CEO early-life disaster experience and corporate innovation

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Abstract

Using a hand-collected database of natural disasters in the U.S., we provide novel evidence that firms led by CEOs with early-life disaster experiences achieve better innovation outcomes. The positive effect is amplified for firms operating in challenging business conditions, such as highly competitive product markets and economic recessions, and firms with higher compensation of risk-taking incentives (Vega). Our further analysis suggests that early-life disaster CEOs are more willing to take risks and invest more in R&D input. Collectively, failure tolerance and risk-taking are two potential mechanisms through which early-life disaster CEOs affect corporate innovation.

Keywords: CEO Early Life Disaster Experiences, Failure Tolerance, Risk Taking, Corporate Innovation
EFM Classification Codes: 150
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1 Introduction

The biological and psychological literature on imprinting theory suggests that individuals' past experiences can impact their decision-making behaviors (Pieper et al., 2015). In this case, human beings exhibit high susceptibility to extreme changes in external environments. Such changes affect human's preferences and thus decision-making. Moreover, the changes persistently exist despite new subsequent developments (Marquis and Tilcsik, 2013). In particular, upper echelons theory states that chief executive officers' past experiences shape their characteristics, which influences corporate decisions and strategies (see Hambrick and Mason, 1984; Bigley and Wiersema, 2002; Hambrick, 2007; Finkelstein et al., 2009; Chin et al., 2013; Crossland et al., 2014, among others). Based on the upper echelons theory, a growing body of finance studies investigates how chief executive officers' past experiences, such as the experiences on military services (Benmelech and Frydman, 2015), pilot licenses (Sunder et al., 2017), great depression (Malmendier et al., 2011), cultural revolution (Kong et al., 2021), and natural disasters (Bernile et al., 2017), affect their corporate decisions [1]. Recent studies emphasize the implications of CEOs' early-life disaster experiences on corporate activities, consisting of corporate social performances (O'Sullivan et al., 2021), stock price crash risk (Chen et al., 2021), and corporate policies such as leverage and acquisitions (Bernile et al., 2017). Although previous research has recognized that CEOs' exposure to fatal disasters in their early life matters for corporate decisions, it is largely unexplored whether and to what extent firms run by CEOs who experience catastrophic disasters in their childhood affect corporate innovation outcomes. Our study on this question extends the research line of CEOs' witnesses to fatal disasters to the implications on corporate innovation success.

Corporate innovation refers to the progress of creating new ideas and technology that lead to increments in firm value and build the long-run and sustainable competitiveness (Romer, 1987, 1990), particular in concentratively competitive industries (Adams, 1990). In theory, Manso (2011) predicts that failure tolerance in the early stages and compensation for long-term success in contracts largely encourage risk-taking and motivate the CEO to pursue innovation, as innovation is a multi-period process with risky and unpredictable outcomes (Holmstrom, 1989). Empirically, much research has supported the crucial determinants of corporate innovation mentioned in theory, such as Hutchison-Krupat and Chao (2014), Mazouz and Zhao (2019), Mao and Zhang (2018), and Tian and Wang (2014). Early empirical work (Malmendier et al., 2011; Galasso and Simcoe, 2011; Hirshleifer et al., 2012) has also been dedicated to identifying overconfidence as an important role because overconfident CEOs often underestimate the risks of innovative projects. By contrast, CEOs' abilities to evaluate and undertake innovation-intensive investment projects has

[1] Bui et al. (2019) state that the investors' natural disaster exposure can also affect their risk preference thus impact the trading behaviors in financial markets.

been regarded as the vital characteristic in the success of corporate innovation in recent work, consisting of the openness to new ideas (Sunder et al., 2017), managerial skills (Custodio et al., 2019), inventor experiences (Islama and Zein, 2020), and the top management teams (Chemmanur et al., 2019). The majority of such abilities and characteristics gained from particular experiences (Sunder et al., 2017; Islama and Zein, 2020), consistent with the upper echelons theory mentioned above.

Our analysis conjectures that CEOs' early life exposures to catastrophes positively stimulate innovation outcomes through two potential channels, failure tolerance and risk-taking. The risk-preference channel is well documented in previous literature (e.g., Bernile et al. (2017)), which will be discussed secondary. By contrast, the failure-tolerance channel has not been widely explored in empirical work. This paper emphasizes the failure-tolerance channel that helps fill this gap. From the psychological aspect, we expect that CEOs whom exposure to fatal disasters will gain psychological strength, which refers to "post-traumatic growth" effects (Colville and Penelope, 2009). Exposure to traumatic events develops psychological gains for CEOs on robust cognition and emotional self-regulation (Calhoun and Tedeschi, 1999; Devine et al., 2010; Janoff-Bulman, 2004; Tedeschi and Calhoun, 2004; Zoellner and Maercker, 2006). This growth reshapes CEOs' psychological strength and rebuilds incredible ability to be more resilient facing future challenges. Namely, the CEO can manage risks even in extreme environments like recession or fierce competition. As such, disaster CEOs have a high tolerance for failure, which leads to better performances in innovation. Distinguish from the theoretical research in Manso (2011), the experimental research in Hutchison-Krupat and Chao (2014), and the particular cases on Venture Capital in Tian and Wang (2014), our study is one of the earliest papers to provide generally empirical shreds of evidence that CEOs early-life disasters experiences enhance their tolerance on failure and then affect innovation success.

Second, we confirm that the risk-taking channel widely discussed in prior research also works in our cases. The youth who are exposed to fatal disasters will compare the traumatic events to less fatal experiences (Ben-Zur and Zeidner, 2009). Hence, they are less likely to estimate adverse outcomes than their peers who did not experience traumatic events (Halpern-Felsher et al., 2001), as everything else seems pale compared to fatal disasters (Ben-Zur and Zeidner, 2009; Taylor and Lobel, 1989). These comparisons make disaster CEOs more likely to accept risks. Besides, the witness of natural disasters may elevate an individual's confidence in her ability to handle risky situations (Aldwin, 2007), making her more risk-seeking (see Eckel et al., 1998; Voors et al., 1908; Page et al., 2014; Hanaoka et al., 2018, among others). Therefore, the event comparison and confidence increase lead disaster CEOs to undertake more risky and innovative projects.

However, it is also possible that early-life traumatic experiences make CEOs more risk-averse.

The early life fatal disasters lead CEOs to recognize the world as a scary place (Lerner and Keltner, 2001; Cameron and Shah, 2015), where they will face uncertainty and loss of control that belongs to two critical determinants in judging risks (Slovic, 1987). Therefore, disaster CEOs seek certainty and turn out to be risk-averse (Callen et al., 2014; Kim and Lee, 2014; Cameron and Shah, 2015). The coexistence of positive and negative effects infers a new conjecture that childhood exposure to natural disasters does not necessarily positively impact CEOs and their firms' innovation achievements. The heterogeneous effects of childhood exposure to natural disasters may attribute to the severity of traumatic events (Bernile et al., 2017; Chen et al., 2021).

Based on a sample of 8,703 firm-year observations representing U.S. firms during 1992–2008, we examine the implications of CEO early-life disaster experiences on corporate innovations. Following Chang et al. (2019), we measure corporate innovations by patent data from the United States Patent and Trademark Office (USPTO) and patent citation data from the Harvard Business School (HBS) Patent Network Dataverse. The most recent year for our patent and citation data is 2010. Consistent with Hall et al. (2001), we end our sample in 2008 to address the truncation bias due to the two-year lag between the date a patent is filed and the date a patent is granted. To measure CEOs' early-life disaster experience, we begin by identifying the birth years and grow-up (birth) places of 1,858 U.S.-born CEOs from 1992 to 2008. Next, we collect U.S. county-level disaster events during 1960-2019 from the United States Spatial Hazard Events and Losses Database (SHELDUS™) and manually collect the disaster events equivalent to SHELDUS™ that covers from 1900 to 1959 to construct a unique database of U.S. county-level natural hazard records during 1900-2019. We then combine these two databases to infer CEOs' early-life disaster experience based on whether CEOs experienced natural disaster fatal events during their formative years. Different from Bernile et al. (2017), we distinguish CEOs' grow-up places from birthplaces and prefer CEOs' grow-up places when measuring their formative years.

Our empirical results support the first prediction that firms run by CEOs with early-life disaster experience have better innovation output than firms run by CEOs without disaster experience. The impact of CEO early-life disaster experience on corporate innovation is statistically and economically insightful. After controlling for other determinants of corporate innovation, firms led by CEOs with early-life disaster experience generate, on average, 19.28% more patents and 19.78% more citations than those led by CEOs without early-life disaster experience. The magnitude of the estimated effects is comparable to that of other widely accepted factors affecting corporate innovation such as Tobin's q and firm age (Mazouz and Zhao, 2019; Custodio et al., 2019).

The proposed associations of CEOs' disaster experiences on corporate innovation success may suffer endogeneity issues. First, the omitted variables in our baseline regression model might impact the likelihood that a CEO who has early life experiences of natural disasters attends focal firms. Second, firms run by disaster CEOs or non-disaster CEOs might be heterogeneous due to unobservable and observable corporate characteristics. Such firm-level heterogeneity instead of CEOs' disaster experiences could make companies achieve better innovation outcomes. Moreover, firms with better innovation performances may employ CEOs with childhood disasters experiences in the job market, which sinks into the reverse causality issue.

To this end, we specify four econometric methodologies to resolve the above endogeneity issues. First, we introduce an additional vector of control variables about CEO education and CEO characteristics to avoid the omitting variables. Second, we adopts the propensity score matching (PSM) regression to assuage the issues that our infer association between disaster CEOs and corporate innovation success dues to the systematic difference caused by firm-level observed characteristics. Third, to capture the observable and unobservable firm-level enduring attributes, we re-estimate our baseline regression model with firm fixed effects. We further control for CEO grow-up state fixed effects and CEO birth year fixed effects to capture the cohort-related effects in our sample and the time-invariant characteristics across states, respectively. Additionally, we consider the interacted fixed effects between year and firm's state (industry) to capture the time-varying differences among states (industries) in corporate innovation. Last, we conduct the difference-in-difference (DID) estimation on the CEO turnover between disaster and non-disaster CEOs to examine the implications on corporate innovation outcomes, mitigating the potential reverse causality issue caused by endogenous CEO-firm matching. Resolving the endogeneity issues, we find that the positive relationship between disaster CEOs and corporate innovation success is still statistically significant.

Our study develops cross-sectional analyses to explore whether the positive effects of disaster exposed CEOs on corporate innovation success are heterogeneous in various types of companies. We show that the positive impact of disaster CEOs on corporate innovation success is more pronounced in firms with higher risk-taking compensations, fierce market competition, and economic downturns. We explain these findings based on contract theory, which predicts that an optimal incentive scheme requires tolerance to the short-run failure and high compensation in the future meanwhile (Manso, 2011). On the one hand, the rewards in risk-taking incentives (Vega) (e.g., executive stock options (Armstrong and Vashishtha, 2012)) in contracts would stimulate CEOs to take more risks and promote innovation (Hutchison-Krupat and Chao, 2014; Mao and Zhang, 2018; Mazouz and Zhao, 2019). On the other hand, for risk-loving CEOs, the economic recession, which amplifies the effects of risk attitudes changes, might be a good opportunity to undertake innovative projects to reallocate the resources. Since firms in the high market concentration industries are more likely to fail, disaster CEOs who choose to work in such industries are more likely to pursue new technology to keep long-term competitiveness. Our study is one of the earliest investigations that identify the implications of failure tolerance on corporate innovation in general. In sum, both high rewards and tolerance to failure motivate CEOs to increase R&D input, improving innovation outcomes.

Furthermore, we propose additional analyses to inspect the potential mechanisms for firms managed by disaster witnessed CEOs to achieve better innovation outcomes. Our evidence confirms that CEOs with early life experiences of natural disasters employ aggressive investment policies and increase firms' potential exposure to the stock market risk and cash flow uncertainty, which is consistent with Malmendier et al. (2011), Galasso and Simcoe (2011), and Hirshleifer et al. (2012). Following Bernile et al. (2017) and Chen et al. (2021), our analysis confirms that the association between the severity of disaster events and risk attitudes is nonmonotonic. In particular, CEOs who exposure to moderate disasters are more aggressive in achieving innovation success. By contrast, their CEO peers who experienced extreme disaster events tend to be conservative and have inferior innovation outcomes. We further find that disaster CEOs invest more in RD.

In the supplemental analysis, our baseline regression result continues to hold when we use an alternative measure of CEO early-life disaster experience. Following Bernile et al. (2017), we construct an alternative window, 5 to 10 years old, as the formative year instead of the 5 to 15 years old in the baseline model.

This research extends two streams of the empirical literature. First, our investigation contributes to the studies examining the implications of CEOs' early-life disaster experiences to corporate activities (Bernile et al., 2017; Chen et al., 2021; O'Sullivan et al., 2021). Bernile et al. (2017) is one of the earliest studies to point out that childhood disaster experiences change CEOs' preferences in an asymmetric way—such a nonmonotonic relationship affect many corporate policies and lead to aggressive financing and investment policies and incur a higher cost of capital (Bernile et al., 2017). Chen et al. (2021) find that CEOs with early life disaster experience are more likely to withhold bad news, which is associated with higher stock price crash risk. In addition, disaster CEOs' risk attitudes asymmetrically respond to positive and adverse events, which is in line with the story of loss aversion (see Kahneman and Tversky, 1979; Benartzi and Thaler, 1995; Koszegi and Rabin, 2006; Barberis et al., 2001; Pagel, 2016, 2018, among others). Distinct from the risk preference story, O'Sullivan et al. (2021) suggests that disaster CEOs could gain psychological strength from rare events, and thus their managed firms perform better in social responsibility. Our examination contributes to the literature by showing that CEOs with early-life disaster experience invest more in R&D in troubled times to achieve better innovation performance.

Second, our analysis expands studies on the determinants driving corporate innovation success (Malmendier et al., 2011; Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Hutchison-Krupat and Chao, 2014; Tian and Wang, 2014; Sunder et al., 2017; Mao and Zhang, 2018; Mazouz and

Zhao, 2019; Kong et al., 2021; Wang et al., 2021). Past literature, such as Hutchison-Krupat and Chao (2014), Mao and Zhang (2018), and Mazouz and Zhao (2019), highlights the importance of risk-incentives in determining the corporate innovations, supporting the contract theory above (Manso, 2011). Additionally, much research above documents that CEOs' overconfidence makes them underestimate the probability of failure of innovative projects. Thus, excessively confident CEOs are more likely to pursue R&D input (Malmendier et al., 2011; Galasso and Simcoe, 2011; Hirshleifer et al., 2012) that raises the possibility of innovation success. By contrast, recent analyses illustrate that CEOs' past experiences shape their cognition and ability that can affect their innovation output (Sunder et al., 2017; Kong et al., 2021). For instance, Sunder et al. (2017) indicates that CEOs who are open to new experiences may also welcome novel ideas and technology, which could be a crucial driver for innovation success. Kong et al. (2021) argue that Chinese CEOs who witness Cultural Revolutions have a lower level of social trust, which adversely impacts corporate innovations. Our research adds the evidence that natural disaster experiences in CEOs' childhood not only make firms' increase the input in R&D but also has the potential to shape their efficiency in increasing innovation output.

The rest of this paper is arranged as follows. Section 2 summarise sample observations in interested variables. Section 3 introduces our main regression model and results. Section 4 shows the econometric specifications to solve potential endogeneity concerns. Section 5 investigates the possible mechanisms about how top executives' early life disaster experiences affect corporate innovations. Section 6 concludes.

2 Sample, Variables, and Summary Statistics

2.1 Sample Selection and Data Sources

We construct our sample from several different sources. Regarding CEOs' early-life disaster experience, we firstly collect the names, gender, and company information of CEOs in the U.S. listed firms during 1992-2019 from Compustat's Execucomp database. Following Chen et al. (2021); Bernile et al. (2017), we retrieve CEO biographical data, including CEOs' birth years and grow up (birth) places, from the following sources: Marquis Who's Who Biographies through LexisNexis, NNDB, Wikipedia, obituary website, university websites, wallmine, company official website, or Google searches in the last instance. Second, we create a database of the U.S. county-level natural disaster events, which comprises earthquakes, floods, landslides, volcanic eruptions, tsunamis, hurricanes, tornadoes, severe storms, and wild-fires from 1900 to 2019. Consistent with Chen et al. (2021) and Bernile et al. (2017), we begin by collecting all available county-level natural hazard records from the United States Spatial Hazard Events and Losses Database (SHELDUS™). The SHELDUS™ records the date, county location, injuries, and fatalities for each disaster event from 1960 to 2019. However, most of the CEOs in our sample are born before 1960, therefore, we further create a set of disaster events equivalent to SHELDUS™ that covers from 1900 to 1959. Appendix A shows the details of the data sources of U.S. county-level disaster events prior to 1960.

To measure firms' corporate innovation, we follow Chang et al. (2019) and rely on patent data from United States Patent and Trademark Office (USPTO) over 1976-2010 [2] We further obtain patent citations from the Harvard Business School (HBS) Patent Network Dataverse [3]. On average, there is a two-year lag between the date a patent is filed and the date a patent is granted. Since the most recent year for our patent and citation data is 2010, the database might not fully include patents filled in 2009 and 2010. We therefore end our sample in 2008 to address this truncation issue, as Hall et al. (2001) suggested. Additionally, firms' financial data is obtained from Compustat. CEOs' education backgrounds are collected from BoardEx.

In line with common practice (e.g., Chang et al. (2019); Hirshleifer et al. (2013)), we exclude firms in financial (SIC code: 6000-6999) and utility (SIC code: 4900-4999) industries. We also exclude observations with insufficient information for measuring the CEO early-life disaster experience or with missing financial data. As a result, our final sample consists of 8,703 firm-year observations during 1992-2008.

2.2 CEO Early-Life Disaster Experience

We initially collect reliable places and birth years for 2,404 U.S.-born CEOs of 6,203 CEOs over the period of 1992-2008 in the Compustat's Execucomp database. This data collection is comparable to Bernile et al. (2017), who search for CEOs' biographical data of firms in the S&P 1500 from 1992 to 2012. After excluding CEOs in firms with missing financial data or firms that come from financial and utility industries, our final sample is left with 1,858 CEOs. Further, our county-level disaster database records 2,891 disaster fatal events prior to 1960, which is also comparable to 2,670 pre-1960 fatal events of Bernile et al. (2017).

[2] The patent data is downloaded from Noah Stoffman's website (`https://iu.app.box.com/patents`). Kogan et al. (2017) illustrate the construction of this dataset. They begin by collecting raw patent data from the USPTO and identifying the firm (the assignee) to which each patent belongs. They then use an automated name matching algorithm to match firm names in the raw patent database and firm names in the CRSP database. Furthermore, they compare their final database with the National Bureau of Economic Research (NBER) Patent and Citation database to verify the accuracy of their data extraction and matching.

[3] We download the raw citation data from `http://thedata.harvard.edu/dvn/dv/patent`, which is constructed by Lai et al. (2009).

We measure CEOs' early-life disaster experience based on whether the CEO experienced natural disaster fatal events during his/her formative years. Consistent with Bernile et al. (2017); Chen et al. (2021), we define the formative period to be CEOs' ages of 5 to 15, since some medical studies (e.g., Nelson (1993)) report that lasting childhood memories typically start forming around age 5, while "early childhood" memories come to an end around the age 15. Following Chen et al. (2021), our main measure of CEOs' early-life disaster experience is constructed by a dummy variable, *Disaster_CEO*, that equals one if the CEO's grow up (birth) county encountered at least one natural disaster fatal events during his/her formative years, and zero otherwise [4]. Finally, our sample covers 854 CEOs with early-life natural disaster experience and 1,004 CEOs without such experience.

According to Bernile et al. (2017), we construct several alternative measures of CEOs' early-life disaster experience. First, we use the average disaster fatality (*Fatality*) [5] experienced by CEOs during their formative years to categorize all CEOs into to three groups: (1) *No_Fatality_Experience*, that is, CEOs who experience no fatal natural disasters during their formative years; (2) *Extreme_Fatality_Experience*, namely, CEOs who are in the top decile of the distribution the measure of *Fatality*; (3)*Medium_Fatality_Experience* (All the other CEOs). Second, we alternatively define our main measure by a different formative period as CEOs' age of 5 to 10. Hence, we construct $Disaster\_CEO_{(5\text{-}10)}$, a dummy that equals one if the CEO experienced disaster fatal events at ages of 5 to 10, and zero otherwise.

2.3 Corporate Innovations

Patent counts are an indicator of innovation output since patenting is a common way for companies to safeguard their technological innovations. Hence, we follow Chang et al. (2019) and construct our first measure of corporate innovation, *Patent*, which is the total number of patent applications that were filled for each firm-year and were eventually granted. However, as patents vary widely in both technological and economic importance, patent counts are an imperfect measure of innovation success (Hirshleifer et al., 2013).

Therefore, consistent with Hall et al. (2001, 2005), we use the number of citations subsequently received by a patent to measure its quality or scientific value. If a patent is cited subsequently, implying the valuation of the patented technology in future invention endeavors (Sunder et al.,

[4] When the grow up county and birth county are different for a CEO, we prefer his/her grow up county. When we are unable to identify a CEO's grow up county, we use his/her birth county.

[5] For each county-year, we calculate the disaster fatality level by the total number of fatalities from natural disasters over the population of the county-year *Fatality* is the average value of the fatality levels for each CEO's grow up (birth) county over his/her formative years.

2017). Because of the finite sample length, the raw citation counts are prone to truncation bias. Citations are accumulated over a long period of time. Hence, patents in the sample's later years have less time to accrue citations. To address this bias, we adopt the fixed-effect method to adjust the raw citation counts. That is, we scale the raw citation counts for a patent using the mean citation counts of all patents applied for in the same year and in the same technology class. As Chang et al. (2019) suggested, our second corporate innovation measure, *Citation*, is constructed by the sum of adjusted citations for each firm-year.

2.4 Control Variables

In line with prior corporate innovation literature, we control the following variables in our benchmark regression model. Our research first controls the logarithm of total assets (Size) because large firms can employ more sources (Guay, 1999) such that they achieve better innovation outcomes compared to small firms (Kim et al., 2004). Second, innovation aims to promote firms' long-run competitiveness (Romer, 1987, 1990), thus, firms with elder age are more patient and associated with better innovation outcomes. We thus include the firm age (Age). Additionally, long-lived tangible assets such as starting capital could be the critical driver of innovation (Heirman and Clarysse, 2017). We, therefore, control the net property, plant, and equipment per employee(PPE_perEM). Besides, firms with higher leverage ratio require more cash flows to pay interests, which makes them less likely to finance the long-run innovative projects. We adopt the debt-to-asset ratio (Leverage) introduced in Li et al. (2018) as one of the control variables. Further, prior research also points out that firms that survive in intensive competition industries are more likely to pursue innovation (Adams, 1990). We then introduce the HHI index (Herfindahl, 1950; Hirschman, 1942, 1964) in our vector of control variables. Finally, it is widely recognized that increasing the research and development input, although not necessarily leading to, will raise the potential of innovation success (Mazouz and Zhao, 2019; Galasso and Simcoe, 2011). Hence, we incorporate the R&D (RD) input into the array of control variables.

2.5 Summary Statistics

Table 1 displays summary statistics for interest variables in our research. For full samples, the Ln (1+Patent) has the mean values of 1.740, which is comparable to empircal evidence in past literature (Galasso and Simcoe, 2011; Amore et al., 2013; Custodio et al., 2019; Mazouz and Zhao, 2019; Kong et al., 2021). The value of adjusted Ln (1+Citation) has the average of 1.207, whose magnitude is also comparable to past studies (Amore et al., 2013; Custodio et al., 2019). We then decompose our observations to disaster CEO cases and non-disaster CEO cases. For the disaster

CEO samples, the mean of Ln (1+Patent) and Ln (1+Citation) are 1.552 and 1.570, respectively. As a comparison, the average of Ln(1+Patent) and Ln (1+Citation) in non-disaster observations are 0.902 and 0.910, respectively. We compute the differences of mean between the disaster CEO and non-disaster CEO cases and conduct the T tests. The differences of innovation outcome between disaster and non-disaster CEOs are significantly different from zero at 1% level. Thus, we expect that the CEOs' exposure to disasters matter for innovation achievements. Except for the net property, the results of T tests of disaster and non-disaster CEO differences in most of the interest variables are significant different from zero.

[Insert Table 1 around here]

3 Empirical Methodology

3.1 Baseline Regression Model

The start point of our research is identifying the empirical implications of CEO exposure to disaster on corporate innovation success, holding other determinants of corporate innovation outcome constant. We adopt the following benchmark regression model:

$$\text{Ln(1+Innovation)}_{i,t} = \alpha + \beta \times \text{Disaster\_CEO}_{i,t-1} + \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t} \quad (1)$$

where the dependent variable, $\text{Innovation}_{i,t}$, has two measurements—the logarithm values of one plus the patent application numbers in year t or plus the corresponding citation numbers. The interested dependent variable in this research, $\text{Disaster\_CEO}_{i,t-1}$, is a dummy variable that is identical to one for a disaster CEO managing firm, and zero otherwise.

Following the research on the determinants driving innovation success (Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Sunder et al., 2017; Custodio et al., 2019; Mazouz and Zhao, 2019), we consider a vector of contemporaneous values in continuously control variables, consisting of the natural logarithm of firm size (Size), the natural logarithm of firm age (Age), the net property intensity (PPE_perEMP), Tobin's q (TBQ), Leverage, the market competition (HHI), and the input on research & development (RD). Our paper incorporates year and industry (i.e., Fama-French 48 industries) fixed effects in the baseline model, while the robust standard errors are corrected by clustering residuals at firm level (Petersen, 2009). All independent variables are measured at past period (t-1), and the detailed definitions for each variable are illustrated in Appendix B.

3.2 Main Empirical Results

Table 2 displays the empirical results of the implications of CEOs' exposure to traumatic events on corporate innovation outcomes in the benchmark regression model. Columns (1) and (2) measure the innovation success by total numbers of patents. In column (1), we merely incorporate the CEO disaster exposure to the year and industry fixed effects. By contrast, column (2) additionally considers a vector of control variables. The estimations of coefficients of CEOs' disaster exposure, $\text{Disaster\_CEO}_{i,t-1}$, are positively and statistically significant at 1% level. Columns (3) and (4) display the corporate innovation output by overall citation numbers. The estimated coefficients of CEOs' disaster exposure, $\text{Disaster\_CEO}_{i,t-1}$, are consistently positive and significant at 1% level for all columns.

Referring to the economic implications, empirical evidence in column (2) states that firms run by disaster CEOs are associated with 19.28% increase (=0.230/1.195) increase in logorithm values of patent numbers on average. Analogously, the OLS results in column (4) demonstrates that the estimated coefficients on disaster exposure of CEOs, $\text{Disaster\_CEO}_{i,t-1}$, is associated with 19.78% (=0.239/1.207) increase in logarithm values of citation numbers at mean. Overall, the positive implication of disaster CEOs on corporate innovation success is both statistically and economically significant. This research compares the effects of disaster CEOs with that of other essential driving factors of corporate innovation outcomes. Take the Tobin's q that significantly impacts corporate innovation achievement as an example. The estimated coefficient and standard deviation of Tobin's are 0.114 and 1.367, suggesting that one-standard deviation increase in Tobin's could improve the patent-measured innovation performance by 0.155 (=0.114×1.367), which is identical to 13.01%(=0.155/1.195) on the logarithm values of patent. Furthermore, the value of estimated coefficients in control variables vector are magnificently comparable to related studies. Our study confirms that the corporate innovation success depends on firm size, firm age, firm leverage, and R&D input.

[Insert Table 2 around here]

4 Identification and Endogeneity

Our empirical findings indicate that firms managed by disaster CEOs are associated with better innovation outcomes. However, the causality of disaster CEOs on corporate innovation success could be challenged by potential endogeneity issues. First, it is possible that some crucial determinants are not controlled in our benchmark regression, resulting in the missing variables problem. Second, CEOs exposed to traumatic events may not be randomly assigned to firms, leading to self-selection bias. Further, we notice that aggressive boards that are more likely to pursue innovation have the potential to appoint disaster CEOs who can undertake more risky but innovative projects. Hence, the positive effects of disaster CEOs on corporate innovation are possibly driven by reverse causality. For the reasons above, our research addresses the potential endogeneity issues by adopting the following econometric specifications: (1) Additional Control Variables, (2) Propensity Score Matching estimation, (3) High-Dimensional Fixed Effects approach, and (4) Difference-in-Difference analysis.

4.1 Additional Controls

To address the omitting variable concerns, Table 3 presents the results of modified regression model that considers additional control variables. Our study controls a vector of CEO attributes involved in previous studies (Kim et al., 2016; Al Mamun et al., 2020; Chen et al., 2021). The main controls consist of the CEO-firm characteristics, including the CEO tenure (CEO_Tenure), CEO delta (CEO_Delta), and CEO Vega (CEO_Vega), as well as the CEOs education information about whether CEOs have a degree in Ivy league schools (CEO_Ivy_Degree), a degree on STEM subjects (CEO_Technical_Degree), a doctoral degree on STEM subjects (CEO_PhDinTechnical_Degree) or not mentioned (No_Education_Info). Detailed information of these controls is defined in Appendix B.

Our conclusions from benchmark results still hold despite introducing additional controls. The estimated coefficients of CEO_Age are negative and significant at 5% level in both of the patent and citation measurements, indicating that the young CEO are more innovate compare to their senior peers. Second, the coefficients of CEO_PhDinTechnical_Degree is positive and significance at 1% and 5 % level significance in the patent and citation measurements, respectively. This findings suggest that firms led by disaster CEOs with higher degree can accept more risks (Chen et al., 2021) and achieve better innovation outcomes.

[Insert Table 3 around here]

4.2 Propensity Score Matching

It is noteworthy that corporate innovation success might attribute to the systematic differences in observable heterogeneity across firms instead of the appointment of disaster CEOs. To alleviate the endogenous matching concern, our research employs the widely recognized PSM analysis introduced in Rosenbaum and Rubin (1983) to investigate the treatment effects of CEOs' early life disaster experiences on corporate innovation output. We recognized firms led by CEOs with early life disaster experiences as the treatment group, as non-disaster CEOs account for the majority part in our observations. Our study then matches the treatment group with a control group of firms managed by non-disaster experienced CEOs who perform similar firm characteristics. Thus, we guarantee that CEOs' exposure to disaster events or not in their early life is the unique distinctive characteristic between the treatment and control groups. Our research first adopts a logit model to estimate the propensity score (i.e., likelihood) of a firm run by a disaster CEO by controlling all discernible firm characteristics from the benchmark regression in Equation (1). This paper then employs the estimated likelihoods from the logit regression to execute a one-to-one, nearest-neighbor matching method without replacement. In particular, the maximum propensity scores differences between the treatment and control groups should satisfy the request that its absolute value is less than 0.5%.

Table 4 displays results of the PSM approach. This paper first propose mean-difference tests to investigate whether the PSM approach mitigates the differences in firm-level discernible characteristics between the treated and control firms. Results in Panel A of Table 4 state that the treatment group and corresponding control group perform no statistically significant differences in covariates. Second, we compare the value of Ln (1+Patent) and Ln (1+Citation) between treated firms and untreated firms and compute the average treatment effects. Results in Panel B of Table 4 indicate that the mean treatment effect is statistically significant different from zero, and firms run by CEOs with disaster experiences are related to significantly higher patents and citations. To end, our investigation re-examine the benchmark regression model in Equation (1) given the propensity score matched observations. Panel C of Table 4 report the outcomes of re-estimation, columns (1) and (2) represent the results of patent-based and citation-based innovation measurements, respectively. The estimated coefficients of $\text{Disaster\_CEO}_{i,t-1}$ on both patent-based and citation-based innovations are positive at 1% significance level. In lie with our expectation, the association of disaster CEOs on corporate innovation success is still statistically significant holding other firm-level discernible characteristics constant. These findings support the causal effect of CEOs disaster experiences to corporate innovation success.

[Insert Table 4 around here]

4.3 High Dimensional Fixed Effects

As discussed above, the PSM analysis can mitigate potential endogeneity issues caused by observable firm-level characteristics. However, the unobserved firm heterogeneity can also affect the causality of CEOs' disaster experiences on corporate innovation outcomes. To address this concern, we follow Gormley and Matsa (2014) to control additional and high-dimensional fixed effects compare to the benchmark model. We first introduce the time-invariant heterogeneity in the firm-level. Second, we follow O'Sullivan et al. (2021) to incorporate the cohort fixed effects on CEO grow-up state and birth year. Moreover, this paper incorporates two interacted fixed effects—the industry–year and state–year fixed effects into Equation (2).

$$\begin{aligned} \text{Ln(1+Innovation)}_{i,t} = {} & \alpha + \beta \text{Disaster\_CEO}_{i,t-1} + \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \text{Firm}_{FE} \\ & + \text{CEO Growth-Up State}_{FE} + \text{CEO Birth Year}_{FE} \\ & + \text{Year}_{FE} \times \text{State}_{FE} + \text{Year}_{FE} \times \text{Industry}_{FE} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

In columns (1) and (2) of Table 5, our paper re-estimates the relationship between CEOs' disaster experiences and corporate innovation achievements for time and firm fixed effects instead of industry fixed effects. In columns (3) and (4) of Table 5, we re-estimate the implication of disaster CEOs on corporate innovation output by controlling the fixed effects from CEO grow-up location and CEO birth-year, respectively. In columns (5) and (6) of Table 5, this study re-estimates the impact of CEOs' disaster experiences on corporate innovation success by introducing two kinds of joint fixed effects: industry-year fixed effects and interacted state-year fixed effects, respectively.

The estimated coefficients of $\text{Disaster\_CEO}_{i,t-1}$ in columns (5) to (7) are significant at 10% level while in other columns are significant at 5% level and are positive across all models. Our findings point out that the positive impact of disaster CEOs on corporate innovation output is not mattered by unobserved time-invariant characteristics, time-variant heterogeneity across firms and their joint effects, as well as CEOs' birth year and grow up location fixed effects.

[Insert Table 5 around here]

4.4 Difference-in-Difference

We follow Huang and Kisgen (2013) and conduct the DID study by examining the transition of CEOs disaster exposures around the CEO turnover events to avoid the reverse causal effects of corporate innovation success on disaster CEOs. We thus implement the DID analysis in two aspects. First, we consider firms with CEO transitions from a non-disaster CEO to a disaster CEO as the treatment group while firms adventuring non-disaster to non-disaster CEO transitions as the control group. Second, we assume treated firms experience CEO transitions from a disaster CEO to a non-disaster CEO while the control firms face disaster-to-disaster CEO transitions. Hence, in both groups, the transition of CEO disasters experiences, instead of CEO turnover events, make differences in the changes in corporate innovation outcomes.

Except for the transition year, we consider samples cover two-year firm-year observations before and after a CEO turnover event in the DID investigation. Thus, we request for two conditions that satisfies our DID sample selection. The first condition is that a new CEO should work in this position for at least two sequential year. Our second condition is, before the transition year, firms should not have missing financial data in Compustat at least two years. Overall, our DID sample consists of 73 non-disaster to disaster transitions and 97 non-disaster to non-disaster transitions in the first investigation, and 75 disaster to non-disaster transitions and 81 disaster-to-disaster transitions in the second investigation. We purpose the DID regression as follows:

$$\begin{aligned}\text{Ln(1+Innovation)}_{i,t} = \alpha &+ \beta_1 \text{Post}_{i,t-1} + \beta_2 \text{CEO\_Transition}_i \times \text{Post}_{i,t-1} \\ &+ \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Firm}_{FE} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where CEO_Transition_i presents a dummy variable for whether a firm experiences a disaster to non-disaster CEO transition or non-disaster to disaster CEO transition. The $\text{Post}_{i,t-1}$ presents an indicator variable that is identical to one for two years after the CEO turnover year. Our research controls all variables as in the benchmark regression model. By contrast to the baseline model, we introduce the firm fixed effects in the DID analysis such that the variable CEO_Transition_i is not necessary to be regressors (Huang and Kisgen, 2013). Instead, we focus on the interaction effect measured by $\text{CEO\_Transition}_i \times \text{Post}_{i,t-1}$.

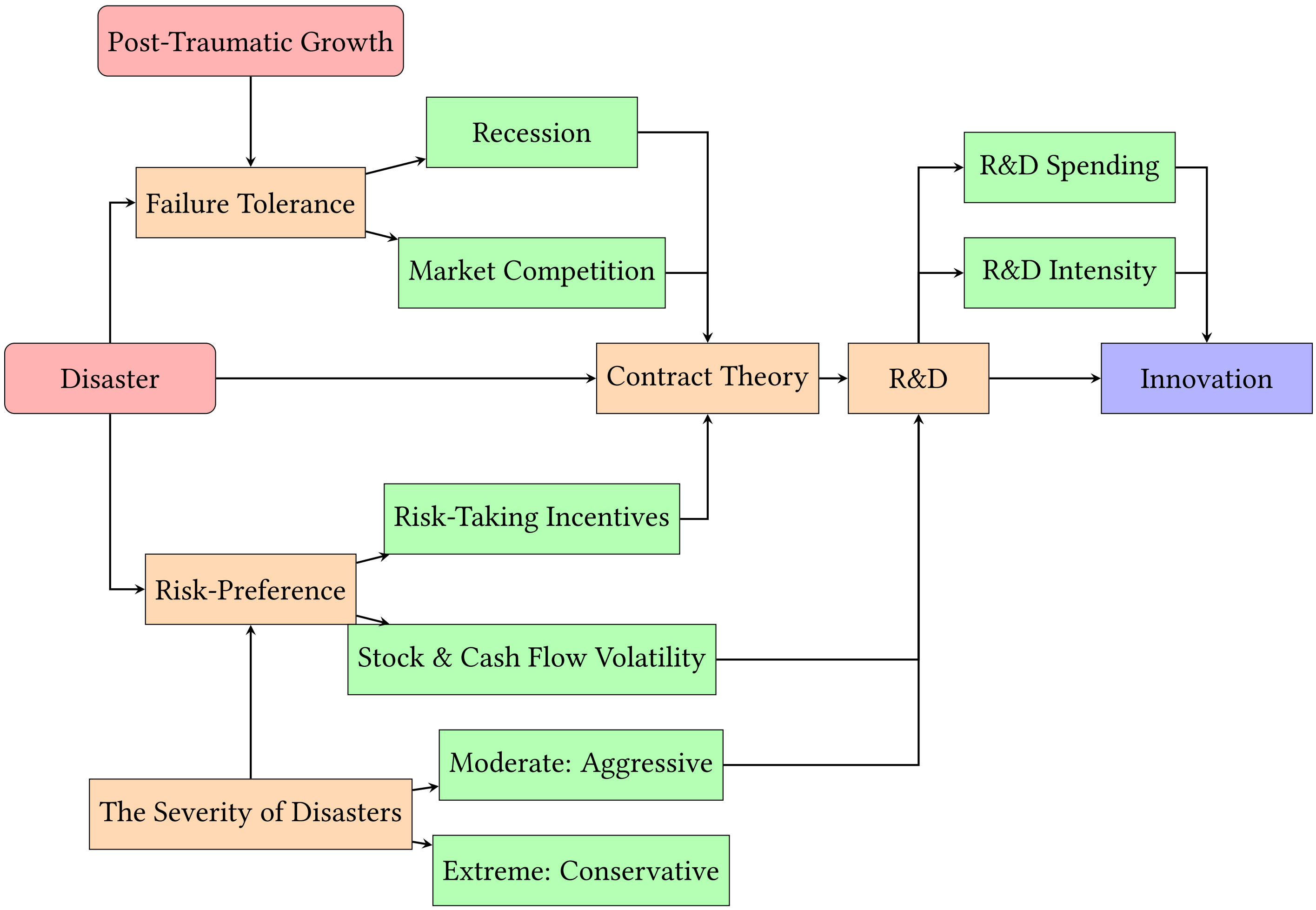
Table 6 reports the empirical findings of DID regressions. The estimated coefficients of interaction terms $\text{CEO\_Transition}_i \times \text{Post}_{i,t-1}$ are positive and statistically significant at 10% in column (1) and 5% at column (2), which implies that firms achieve better innovation outcome after disaster CEO appointments than after non-disaster CEO appointment. By contrast, the estimated coefficients of mutual reciprocity effect $\text{CEO\_Transition}_i \times \text{Post}_{i,t-1}$ are negative and at 5% significance level in columns (3) and (4), which suggests that firms achieve less innovation success after disaster CEO resignations. Hence, the argument in the benchmark regression model is still robust after implementing the DID analysis.

[Insert Table 6 around here]

5 Inspecting the Mechanism

Our empirical analysis so far suggests that firms led by disaster CEOs achieve better innovation success than those run by non-disaster CEOs. We attempt to understand the economic mechanisms through which CEO exposure to rare disaster events impacts corporate innovation success: (1) failure tolerance; (2) risk-loving. We also highlight the difference between R&D input and innovation efficiency. It has been confirmed that the severity of disasters matters for CEOs' risk preferences then affect firms' innovation performances. The overall mechanism displays in Figure 1.

Figure 1: Mechanism



5.1 Failure Tolerance

The contract theory predicts that the long-run compensation and short-run tolerance for failure could incentive innovation (Manso, 2011). Hence, one can conjecture that risk-taking incentives will motivate CEOs to achieve better innovation performances. This research will test both conjectures below.

The first condition from the contract theory is failure tolerance (Manso, 2011), which are mainly gained from CEOs' "post-traumatic growth" effects. It would be difficult to investigate the failure tolerance conditions in the optimal contract empirically. Hence, we conjecture a “fictitious contract” that the external environment plays as the failure tolerance condition. In this case, we assume firms face two kinds of challenges–growing intensive competition industries or recession. CEOs who insist to pursue innovations in a challenging time or industry could be considered offered a contract with failure tolerance items like the golden parachutes by director boards.

We start our discussion based on this series of assumptions. First, it is widely agreed that firms in competitive industries are more likely to pursue innovation, as the fierce the competition, the less the economic profits (Adams, 1990). Facing the challenges of peers, innovation barges firms to the forefront. Second, the creative destruction theory states that innovations in technologies will create a new economic structure to destroy and replace the old one, leading to business cycle fluctuations (Schumpeter, 1942). Therefore, the economic downturns provide opportunities for technical innovation. These outside challenges can "externally" suggest the condition of a "contract"—if the proposed positive relationship is more pronounced, the propagation on CEOs' risk-tolerant is more considerable, promoting innovation success better.

5.1.1 Market Competition

First, this study investigates whether the proposed relationship between disaster CEOs and firms' innovation success is heterogeneous across different degrees of industries competition by following equation:

$$\begin{aligned} \text{Ln(1+Innovation)}_{i,t} = \alpha &+ \beta_1 \times \text{Disaster\_CEO}_{i,t-1} + \beta_2 \times \text{High\_Market\_Competition}_{i,t-1} \\ &+ \beta_3 \times \text{Disaster\_CEO}_{i,t-1} \times \text{High\_Market\_Competition}_{i,t-1} + \gamma \text{Controls}_{i,t-1} \\ &+ \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where we adopt the HHI index proposed by Herfindahl (1950) and Hirschman (1942, 1964) to measure the market concentration, a lower value of the HHI index implies that firms are in a high competition industry. Hence, High_Market_Competition$_{i,t-1}$ is captured by Low_HHI$_{i,t-1}$, a dummy variable that equals one if the firm is in an industry in which HHI is below the median HHI level in the sample and zero otherwise. This paper also considers all control variables in the benchmark regression model in Equation (1) and control for year and industry fixed effects under the OLS estimation.

Table 7 reports the moderating effects of market competition on the implication of disaster CEOs and corporate innovation output. Columns (1) and (2) present the OLS regression findings of innovation measured by the logarithm values of patent and citation numbers. On average, the significantly positive estimator on Disaster_CEO$_{i,t-1}$×High_Market_Competition$_{i,t-1}$ predicts that our proposed association between CEOs' childhood exposure to natural disasters is prominent in firms belonging to high concentrate industries.

[Insert Table 7 around here]

5.1.2 Economic Downturn

Second, we investigate the adjusting role of economic recession on the relationship between CEOs' traumatic experiences and corporate innovation outcomes as the following equation:

$$\begin{aligned}\text{Ln(1+Innovation)}_{i,t} = \alpha &+ \beta_1 \times \text{Disaster\_CEO}_{i,t-1} + \beta_2 \times \text{Recession}_{i,t-1} \\ &+ \beta_3 \times \text{Disaster\_CEO}_{i,t-1} \times \text{Recession}_{i,t-1} + \gamma \text{Controls}_{i,t-1} \\ &+ \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where we employ the NBER recession indicator as the measurement of economic downturn. The indicator variable, $\text{Recession}_{i,t-1}$, that equals one if the current year is in the recession period, and zero otherwise. We consistently incorporate all control variables and both year and industry fixed effects in Equation (1) into our OLS regression.

Table 8 presents that the effect of CEOs' early life disaster experiences on corporate innovation success is related to the business cycle fluctuations. Columns (1) and (2) displays the results that measure innovation by patent and citation, respectively. In both measurements, the estimated coefficients of $\text{Disaster\_CEO}_{i,t-1} \times \text{Recession}_{i,t-1}$, are statistically positive at the 10% significance level, implying that the positive impact of disaster CEOs on corporate innovation output is more strength in economic contraction. This finding is corresponding to our expectation that economic downturn amplifies the risk-taking effects and motivates innovation.

[Insert Table 8 around here]

5.2 Firm Risk-Taking

Prior literature points out that disaster experiences change CEOs' risk preferences (Bernile et al., 2017; Chen et al., 2021; O'Sullivan et al., 2021), making them undertake more aggressive investments. Let us assume that the risky projects are also innovative, such that taking the aggressive investments is identical to pursuing innovation (Mazouz and Zhao, 2019). We then confirm that firms led by disaster CEOs who invest aggressively are more likely to manage innovative projects. Our analysis also confirms that this effect is non-monotonic.

5.2.1 Risk-Taking Incentives (Vega)

The second condition in contract theory that motivates CEOs to be more innovative is the risk-taking compensation (i.e., Vega). Using the cross-sectional analysis again, section 5.2.1 studies the moderating role of risk-taking incentives on the relationship between CEOs' early-life disaster exposure on corporate innovation outcomes. We explore this adjusting role by the following equation:

$$\begin{aligned}\text{Ln(1+Innovation)}_{i,t} &= \alpha + \beta_1 \times \text{Disaster\_CEO}_{i,t-1} + \beta_2 \times \text{High\_Vega}_{i,t-1} \\ &+ \beta_3 \times \text{Disaster\_CEO}_{i,t-1} \times \text{High\_Vega}_{i,t-1} + \gamma \text{Controls}_{i,t-1} \\ &+ \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

where we employ Vega as the measurement of risk-taking incentives. The dummy variable, $\text{High\_Vega}_{i,t-1}$, is identical to one if the CEO's compensation Vega is greater than the sample median, and zero otherwise. Similar to cross-sectional analyses above, we also include all control variables and both year and industry fixed effects in Equation (1) into our OLS estimation.

Table 9 reports that the influence of CEOs' childhood traumatic experiences on corporate innovation outcomes is adjusted by risk-taking compensations. In patent and citation measurements, the estimated coefficients of $\text{Disaster\_CEO}_{i,t-1} \times \text{High\_Vega}_{i,t-1}$, are statistically positive at the 1% and 5% significance level, respectively. Our findings indicate that the positive influence of disaster CEOs on corporate innovation output is more prominent in CEOs who have high risk-taking compensation in their contract. This finding is corresponding to contract theory that that CEO Vega incentives innovation.

[Insert Table 9 around here]

5.2.2 Stock and Cash Flow Volatility

To confirm a channel through which disaster CEOs achieve more better innovation outcomes in the past literature, we emphasize on the risk-preference channel. Bernile et al. (2017) point out that exposure to traumatic events in childhood reshape CEOs' preference to be risk-loving. Chen et al. (2021) provide evidence that high risk-tolerant CEOs are more likely to accept stock market risks. The overconfidence story (Malmendier et al., 2011; Galasso and Simcoe, 2011; Hirshleifer et al., 2012) states that taking more risks promotes innovation input that raises the probability to success. To test this hypothesis, we adopt the following regression:

$$\text{Vol}_{i,t} = \alpha + \beta \times \text{Disaster\_CEO}_{i,t-1} + \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t} \tag{7}$$

where $\text{Vol}_{i,t}$ is captured by the stock return volatility Stock_Vol_{t+1} and the cash flow volatility Cash_Vol_{t+1}. We follow Zhang (2006), Bernile et al. (2017), and Chen et al. (2021) to adopt the daily equity return over the last year and to employ the operating cash flows covering total assets over past five years. Our OLS regressions cover more control variables than the principal regression, including CEOs' age (CEO_Age), its squares (CEO_Age^2), gender (CEO_Gender) and firm-level financial position and financial performances characteristics, such as tangible assets (Tangibility), dividend payout (Dividend), return on assets (ROA), growth of sales (Sales_Growth). In common with the benchmark model in Equation (1), we also introduce the year and industry fixed effects (Fama-French 48 industries) in our OLS regression.

Table 10 reports the empirical results of firm risk-taking channel. Columns (1) and (2) presents that the estimated coefficients of Disaster_CEO on Stock_Vol_{t+1} and Cash_Vol_{t+1} are significant and positive at 5% and 10% significance levels, respectively. The empirical findings supports our risk-loving assumption that firms led by disaster CEOs achieve innovation success by taking more risks on financial market.

[Insert Table 10 around here]

5.2.3 The Severity Effects

Our previous investigations focus on the overall risk attitude responses to the exposure to traumatic events. Unlike the standard monotonic assumption in the prior literature (Yerkes and Dodson, 1908), the psychological responses are asymmetric due to different severities of disasters. More specifically, Bernile et al. (2017), Chen et al. (2021), and O'Sullivan et al. (2021) suggest that only exposures to medium fatal disasters change CEOs' preferences to be risk-seeking. By contrast, CEOs' who experience extreme traumatic events still keep risk-averse. Despite different hand-collected data sources, we expect that this nonlinear relationship still holds in our cases and test our hypothesis below. To this end, we run the following regression:

$$\begin{aligned}\text{Ln(1+Innovation)}_{i,t} = &\alpha + \beta_1 \text{Medium\_Fatality\_Experience}_{i,t-1} \\ &+ \beta_2 \text{Extreme\_Fatality\_Experience}_{i,t-1} \\ &+ \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \text{Firm}_{FE} + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where we adopt the variables Medium_Fatality_Experience and Extreme_Fatality_Experience to present the heterogeneity in disaster severity. Except for the the year and Fama-French 48 industries, we further introduce the firm fixed effects in our OLS regression.

Table 11 reports the empirical results of how the moderate and extreme disasters experiences in CEOs' early life affect the innovation success. Columns (1) and (2) present the results of patent-measured innovation, while columns (3) and (4) report the citation-based innovation findings. The insignificant coefficients of Extreme_Fatality_Experience suggest that high severity disasters has marginal effects on CEOs' risk preference, thus the risk-averse CEOs are less likely to achieve innovation success. By contrast, The estimated coefficients of Medium_Fatality_Experience is positive and at 5% significance levels in all regressions. This findings state that moderate disaster events change CEOs' preference to be risk-tolerant, which raises the potential to innovation success through stimulating the innovation input. Our findings also support the previous literature about nonlinear risk-preference responses to disaster (Bernile et al., 2017; Chen et al., 2021; O'Sullivan et al., 2021).

[Insert Table 11 around here]

5.3 R&D Spending and Intensity

Following previous studies in overconfidence story (Malmendier et al., 2011; Galasso and Simcoe, 2011; Hirshleifer et al., 2012), we understand that the risk attitudes changes drive the innovation success through promoting innovation input. In our previous investigations, we understand that the disaster exposure changes the risk attitudes and the cross-sectional analyses amplifies the effects of our proposed association. Hence, we expect that innovation input is a critical mediator in our story. We conjecture that the disaster CEOs achieve better innovation outcomes by rasing both of the spending and intensity of R&D.

To test this conjecture, we propose a structural equation model to examine the potential mechanism through which disaster CEOs improve innovation outcome by identifying the crucial mediating variables from research and development (R&D). The structural equation model is denoted by:

$$\begin{aligned}\text{Ln(1+Innovation)}_{i,t} =& \alpha + \beta_1 \text{Disaster\_CEO}_{i,t-1} + \beta_2 \text{R\&D}_{i,t-1} + \gamma \text{Rest\_Controls}_{i,t-1} \\ &+ \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t}\end{aligned} \tag{9}$$

$$\text{R\&D}_{i,t} = \alpha + \beta \times \text{Disaster\_CEO}_{i,t-1} + \gamma \text{Rest\_Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t} \tag{10}$$

in which the R&D intensity and Spending are defined as the research and development expenditure divided by lagged total assets, and the natural logarithm of research and development expenditure, respectively. Like the Equation (1), both of year and the industry fixed effects are considered in our path investigations.

Table 12 demonstrates the empirical implications of disaster CEOs on both of the input and quality on research and development. Column (1) and (2) state the R&D intensity and spending as dependent variables, respectively. The estimated coefficients of R&D $\text{Spending}_{i,t}$ and R&D $\text{Intensity}_{i,t}$

are positive and significant at 1% and 5% level, respectively.

Our findings first confirm the argument that the R&D input matters for innovation success. One step fruther, we follow Sunder et al. (2017), who controls the R&D input, to investigates the effects between innovation input and efficiency with the PSM estimation above. Our PSM analysis states that, given the similar levels in firm size, age, net property, leverage, Tobin's Q, market competition, and R&D input, firms led by disaster CEOs achieve more patents and citations than firms managed by no-disaster CEOs. Even we control similar variable in further analysis, unlike (Sunder et al., 2017), we argue that it is hard to identify that innovation success comes from the R&D transfer efficiency—it may also be due to the efficiency of reallocating capital sources. Thus, the R&D input is a more reliable channel while the innovation effectiveness only has the potential and need further identification.

Note that the variable of research and development $\text{R\&D}_{i,t}$ belongs one of the control variables in the main regression, we can rearrange the Equation (9) as:

$$\text{Ln(1+Innovation)}_{i,t} = \alpha + \beta \times \text{Disaster\_CEO}_{i,t-1} + \gamma \text{Controls}_{i,t-1} + \text{Year}_{FE} + \text{Industry}_{FE} + \varepsilon_{i,t}$$

which is identical to our main regression Equation (1). Hence, we only need to report the results of Equation (10).

[Insert Table 12 around here]

5.4 Supplemental Analyses: Alternative Measure of CEO Formative Years

Prior research considers how youth's traumatic experiences at 5 to 15 years old reshape their cognition (Nelson, 1993), and our benchmark model follows this rule. As the robustness check, we redefine the "childhood experiences" as the experiences during 10 to 15 years old for robustness check. Our re-examination rules out the traumatic experiences from 10 to 15 years old, as these ages are not young enough—individuals exposed to traumatic events during this period are less likely to reshape their cognition. We use an alternative definition for the childhood period to address this concern, which only considers the CEOs' early life trauma experiences during 5 to 10 years old.

Table 13 displays the empirical results of the robustness check using CEOs' 5 to 10 years old disaster experiences as the independent variable, which is denoted by $\text{Disaster\_CEO}_{5-10}$. Columns (1) and (2) illustrate the results measuring innovation by patent metrics, and columns (3) and (4) demonstrate the empirical findings of innovation measured by citation metrics. The estimated coefficients of $\text{Disaster\_CEO}_{5-10}$ in all regressions are positive. In columns (1) and (3), the coefficients are significant at 1% level without any control variables, and the estimators in columns (2) and (4) are significant at 5% level with standard control variables. The positive and significant estimators of Disaster_CEO$_{5-10}$ states that CEOs who exposure to traumatic events at 5 to 10 years old still achieve better innovation outcomes, suggesting our empirical findings are robust in the experiences of various ages. Our results are also consistent with the prior literature (Bernile et al., 2017).

[Insert Table 13 around here]

6 Conclusions

This paper offers robust evidence that firms led by disaster CEOs achieve better innovation outcomes than firms run by non-disaster CEOs. Our empirical findings still hold when addressing endogeneity concerns with additional control variables, PSM estimation, high-dimensional fixed-effect analyses, and DID approach based on CEO turnover events. We argue this implication work by two aspects: failure-tolerance and risk-loving. From the perspective of contract theory, the extreme conditions satisfying optimal contract schemes can amplify risk-seeking effects in the second aspect and stimulate innovations.

More specifically, our analyses on potential channels reveal that disaster CEOs can manage firms' risks when pursuing innovations, and offering risk-taking compensation can also make this relationship more pronounced. As for supplements, our cross-sectional studies point out that the positive association between disaster CEOs and corporate innovation success is more prominent for firms that are in concentrated market competitions or economic recessions. These external environments act as the proxy of optimal contract conditions and propagate the risk-seeking effects. Besides, undertaking risky but innovative projects, consisting of R&D spending and R&D intensity, matters for the innovation output. By controlling the research and development input, our results argue that disaster CEOs have the potential to improve innovation efficiency to achieve better innovation outcomes. We attribute this efficiency to the gain from post-traumatic growth.

Our research expands the empirical studies examining the influences of CEO early life disaster experiences on corporate activities. Our novel findings suggest that disaster CEOs change their preferences, gain strength from traumatic events, and achieve better innovation outcomes. Second, we also contribute to the growing strands of literature exploring the determinants driving innovation success by showing that the CEOs' early life disaster exposures are crucial factors in determining corporate innovation output. In particular, our essential contribution is distinguishing the impacts of innovation effectiveness from R$D spending.

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Table 1: **Summary Statistics: Samples**

Table 1 documents the summary statistics of the full sample, the subsample of firms run by CEOs with early-life disaster experience (a), and the subsample of firms run by CEOs without early-life disaster experience (b). We report the available observations, the mean in addition to standard deviation. We also show the differences between these two subsamples and their p-Values. Detailed definitions of all variables are described in Appendix B.

	Full Sample			Non-CEO-disaster Sample (a)		CEO-disaster Sample (b)		(a)-(b)	
Variables	N	Mean	Std.Dev	N	Mean	N	Mean	Mean.Diff	p-Value
Patent	8703	28.343	101.149	4778	19.261	3925	39.400	-20.140	0.000***
Ln(1+Patent)	8703	1.195	1.740	4778	0.902	3925	1.552	-0.649	0.000***
Citation	8703	31.995	113.907	4778	21.651	3925	44.588	-22.937	0.000***
Ln(1+Citation)	8703	1.207	1.796	4778	0.910	3925	1.570	-0.660	0.000***
Size	8703	7.371	1.589	4778	7.225	3925	7.547	-0.322	0.000***
Age	8703	2.864	0.872	4778	2.828	3925	2.908	-0.081	0.000***
PPE_perEMP	8703	3.840	1.169	4778	3.837	3925	3.844	-0.007	0.787
TBQ	8703	2.099	1.367	4778	2.045	3925	2.165	-0.120	0.000***
Leverage	8703	0.227	0.170	4778	0.224	3925	0.232	-0.008	0.028**
HHI	8703	0.203	0.162	4778	0.205	3925	0.199	0.006	0.095*
RD	8703	0.025	0.047	4778	0.021	3925	0.029	-0.008	0.000***

Table 2: **CEO Early-Life Disaster Experience and Corporate Innovation**

Table 2 reports the regression results of the impact of CEO early-life disaster experience on corporate innovation. This sample consists of 8,703 firm–year observations with non-missing values for key variables during 1992–2008. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). Patent is the total number of patents applied of a firm for a given year. Citation is the total number of citations summed across all patents applied of a firm for a given year, which is adjusted by the time-technology class fixed effects. The independent variable of interest is CEO early-life disaster experience: Disaster_CEO, a dummy variable that equals one if a firm run by a CEO with early-life disaster experience, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Ln(1+Patent)		Ln(1+Citation)	
Models	(1)	(2)	(3)	(4)
Disaster_CEO	0.4860***	0.2304***	0.4942***	0.2388***
	(0.0076)	(0.0583)	(0.0801)	(0.0621)
Size		0.5563***		0.5603***
		(0.0338)		(0.0351)
Age		0.0903**		0.0866**
		(0.0402)		(0.0426)
PPE_perEMP		0.0030		-0.0019
		(0.0580)		(0.0606)
TBQ		0.1137***		0.1239***
		(0.0209)		(0.0224)
Leverage		-0.5311***		-0.5625***
		(0.1779)		(0.1834)
HHI		0.2642		0.2766
		(0.2133)		(0.2213)
RD		8.2889***		7.9396***
		(0.8423)		(0.9315)
Constant	1.0989***	-3.5536***	1.1257***	-3.5320***
	(0.3521)	(0.4569)	(0.3445)	(0.4584)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	8703	8703	8703	8703
R^2	0.3673	0.5968	0.3535	0.5696

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: **Additional Controls**

Table 3 considers the additional CEO-specific controls and re-estimate the baseline regression. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is CEO early-life disaster experience: Disaster_CEO. Apart from the firm-specific controls (Size, Age, PPE_perEMP, TBQ, Leverage, HHI, RD) covered in the baseline regression, this table further controls for CEO_Age, CEO_Tenure, CEO_Delta, CEO_Vega, CEO_Ivy_Degree, CEO_Technical_Degree, CEO_PhDinTechnical_Degree, and No_Education_Info. Detailed definitions of all variables are described in Appendix B. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)
Disaster_CEO	0.2678***	0.2759***
	(0.0740)	(0.0789)
Size	0.5952***	0.5943***
	(0.0478)	(0.0501)
Age	0.1149**	0.1222**
	(0.0524)	(0.0554)
PPE_perEMP	-0.0147	-0.0126
	(0.0654)	(0.0690)
TBQ	0.1183***	0.1265***
	(0.0256)	(0.0272)
Leverage	-0.6693***	-0.7393***
	(0.2312)	(0.2365)
HHI	0.4934**	0.4866*
	(0.2449)	(0.2588)
RD	9.4439***	8.8680***
	(1.1386)	(1.2021)
CEO_Age	-0.7025**	-0.7762**
	(0.2850)	(0.3078)
CEO_Tenure	-0.0263	-0.0253
	(0.0529)	(0.0551)
CEO_Delta	-0.0153	-0.0204
	(0.0312)	(0.0324)
CEO_Vega	-0.0020	0.0032
	(0.0278)	(0.0297)
CEO_Ivy_Degree	-0.0022	-0.0248
	(0.1091)	(0.1198)
CEO_Technical_Degree	0.1210	0.1227
	(0.1015)	(0.1066)
CEO_PhDinTechnical_Degree	2.0771***	2.0429**
	(0.7591)	(0.8675)
No_Education_Info	0.0129	-0.0024
	(0.1316)	(0.1377)
Constant	-1.0125	-0.7656
	(1.1848)	(1.2562)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	5,871	5,871
R-squared	0.6356	0.6093

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: **Propensity Score Matching Estimators.**

Table 4 reports the estimation results with the propensity-score matched samples. Panel A shows the diagnostics statistics-difference in observable firm characteristics in our baseline regressions between the treated and control groups. Panel B tabulates the average treatment effects. Panel C shows the regression results. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses.***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Diagnostics Statistics-Difference in Means of Variables					
Variables	Treated	Control	%Bias	T-stat.	p-value
Size	7.313	7.295	1.20	0.470	0.636
Age	2.839	2.828	1.30	0.480	0.632
PPE_perEMP	3.803	3.798	0.40	0.160	0.874
TBQ	2.062	2.075	-1.00	-0.390	0.697
Leverage	0.229	0.228	0.80	0.310	0.753
HHI	0.201	0.199	1.30	0.480	0.63
RD	0.025	0.025	0.70	0.260	0.791

Panel B. Average Treatment Effects				
	Disaster CEO (N=3244)	Non-Disaster CEO (N=2677)	Difference	T-stat.
Ln(1+Patent)	1.267	1.141	0.126	3.280
Ln(1+Citation)	1.287	1.150	0.136	3.410

Panel C. Regressions with the Propensity-Score Matched Sample		
Dependent Variable	Ln(1+Patent)	Ln(1+Citation)
Model	(1)	(2)
Disaster_CEO	0.2421***	0.2557***
	(0.0608)	(0.0652)
Size	0.5455***	0.5444***
	(0.0342)	(0.0358)
Age	0.1115***	0.1147**
	(0.0424)	(0.0456)
PPE_perEMP	0.0094	0.0022
	(0.0602)	(0.0641)
TBQ	0.1121***	0.1276***
	(0.0225)	(0.0254)
Leverage	-0.5033***	-0.5327***
	(0.1856)	(0.1940)
HHI	0.2164	0.2190
	(0.2382)	(0.2522)
RD	7.7024***	7.2669***
	(0.8327)	(0.9896)
Constant	-3.8495***	-3.7914***
	(0.4625)	(0.4678)
Year FE	YES	YES
Industry FE	YES	YES
Observations	5921	5921
R^2	0.5592	0.5265

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: **Higher Dimensional Fixed-Effect Regressions**

Table 5 shows the fixed effect model results of the impact of CEO early-life disaster experience on corporate innovation. In columns (1)-(2), we control for the firm and year fixed effects. In columns (3)-(4), we control for firm and cohort fixed effects, that is, firm fixed effects, year fixed effects, CEO grow-up state fixed effects, and CEO birth year fixed effects. From column (5) to (8), we control for higher dimensional fixed effects. In columns (5)-(6), we consider the firm and interacted year-state fixed effects. In columns (7)-(8), we control for the firm and interacted year-industry fixed effects. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Firm FE		Firm & Cohort FE		Firm & High Dimensional Firm FE			
Dependent Variable	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster_CEO	0.1142**	0.1271**	0.1431**	0.1659**	0.1027*	0.1183*	0.1135*	0.1212**
	(0.0554)	(0.0574)	(0.0692)	(0.0733)	(0.0595)	(0.0619)	(0.0588)	(0.0607)
Size	0.2591***	0.2634***	0.2535***	0.2641***	0.2316***	0.2298***	0.2721***	0.2708***
	(0.0544)	(0.0530)	(0.0475)	(0.0459)	(0.0534)	(0.0527)	(0.0586)	(0.0575)
Age	0.0137	0.0140	0.0567	0.0586	0.0380	0.0340	-0.0288	-0.0468
	(0.0561)	(0.0622)	(0.0560)	(0.0628)	(0.0566)	(0.0642)	(0.0617)	(0.0696)
PPE_perEMP	0.1128**	0.1176**	0.1010**	0.1102**	0.1057**	0.1083**	0.1254**	0.1148**
	(0.0480)	(0.0512)	(0.0400)	(0.0458)	(0.0441)	(0.0487)	(0.0518)	(0.0563)
TBQ	0.0319**	0.0433***	0.0368***	0.0468***	0.0381***	0.0495***	0.0286**	0.0402***
	(0.0126)	(0.0138)	(0.0114)	(0.0135)	(0.0122)	(0.0138)	(0.0133)	(0.0150)
Leverage	0.0221	0.0071	0.0100	-0.0234	0.1148	0.1086	0.0156	0.0050
	(0.1148)	(0.1222)	(0.1137)	(0.1199)	(0.1133)	(0.1245)	(0.1221)	(0.1288)
HHI	0.2436	0.2413	0.2243	0.2491	0.3649*	0.3773*	0.2090	0.2201
	(0.2050)	(0.2139)	(0.2108)	(0.2205)	(0.2025)	(0.2119)	(0.2376)	(0.2563)
RD	0.1035	0.3555	0.0227	0.2440	-0.0920	0.0806	0.4831	0.5658
	(1.0421)	(1.1169)	(0.9572)	(1.0026)	(1.0609)	(1.1362)	(1.0473)	(1.1340)
Constant	-1.1139***	-1.1335***	-0.0602	-0.0896	-1.2457***	-1.2539***	-1.3662***	-1.2821***
	(0.4011)	(0.4019)	(0.8038)	(0.7802)	(0.4267)	(0.4305)	(0.4686)	(0.4720)
Year FE	YES	YES	YES	YES	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
CEO Grow-up State FE	NO	NO	YES	YES	NO	NO	NO	NO
CEO Birth Year FE	NO	NO	YES	YES	NO	NO	NO	NO
Year*State FE	NO	NO	NO	NO	YES	YES	NO	NO
Year*Industry FE	NO	NO	NO	NO	NO	NO	YES	YES
Observations	8703	8703	8703	8703	8703	8703	8703	8703
R^2	0.1056	0.0893	0.1534	0.1274	0.9274	0.9118	0.9269	0.9114

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Difference-in-Difference**

Table 6 reports the difference-in-difference (DID) regression results of the impact of CEO early-life disaster experience on corporate innovation. In Panel A, the data sample includes all the ND-to-D and ND-to-ND CEO turnovers. ND denotes CEO without early-life disaster experience, while D means CEO with early-life disaster experience. In Panel B, the data sample includes all the D-to-ND and D-to-D CEO turnovers. These two samples cover firm–year observations three years before and three years after an CEO transition, excluding the year of the transition. Following Huang and Kisgen (2013), we require that firms have at least two years of non-missing data for all variables before the CEOs' Transition. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is CEO_Transition×Post, Post is an indicator to one for the years after the transition year. In Panel A, CEO_Transition is an indicator variable for a firm that has a ND-to-D transition, zero for a ND-to-ND transition firm. In Panel B, CEO_Transition is a dummy for a firm that has a D-to-ND turnover, zero for a D-to-D CEO turnover firm. CEO_Transition is not included as an independent variable because it is absorbed by firm fixed effects. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and firm fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: ND-to-D V.S. ND-to-ND		Panel B: D-to-ND V.S. D-to-D	
Dependent Variable	Ln(1+Patent)	Ln(1+Citation)	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)	(3)	(4)
Post	-0.0231	-0.0279	0.1025	0.1500**
	(0.0672)	(0.0775)	(0.0646)	(0.0748)
CEO_Transition×Post	0.1251*	0.1899**	-0.1773*	-0.1842*
	(0.0669)	(0.0772)	(0.0924)	(0.1070)
Size	0.3534***	0.4028***	0.1957*	0.2717**
	(0.0644)	(0.0744)	(0.1068)	(0.1236)
Age	0.3476**	0.2440	0.0310	0.1454
	(0.1387)	(0.1600)	(0.2740)	(0.3171)
PPE_perEMP	-0.1389*	-0.2143**	0.2140*	0.2962**
	(0.0807)	(0.0931)	(0.1257)	(0.1455)
TBQ	-0.0013	0.0192	-0.0127	-0.0336
	(0.0279)	(0.0322)	(0.0377)	(0.0436)
Leverage	-0.1386	0.0045	0.0287	-0.0827
	(0.2387)	(0.2755)	(0.4191)	(0.4851)
HHI	0.4878	0.4178	-0.2056	0.2971
	(0.4636)	(0.5350)	(0.6101)	(0.7061)
RD	5.1666***	5.5510***	0.9798	0.4821
	(1.7360)	(2.0034)	(2.3549)	(2.7254)
Constant	-2.1163***	-1.9589***	-0.7889	-2.1793
	(0.6034)	(0.6963)	(1.3286)	(1.5376)
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	871	871	666	666
R^2	0.9529	0.9407	0.9433	0.9261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: **Cross-Sectional Analysis: Market Competition**

Table 7 reports the effect of market competition on the relation between CEO early-life disaster experience and corporate innovation. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is CEO early-life disaster experience interacted with market competition: Disaster_CEO×Low_HHI. Low_HHI is a dummy variable that equals one if the firm is in an industry which HHI is below the median HHI level in the sample, and zero otherwise. A lower HHI indicates a higher market competition. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)
Disaster_CEO	0.0899	0.0821
	(0.0725)	(0.0764)
Low_HHI	-0.0436	-0.0726
	(0.0693)	(0.0730)
Disaster_CEO×Low_HHI	0.2655***	0.2953***
	(0.1004)	(0.1066)
Size	0.5542***	0.5579***
	(0.0341)	(0.0354)
Age	0.0910**	0.0874**
	(0.0401)	(0.0425)
PPE_perEMP	0.0019	-0.0033
	(0.0584)	(0.0610)
TBQ	0.1147***	0.1250***
	(0.0209)	(0.0223)
Leverage	-0.5181***	-0.5480***
	(0.1778)	(0.1833)
RD	8.1660***	7.7964***
	(0.8335)	(0.9264)
Constant	-3.4478***	-3.4007***
	(0.4510)	(0.4546)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	8703	8703
R-squared	0.5980	0.5709

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Cross-Sectional Analysis: NBER Recession**

Table 8 reports the influence of recession period on the relation between CEO early-life disaster experience and corporate innovation. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is CEO early-life disaster experience interacted with market competition: Disaster_CEO×Recession. Dummy variable that equals one if the current year is in the recession period, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)
Disaster_CEO	0.2543***	0.2635***
	(0.0592)	(0.0630)
Recession	-0.2773***	-0.2894***
	(0.0369)	(0.0394)
Disaster_CEO×Recession	0.1071*	0.1061*
	(0.0576)	(0.0619)
Size	0.5309***	0.5345***
	(0.0337)	(0.0350)
Age	0.0710*	0.0672
	(0.0401)	(0.0426)
PPE_perEMP	-0.0362	-0.0425
	(0.0563)	(0.0588)
TBQ	0.1043***	0.1150***
	(0.0211)	(0.0226)
Leverage	-0.4545**	-0.4841***
	(0.1770)	(0.1832)
HHI	0.2187	0.2497
	(0.2092)	(0.2162)
RD	8.3517***	7.9993***
	(0.8704)	(0.9636)
Constant	-3.4623***	-3.4616***
	(0.4495)	(0.4482)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	8703	8703
R-squared	0.5727	0.5462

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: **CEO Risk-taking Incentives (Vega)**

Table 9 reports the effect of CEO risk-taking incentives (Vega) on the relation between CEO early-life disaster experience and corporate innovation. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is CEO early-life disaster experience interacted with risk-taking compensation: Disaster_CEO× High_Vega. High_Vega is a dummy variable that equals one if the CEO's compensation Vega is greater than the sample median, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	Ln(1+Patent)	Ln(1+Citation)
Models	(1)	(2)
Disaster_CEO	0.0988	0.1306*
	(0.0677)	(0.0727)
High_Vega	-0.0767	-0.0491
	(0.0741)	(0.0789)
Disaster_CEO×High_Vega	0.2486***	0.2052**
	(0.0945)	(0.1006)
Size	0.5690***	0.5716***
	(0.0391)	(0.0406)
Age	0.0908**	0.0861*
	(0.0446)	(0.0476)
PPE_perEMP	-0.0076	-0.0124
	(0.0613)	(0.0644)
TBQ	0.1040***	0.1147***
	(0.0224)	(0.0239)
Leverage	-0.5881***	-0.6152***
	(0.1870)	(0.1922)
HHI	0.1593	0.1939
	(0.2193)	(0.2274)
RD	8.7140***	8.3136***
	(0.8872)	(0.9973)
Constant	-3.6400***	-3.6574***
	(0.4775)	(0.4769)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	7673	7673
R-squared	0.6128	0.5836

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: **CEO Early-Life Disaster Experience and Firm Risk Taking**

Table 10 presents the regression results of the impact of CEO early-life disaster experience on firms' risk taking. The dependent variable is the firm risk: (1) Stock_Vol, measured by standard deviation of daily stock return over the last year; (2) Cash_Vol, measured by the standard deviation of the ratio of operating cash flows over total assets over the past five years. The independent variable of interest is CEO early-life disaster experience: Disaster_CEO, a dummy variable that equals one if a firm run by a CEO with early-life disaster experience, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All the continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	Stock_Vol$_{t+1}$	Cash_Vol$_{t+1}$
Models	(1)	(2)
Disaster_CEO	0.0669**	0.2193*
	(0.0341)	(0.1312)
Size	-0.1668***	-0.3703***
	(0.0154)	(0.0633)
Age	-0.1481***	-0.2038
	(0.0273)	(0.1276)
Leverage	0.1095	-0.6756
	(0.1219)	(0.5916)
Tangibility	-0.1284	-0.3599
	(0.1080)	(0.4319)
Dividend	-0.4317***	-0.8918***
	(0.0468)	(0.1608)
ROA	-4.4990***	-10.4603***
	(0.2795)	(1.8212)
Sales_Growth	0.3672***	0.6476**
	(0.0634)	(0.3137)
CEO_Age	-4.1903	0.2791
	(3.4479)	(10.5722)
CEO_Age2	0.4800	-0.1599
	(0.4302)	(1.2934)
CEO_Gender	-0.2393	0.7779
	(0.1547)	(0.8085)
Constant	13.6712**	12.2249
	(6.8938)	(21.5674)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	7124	6105
R-squared	0.5647	0.2577

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: **Severity of CEO Early-Life Disaster Experience and Corporate Innovation**

Table 11 shows how the severity of disaster affects the relationship between CEO early-life disaster experience and corporate innovation. The dependent variable is the corporate innovation: Ln(1+Patent) and Ln(1+Citation). The independent variable of interest is the severity of CEO early-life disaster experience: (1) Medium_Fatality_Experience, a dummy variable that equals one if the CEO has moderate early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the 2th to 10th deciles), and zero otherwise; (2) Extreme_Fatality_Experience, a dummy variable that equals one if the CEO has extreme early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the first decile), and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance atthe 1%, 5%, and 10% level, respectively.

Dependent Variable	Ln(1+Patent)		Ln(1+Citation)	
Models	(1)	(2)	(3)	(4)
Medium_Fatality_Experience	0.1330**	0.1249**	0.1463**	0.1378**
	(0.0584)	(0.0552)	(0.0606)	(0.0578)
Extreme_Fatality_Experience	0.0609	0.0375	0.0733	0.0500
	(0.1247)	(0.1216)	(0.1310)	(0.1289)
Size		0.2585***		0.2628***
		(0.0543)		(0.0530)
Age		0.0178		0.0181
		(0.0561)		(0.0624)
PPE_perEMP		0.1136**		0.1184**
		(0.0482)		(0.0513)
TBQ		0.0319**		0.0432***
		(0.0126)		(0.0138)
Leverage		0.0253		0.0103
		(0.1145)		(0.1219)
HHI		0.2451		0.2428
		(0.2050)		(0.2140)
RD		0.1225		0.3746
		(1.0421)		(1.1165)
Constant	1.1932***	-1.1218***	1.2470***	-1.1415***
	(0.0751)	(0.4009)	(0.0823)	(0.4017)
YEAR FE	YES	YES	YES	YES
INDUSTRY FE	NO	NO	NO	NO
FIRM FE	YES	YES	YES	YES
Observations	8703	8703	8703	8703
R-squared	0.0687	0.1059	0.0588	0.0896

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: **CEO Early-Life Disaster Experience and R&D**

Table 12 reports the regression results of the impact of CEO early-life disaster experience on firms' research and development expenditure. The dependent variable is the corporate innovation: (1) R&D Intensity, measured by the research and development expenditure divided by lagged total assets; (2) R&D Spending, measured by the natural logarithm of research and development expenditure. The independent variable of interest is CEO early-life disaster experience: Disaster_CEO, a dummy variable that equals one if a firm run by a CEO with early-life disaster experience, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable=	R&D Intensity	R&D Spending
Models	(1)	(2)
Disaster_CEO	0.4047*	0.2293***
	(0.2189)	(0.0781)
Size	-0.2900***	0.6260***
	(0.0916)	(0.0420)
Age	-0.2732**	0.0186
	(0.1302)	(0.0561)
PPE_perEMP	0.4200***	-0.0344
	(0.1397)	(0.0698)
TBQ	1.1793***	0.2843***
	(0.1115)	(0.0329)
Leverage	-2.4083***	-0.6927***
	(0.6563)	(0.2643)
HHI	-3.5734***	-0.4850
	(0.6657)	(0.3068)
Constant	2.4399	-3.4631***
	(1.5681)	(0.7168)
YEAR FE	YES	YES
INDUSTRY FE	YES	YES
Observations	8703	8703
R-squared	0.4500	0.6461

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: **Alternative Measure of CEO Early-Life Disaster Experience**

Table 13 reports the regression results of the impact of CEO early-life disaster experience on corporate innovation. We use an alternative measure of the CEO early-life disaster experience: Disaster_CEO$_{5-10}$, a dummy variable that equals one if the CEO experienced disaster fatal events at ages of 5 to 10, and zero otherwise. Detailed definitions of all variables are described in Appendix B. All independent variables are measured at t-1 in the regressions, and continuous independent variables are winsorized by 1% and 99% level. Regressions include year and industry fixed effects. Standard errors are clustered by firm in all columns and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Ln(1+Patent)		Ln(1+Citation)	
Models	(1)	(2)	(3)	(4)
Disaster_CEO$_{5-10}$	0.3115***	0.1305**	0.3106***	0.1303**
	(0.0843)	(0.0623)	(0.0867)	(0.0657)
Size		0.5633***		0.5677***
		(0.0342)		(0.0354)
Age		0.0906**		0.0871**
		(0.0401)		(0.0425)
PP_perEMP		0.0025		-0.0024
		(0.0589)		(0.0616)
TBQ		0.1169***		0.1272***
		(0.0209)		(0.0224)
Leverage		-0.5160***		-0.5467***
		(0.1785)		(0.1837)
HHI		0.2358		0.2653
		(0.2157)		(0.2233)
RD		8.3732***		8.0294***
		(0.8448)		(0.9347)
Constant	1.2227***	-3.5499***	1.2539***	-3.5274***
	(0.3373)	(0.4490)	(0.3330)	(0.4514)
YEAR FE	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES
Observations	8703	8703	8703	8703
R-squared	0.3557	0.5940	0.3421	0.5667

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A Appendix: Rare Disaster Events Before 1960

Table 14: **Data sources of U.S. county-level disaster events prior to 1960**

Disaster Events	Data Sources
Earthquakes, Floods, and Landslides	(1) United States Geological Survey (USGS) (2) National Geophysical Data Center (NGDC) (3) GenDisasters.com (4) Google searches: in the last instance
Volcanic Eruptions	(1) United States Geological Survey (USGS) (2) National Geophysical Data Center (NGDC) (3) Science Daily's database (4) Google searches: in the last instance
Tsunamis	(1) National Geophysical Data Center (NGDC) (2) Tsunamis.findthedata.org (3) Google searches: in the last instance
Hurricanes, Tornadoes and Severe storms	(1) National Climatic Data Center (NCDC) (2) National Weather Service (NWS) of the National Oceanic and Atmospheric Administraion (3) GenDisasters.com (4) Google searches: in the last instance
Wild-fires	(1) Wikipedia (2) GenDisasters.com (3) Google searches: in the last instance

B Appendix: Variables

Table 15: **Variable Descriptions.**

Variable	Definitions
Patent	The total number of patents applied of a firm for a given year.
Citation	The total number of citations summed across all patents applied of a firm for a given year, which is adjusted by the time-technology class fixed effects.
Disaster_CEO	Dummy variable that equals one if a firm run by a CEO with early-life disaster experience, and zero otherwise.
Size	Natural logarithm of total assets.
Age	Natural logarithm of firm age.
PPE_perEMP	Net property, plant, and equipment divided by the number of employees.
TBQ	Market value of assets divided by the book value of assets. Market value of assets = Book value of assets + Market value of common equity - (Book value of common equity + Balance sheet deferred taxes).
Leverage	Book value of debts divided by total assets.
HHI	The sum of squared market shares in sales of a firm's three-digit SIC industry.
RD	Research and development expenditure divided by total assets.
Tangibility	Net property, plant, and equipment divided by total assets.
Dividend	Dummy variable that equals one if a firm is paying a dividend in the current year, and zero otherwise.
ROA	Return on total assets.
Sales_Growth	Growth of sales from the last year to the current year.
CEO_Age	Natural logarithm of CEO age.
CEO_Gender	Dummy variable that equals one if the CEO is a female, and zero otherwise.
CEO_Tenure	Natural logarithm of (1 + CEO tenure in months).
CEO_Delta	Dollar change in CEO stock and option portfolio for a 1% change in stock price.
CEO_Vega	Dollar change in CEO option holdings for a 1% change in stock return volatility.
CEO_Ivy_Degree	Dummy variable that equals one if the CEO received a degree from the Ivy universities, and zero otherwise.
CEO_Technical_Degree	Dummy variable that equals one if the CEO received a degree in engineering, physics, chemistry, mathematics, operations research, biology, or applied sciences, and zero otherwise.
CEO_PhDinTechnical_Degree	Dummy variable that equals one if the CEO received a degree of PhD in engineering, physics, chemistry, mathematics, operations research, biology, or applied sciences, and zero otherwise.
No_Education_Info	Dummy variable that equals one if the there is no information about the CEO's education, and zero otherwise.
High_Vega	Dummy variable that equals one if the CEO's Vega is above the sample median level, and zero otherwise.
Stock_Vol	The standard deviation of daily stock return over the last year.
Cash_Vol	The standard deviation of the ratio of operating cash flows over total assets over the past five years.
R&D Intensity	Research and development expenditure divided by lagged total assets.
R&D Spending	Natural logarithm of (1 + Research and development expenditure).
Low_HHI	Dummy variable that equals one if the firm is in an industry which HHI is below the median HHI.
Recession	Dummy variable that equals one if the current year is in the recession period, and zero otherwise.
Medium_Fatality_Experience	Dummy variable that equals one if the CEO has moderate early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the 2th to 10th deciles), and zero otherwise.
Extreme_Fatality_Experience	Dummy variable that equals one if the CEO has extreme early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the first decile), and zero otherwise.
Disaster_CEO$_{5-10}$	Dummy variable that equals one if the CEO experienced disaster fatal events at ages of 5 to 10, and zero otherwise.