenure	-0.0187	-0.0600*	-0.0236	-0.0182	-0.0173	-0.0176	-0.0328*	-0.0326*	-0.0347*
	(0.297)	(0.057)	(0.211)	(0.291)	(0.294)	(0.307)	(0.072)	(0.077)	(0.060)
N	209	209	209	209	209	209	209	209	209

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 5 – Continued

Panel B: Average Marginal Effects for Probit Coefficients

Dependent:	Lower_Grade								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.075								
	(0.605)								
Top_50_UG		-0.298**							
		(0.011)							
Top_50_GRAD			0.178**						
			(0.046)						
Top_50_MBA				0.121					
				(0.545)					
LAW					0.097				
					(0.761)				
MBA						0.111			
						(0.279)			
ACTUARY							-0.032		
							(0.747)		
BUSINESS								-0.051	
								(0.433)	
QUANT									0.035
									(0.758)
CPA	0.039	-.205	0.040	0.042	0.053	0.027			
	(0.850)	(0.332)	(0.849)	(0.831)	(0.794)	(0.894)			
INS_Cert	-0.192	-0.209	-0.193	-0.214	-0.215	-0.174			
	(0.313)	(0.275)	(0.389)	(0.340)	(0.387)	(0.360)			
ln(Assets)	-0.139**	-0.185***	-0.134**	-0.113	-0.107	-0.126*	-0.144**	-0.139	-0.152**
	(0.046)	(0.002)	(0.025)	(0.110)	(0.135)	(0.067)	(0.042)	(0.433)	(0.031)
ROA	-0.200	0.232	-0.066	-0.232	-0.133	-0.332	-0.270	-0.239	-0.285
	(0.767)	(0.747)	(0.916)	(0.731)	(0.835)	(0.585)	(0.750)	(0.786)	(0.738)
Leverage	.645	1.281	.598	.519	.647	0.566	0.788	0.779	0.832
	(0.368)	(0.134)	(0.375)	(0.500)	(0.371)	(0.411)	(0.384)	(0.410)	(0.372)
ret	0.067	0.069	0.064	0.062	0.058	0.066	0.084	0.084	0.087
	(0.334)	(0.313)	(0.391)	(0.377)	(0.377)	(0.344)	(0.224)	(0.219)	(0.196)
ln(TDC1)	-0.023	-0.024	-0.033	-0.020	-0.024	-0.016	0.007	0.007	0.006
	(0.792)	(0.759)	(0.704)	(0.814)	(0.781)	(0.848)	(0.928)	(0.935)	(0.939)
CEO_AGE	0.005	0.011*	0.008	0.005	0.005	0.003	0.003	0.003	0.003
	(0.474)	(0.056)	(0.263)	(0.510)	(0.513)	(0.600)	(0.635)	(0.614)	(0.583)
Tenure	-0.006	-0.019**	-0.007	-0.006	-0.006	-0.006	-0.011**	-0.011**	-0.012**
	(0.290)	(0.025)	(0.201)	(0.283)	(0.285)	(0.293)	(0.037)	(0.037)	(0.027)

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 5 – Continued

Panel C: Fixed Effects OLS Regressions for Distance to Default

Dependent:	ln(Z)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	-0.405								
	(0.202)								
Top_50_UG		1.110**							
		(0.029)							
Top_50_GRAD			0.940**						
			(0.020)						
Top_50_MBA				1.415***					
				(0.000)					
LAW					0.344				
					(0.388)				
MBA						-0.554**			
						(0.049)			
ACTUARY							0.151		
							(0.602)		
BUSINESS								-0.341**	
								(0.039)	
QUANT									0.123
									(0.826)
CPA	-0.770***	0.129	-0.769**	-0.730**	-0.783***	-0.808***			
	(0.009)	(0.792)	(0.015)	(0.017)	(0.006)	(0.006)			
INS_Cert	0.104	0.207	0.220	0.165	0.303	0.105			
	(0.758)	(0.278)	(0.312)	(0.401)	(0.232)	(0.684)			
ln(Assets)	0.745***	0.710***	0.723***	0.681***	0.781***	0.797***	0.632***	0.657***	0.624***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.006)
Leverage	-4.379**	-4.887***	-4.403**	-4.239**	-4.646**	-4.853**	-3.333	-3.584	-3.229
	(0.018)	(0.009)	(0.016)	(0.020)	(0.013)	(0.015)	(0.140)	(0.127)	(0.141)
ret	0.985**	0.982**	1.012**	1.013**	0.966**	0.967**	1.009**	1.025**	1.006**
	(0.025)	(0.026)	(0.022)	(0.023)	(0.027)	(0.027)	(0.027)	(0.024)	(0.028)
ln(TDC1)	-0.366**	-0.363**	-0.360**	-0.332**	-0.411**	-0.394**	-0.273*	-0.306*	-0.270*
	(0.028)	(0.019)	(0.023)	(0.033)	(0.021)	(0.015)	(0.065)	(0.053)	(0.061)
CEO_AGE	-0.0160	-0.0108	-0.0146	-0.00701	-0.0163	-0.0213	-0.00182	-0.00450	-0.000476
	(0.366)	(0.494)	(0.347)	(0.651)	(0.322)	(0.309)	(0.923)	(0.811)	(0.978)
Tenure	0.0443***	0.0104	0.0338**	0.0305**	0.0420***	0.0494**	0.0365**	0.0369**	0.0350**
	(0.008)	(0.587)	(0.020)	(0.039)	(0.007)	(0.015)	(0.042)	(0.036)	(0.024)
N	234	234	234	234	234	234	234	234	234
adj. R^2	0.126	0.138	0.132	0.136	0.124	0.126	0.099	0.103	0.099

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 6: CEO Education and Operational Risk Frequency – Poisson Regressions

Dependent:	Operational_Freq									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GRAD	0.697* (0.054)									
Top_50_UG		-0.147 (0.690)								
Top_50_GRAD			-0.286 (0.466)							
Top_50_LAW				-14.86*** (0.000)						
Top_50_MBA					-0.328 (0.577)					
LAW						-1.724 (0.124)				
MBA							1.297*** (0.001)			
ACTUARY								-0.388 (0.592)		
BUSINESS									1.192*** (0.010)	
QUANT										-0.699 (0.245)
CPA	0.0956 (0.863)	-0.0816 (0.880)	-0.0616 (0.911)	-0.116 (0.834)	-0.0387 (0.945)	0.00921 (0.987)	-0.207 (0.764)			
INS_Cert	-0.265 (0.631)	-0.435 (0.426)	-0.414 (0.447)	-0.415 (0.440)	-0.409 (0.445)	-0.418 (0.438)	0.00736 (0.991)			
ln(Assets)	0.596*** (0.000)	0.572*** (0.000)	0.563*** (0.000)	0.538*** (0.000)	0.580*** (0.000)	0.567*** (0.000)	0.580*** (0.000)	0.568*** (0.000)	0.632*** (0.000)	0.591*** (0.000)
ROA	7.904 (0.266)	8.627 (0.247)	9.297 (0.215)	9.296 (0.221)	8.900 (0.233)	9.308 (0.243)	10.34 (0.215)	9.810 (0.189)	11.55 (0.162)	13.65 (0.135)
Leverage	-0.409 (0.829)	0.309 (0.871)	0.646 (0.739)	0.763 (0.702)	0.491 (0.801)	0.394 (0.840)	1.043 (0.638)	0.581 (0.756)	0.810 (0.697)	1.601 (0.460)
ln(TDC1)	0.0845 (0.744)	0.0762 (0.785)	0.0585 (0.831)	0.0636 (0.809)	0.0336 (0.903)	0.123 (0.628)	0.198 (0.394)	0.101 (0.694)	0.200 (0.383)	0.0769 (0.760)
CEO_AGE	-0.0254 (0.307)	-0.0285 (0.239)	-0.0301 (0.200)	-0.0309 (0.191)	-0.0289 (0.240)	-0.0220 (0.351)	-0.0392 (0.146)	-0.0300 (0.220)	-0.0377 (0.152)	-0.0313 (0.201)
Tenure	0.00658 (0.756)	0.000931 (0.963)	-0.00221 (0.919)	0.00234 (0.908)	-0.00113 (0.958)	0.0244 (0.278)	0.0106 (0.621)	0.000824 (0.968)	0.0157 (0.479)	0.00128 (0.949)
N	490	490	490	490	490	490	490	490	490	490
pseudo R^2	0.145	0.132	0.133	0.137	0.133	0.143	0.182	0.130	0.167	0.137

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 7: CEO Education and Operational Risk Severity – OLS Panels

Dependent:	Operational_Loss								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRAD	0.0310								
	(0.853)								
Top_50_UG		-0.225							
		(0.196)							
Top_50_GRAD			-0.284						
			(0.251)						
Top_50_MBA				-0.151					
				(0.137)					
LAW					-0.499**				
					(0.026)				
MBA						0.297			
						(0.387)			
ACTUARY							-0.203		
							(0.113)		
BUSINESS								-0.0758	
								(0.511)	
QUANT									-0.136
									(0.330)
CPA	-0.0403	-0.0276	0.0711	-0.0142	-0.0407	-0.0982			
	(0.821)	(0.876)	(0.760)	(0.940)	(0.833)	(0.624)			
INS_Cert	0.130	0.141	0.193	0.140	0.0461	0.170			
	(0.263)	(0.349)	(0.176)	(0.242)	(0.651)	(0.187)			
ln(Assets)	-0.0390	-0.0405	-0.000113	-0.0307	-0.0556	-0.0534	-0.0413	-0.0218	-0.0191
	(0.606)	(0.624)	(0.999)	(0.690)	(0.540)	(0.505)	(0.595)	(0.786)	(0.810)
ROA	0.576	0.618	0.611	0.638	0.167	0.208	0.540	0.709	0.596
	(0.668)	(0.645)	(0.652)	(0.639)	(0.904)	(0.895)	(0.694)	(0.607)	(0.665)
Leverage	0.396	0.571	0.372	0.417	0.449	0.299	0.452	0.421	0.370
	(0.519)	(0.396)	(0.551)	(0.496)	(0.475)	(0.643)	(0.451)	(0.483)	(0.540)
ln(TDC1)	0.0339	0.0445	0.0426	0.0295	0.0610	0.0430	0.0325	0.0275	0.0305
	(0.731)	(0.670)	(0.678)	(0.767)	(0.597)	(0.689)	(0.757)	(0.794)	(0.762)
CEO_AGE	-0.00177	-0.000627	-0.00451	-0.00242	-0.00256	-0.00216	-0.000458	-0.00108	-0.00123
	(0.704)	(0.880)	(0.345)	(0.556)	(0.547)	(0.579)	(0.910)	(0.790)	(0.766)
Tenure	-0.0175**	-0.0165**	-0.0164*	-0.0177**	-0.0155***	-0.0170**	-0.0171**	-0.0170**	-0.0154*
	(0.031)	(0.027)	(0.051)	(0.026)	(0.005)	(0.034)	(0.024)	(0.023)	(0.056)
N	490	490	490	490	490	490	490	490	490
adj. R^2	0.003	0.010	0.009	0.004	0.010	0.010	0.006	0.006	0.006

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 8: CEO Education Using Rankings

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent:	ROA/σ_{ret}	Operational_Freq	Lower_Grade	ROA/σ_{ret}	Operational_Freq	Lower_Grade
Model:	OLS	Poisson	Probit	OLS	Poisson	Probit
USN_UG_Rank	-0.00197*	0.00765*	0.0118***			
	(0.093)	(0.066)	(0.007)			
USN_GRAD_Rank				0.000486	0.00939	0.00544
				(0.311)	(0.293)	(0.666)
ln(Assets)	0.0115	0.718***	-1.223***	0.0794	0.585***	-2.083***
	(0.895)	(0.003)	(0.000)	(0.315)	(0.001)	(0.000)
Leverage	-1.504***	1.441	14.29***	-2.460***	-4.901	26.70***
	(0.002)	(0.667)	(0.001)	(0.000)	(0.153)	(0.002)
ln(TDC1)	0.0845	0.171	0.455	0.0779	0.258	0.497
	(0.112)	(0.590)	(0.172)	(0.104)	(0.409)	(0.313)
CEO_AGE	0.00371	-0.0518	-0.00833	-0.00265	-0.0631	0.0634
	(0.262)	(0.162)	(0.788)	(0.541)	(0.112)	(0.288)
Tenure	-0.00662	0.00513	-0.119**	0.0106**	-0.00436	-0.184
	(0.590)	(0.821)	(0.016)	(0.011)	(0.912)	(0.105)
ROA		20.30	4.384		-0.0994	-24.46*
		(0.252)	(0.759)		(0.991)	(0.068)
ret			-0.0223			3.457***
			(0.975)			(0.000)
N	261	265	103	212	222	90

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 9: CEO Education and Operational Risk Frequency – ZIP Regressions

Dependent:	Operational_Freq								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Top_50_UG	-0.0819 (0.829)								
Top_50_GRAD		-1.090** (0.034)							
Top_50_LAW			-10.16 (0.993)						
Top_50_MBA				0.248 (0.725)					
LAW					-2.842* (0.070)				
MBA						2.218*** (0.000)			
ACTUARY							-13.71 (0.988)		
BUSINESS								1.523*** (0.001)	
QUANT									-1.331** (0.039)
CPA	-0.671 (0.438)	-0.957 (0.305)	-0.660 (0.441)	-0.667 (0.436)	-0.501 (0.584)	0.0917 (0.924)			
INS_Cert	-1.571 (0.145)	-1.613 (0.139)	-1.543 (0.150)	-1.558 (0.147)	-1.783 (0.126)	-0.396 (0.745)			
ln(Assets)	0.368* (0.074)	0.219 (0.319)	0.372* (0.068)	0.405* (0.067)	0.341 (0.160)	0.491** (0.031)	0.298 (0.137)	0.367* (0.096)	0.268 (0.186)
ROA	-4.881 (0.692)	-5.507 (0.650)	-4.731 (0.698)	-4.584 (0.708)	-8.738 (0.491)	-8.685 (0.494)	-3.016 (0.798)	1.598 (0.912)	5.334 (0.693)
Leverage	-3.906 (0.262)	-4.296 (0.212)	-3.840 (0.258)	-4.216 (0.242)	-6.102 (0.102)	-6.316* (0.092)	-2.625 (0.386)	-2.878 (0.395)	-0.493 (0.882)
ln(TDC1)	0.275 (0.393)	0.481 (0.169)	0.258 (0.410)	0.242 (0.435)	0.473 (0.224)	0.471 (0.182)	0.460 (0.114)	0.425 (0.160)	0.368 (0.226)
CEO_AGE	-0.0663* (0.056)	-0.0848** (0.017)	-0.0674** (0.048)	-0.0703** (0.048)	-0.0559 (0.127)	-0.145*** (0.004)	-0.0692** (0.043)	-0.106** (0.014)	-0.0903** (0.015)
Tenure	0.0187 (0.353)	0.0177 (0.367)	0.0183 (0.349)	0.0195 (0.332)	0.0676* (0.083)	0.0564** (0.033)	0.0191 (0.323)	0.0556** (0.023)	0.0277 (0.163)
Inflation Variables									
σ_{ret}	54.40 (0.487)	40.25 (0.158)	52.78 (0.423)	53.72 (0.467)	35.55 (0.160)	29.97 (0.192)	44.80 (0.269)	35.19 (0.184)	32.30 (0.178)
Firm_Age	-0.369 (0.463)	-0.269 (0.101)	-0.356 (0.397)	-0.363 (0.444)	-0.246** (0.049)	-0.186 (0.102)	-0.284 (0.222)	-0.227* (0.081)	-0.207* (0.094)
N	324	324	324	324	324	324	324	324	324
Vuong Statistic	3.02***	2.73***	2.98***	3.00***	2.46***	2.64***	2.96***	2.26***	2.73***

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 10: 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 10 – 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 10 – 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 11: 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.

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.

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.

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

$$\mathrm{Z} = \frac{(\mathrm{ROA} + \mathrm{CAR})}{\sigma(\mathrm{ROA})}, \tag{23}$$

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

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.

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

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