CEO Early-Life Disaster Experience and Corporate Hedging Behaviour*

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Abstract

We study how traumatic experiences in childhood shape CEOs' risk preferences and corporate financial hedging decisions. Based on a sample of US public firms spanning from 1993 to 2020, we document a positive relation between CEOs' early-life disaster experiences and the likelihood of firms using financial derivatives. We also find that the interactive impact of disaster experiences and financial hedging on firm value is negative, suggesting that early-life disaster experiences increases the gap between CEOs' and shareholders' risk preferences, potentially creating a conflict of interest. Furthermore, our cross-sectional analysis suggests that the positive relation between disaster experiences and financial hedging is more pronounced in firms with weaker corporate governance, fewer financial constraints, and more firm-specific risk. The implication of our finding is that corporate boards and regulators should maintain active oversight of corporate risk management practices, especially when early-life disaster experiences are known to influence a CEO's risk preferences.

JEL classification: G32, G34, G41
Keywords: CEO; Early-life disaster experiences; Corporate financial hedging; Financial derivatives

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"*Surviving a calamity leaves a permanent mark. It forever alters your definition of uncertainty, and changes how you take on challenges. — Indra Nooyi, former Pepsi CEO* "

1. Introduction

Corporate risk management theory suggests that firms engage in value-enhancing financial hedging activities to mitigate financial constraints (Stulz and Johnson, 1985; Purnanandam, 2008), improve credit rationing (Froot et al., 1993; Leland, 1998), and alleviate information asymmetry (DeMarzo and Duffie, 1995; Dadalt et al., 2002). The foundational assumption underlying this theory is that managers can diversify their wealth portfolios similarly to shareholders, thus acting as risk-neutral agents. However, agency models of risk management present a different perspective that since managers' wealth is closely tied to their firms, they are inherently more risk-averse than shareholders (Stulz and Johnson, 1985; Smith and Stulz, 1985; Stulz, 1988). By deviating from the risk neutrality assumption, agency models emphasize the importance of CEO personal risk preferences in financial hedging decisions. Recent studies show that CEO personal attributes and preferences, such as CEO compensation incentives (Knopf et al., 2002; Bakke et al., 2016), age (Croci et al., 2017), and tenure (Bodnar et al., 2019), are linked to corporate financial hedging decisions. Surprisingly, little attention has been dedicated to a CEO's personal experiences, especially those acquired during their early life. Psychology research highlights the influence of past experiences on an individual's future decision-making process (e.g., Lichtenstein et al., 1978; Nisbett and Ross, 1980; Yechiam et al., 2005), with early-life experiences having an enduring and pronounced effect, especially when the experience is traumatic (e.g., Parry and Chesler, 2005; Cryder et al., 2006; Duran, 2013). In this paper, we address this gap in the financial hedging literature by examining the relation between CEOs' exposure to natural disasters during their childhood or early adolescence, which we refer to as "early-life disaster experiences", and corporate financial hedging policies.

Existing literature has demonstrated a clear connection between CEOs' formative experiences and subsequent corporate policies.[1] Recent studies highlight the implications of CEOs' early-life disaster experiences on corporate risk-taking (Bernile et al., 2017; Tian et al., 2023), corporate social performance (O'Sullivan et al., 2021), and stock price crash risk (Chen et al., 2021). Financial hedging represents a distinctive tool in risk management that provides direct insights into CEOs' risk preferences, setting it apart from the corporate outcomes previously examined. We expect that early-life disaster experiences can affect CEOs' financial hedging decisions for the following two reasons.

First, childhood trauma can have lasting impacts on an individual's risk perception and behavior throughout adulthood. Traumatic events disrupt the perception of personal invulnerability, leading to persistent anxiety and heightened vigilance (Vogel and Bolino, 2020). Neuroscience research shows that early adversity can result in lasting physiological changes in the brain, particularly in the areas related to threat sensitivity and avoidance (Boling et al., 2016). Consequently, trauma survivors often exhibit a greater propensity for risk aversion and a preference for stability (Malmendier and Nagel, 2011; Bucciol and Zarri, 2013). In the context of corporate decision-making, this trauma-induced risk aversion is likely to manifest in a preference for mitigating volatility through financial hedging instruments. For CEOs with early-life disaster experiences, financial hedging offers a means of providing security and maintaining control by stabilizing cash flows and reducing downside risk (Stulz and Johnson, 1985). Second, CEOs who have experienced natural disasters during their early years have firsthand knowledge of the severe consequences of volatility and unpreparedness. Therefore, these CEOs are more likely to implement precautionary hedging strategies to prevent reliving the distressing experiences of their past. Their firsthand trauma sensitizes them to crisis scenarios, motivating them to take proactive measures to safeguard their firms against unforeseen negative shocks.

Based on the above two reasons, we posit that CEOs' early-life disaster experiences

[1] For example, the Great Depression (Malmendier and Nagel, 2011), military service (Benmelech and Frydman, 2015), natural disasters (Bernile et al., 2017), pilot training (Sunder et al., 2017), the Great Chinese Famine (Feng and Johansson, 2018), and the Cultural Revolution (Kong et al., 2021).

are positively associated with corporate financial hedging activities. Our expectation aligns with the concept of the "Hot-Stove" effect, well-documented in the literature, which suggests that when past experiences result in adverse outcomes, individuals tend to exhibit a bias against risky decisions (e.g., March, 1996; Denrell and March, 2001; Denrell, 2007). While our hypothesis is framed in only one direction, we acknowledge the possibility that experiencing a natural disaster could increase an individual's willingness to take risks by making other challenges seem less daunting by comparison (Taylor and Lobel, 1989; Ben-Zur and Zeidner, 2009). Moreover, surviving a traumatic event might enhance one's confidence in their ability to handle risky situations, leading to increased risk-taking behavior (Aldwin, 2009). In line with these alternative viewpoints, prior research presents empirical evidence that individuals exposed to natural disasters may become more risk-tolerant (Eckel et al., 2009; Page et al., 2014; Hanaoka et al., 2018). Consequently, the relation between CEOs' early-life disaster experiences and their corporate financial hedging behavior remains an empirical question to be explored.

To investigate our hypothesis, we examine the relation between CEOs' early-life disaster experiences and the financial hedging policies adopted by their respective firms. Our analysis begins by identifying CEOs covered by the ExecuComp database spanning from 1993 to 2020. We manually collect information on their names, birth dates, and birthplaces through various sources. Additionally, we compile a comprehensive database of natural disaster events at the U.S. county level during this period, covering earthquakes, volcanic eruptions, tsunamis, hurricanes, tornadoes, severe storms, floods, landslides, and wildfires. By merging these two databases, we determine which CEOs experienced natural disasters between the ages of 5 and 15 or between the ages of 1 and 5, two periods defined as their formative years (Nelson, 1993; Bernile et al., 2017; O'Sullivan et al., 2021). Our effective sample covers 1,823 U.S. born CEOs for whom we can identify whether they experienced natural disasters during their childhood.

Furthermore, we conduct textual analyses on firms' annual reports from the Electronic Data Gathering, Analysis, and Retrieval System (EDGAR) database to collect data on the use of financial derivatives. Following conventions in financial hedging studies (e.g., Allayannis and Weston, 2001; Graham and Rogers, 2002; Bartram et al., 2011; Manconi et al., 2018), we construct two binary variables, *IR/FX* and *Hedging*, as proxies for firms' financial hedging activities. *IR/FX* indicates whether a firm uses at least one of interest rate (IR) and foreign currency (FX) derivatives. *Hedging* indicates whether a firm uses at least one of IR, FX, and commodity (COMMD) derivatives.

In our baseline regression, we find strong evidence that after controlling for a set of firm-level determinants of corporate financial hedging as well as the firm and year fixed effects, CEOs' early-life disaster experiences are positively related to the likelihood of a firm using financial derivatives. Firms managed by CEOs with disaster experiences between the ages of 5 and 15 exhibit a 1.40 to 1.53 times higher probability of using financial derivatives compared to firms managed by CEOs without such incidents. Similarly, compared to firms managed by CEOs without early childhood disaster experiences (before age 5), firms managed by CEOs with such experiences are 1.31 to 1.86 times more likely to employ financial derivatives. These results align with the "Hot-Stove" concept, which posits that experience-driven conservatism can manifest as both cautious risk-taking behavior within the firm and a more aggressive risk management approach.

We address the potential endogeneity concerns in our empirical analysis through various identification strategies and robustness tests. First, we utilize a sample of exogenous CEO turnovers and conduct a univariate comparison between two sets of turnover events with variations in the early-child disaster experiences during CEO turnovers. We find that the likelihood of using financial derivatives increases when the outgoing CEOs do not have early-child disaster experiences while the incoming CEOs have early-child disaster experiences. On the contrary, the likelihood of using financial derivatives decreases when the outgoing CEOs have early-child disaster experiences while the incoming CEOs do not have early-child disaster experiences. Then we conduct a difference-in-differences (DID) analysis, also based on exogenous turnovers. After controlling for firm-level determinants of corporate financial hedging, the likelihood of financial hedging is higher when firms undergo no-disaster experience to disaster experience CEO turnovers than when firms undergo no-disaster experience to disaster experience CEO turnovers. These two tests suggest that the changes in the use of financial derivatives around these exogenous CEO turnover events can be attributed to the variations in the risk tolerance levels of incoming and outgoing CEOs, as measured by their early-child disaster experiences. Second, to mitigate the concern that our finding is driven by observed firm-specific characteristics, we employ propensity-score matching (PSM) and Entropy Balancing (EB) matching methods and show that our main finding remains robust. Third, to alleviate the concern that our finding is driven by CEO traits, corporate governance, and corporate culture, we incorporate these factors as additional controls in our baseline regression and show that our main finding remains robust.

In our supplementary tests, we first examine whether the use of financial derivatives associated with CEOs' early-child disaster experiences affects firm value. Although we find weak evidence that both disaster experiences and financial hedging are positively related to firm value, the interacted impact of disaster experiences and financial hedging on firm value is negative and statistically significant. Our firm value test suggests that experience-driven conservatism drives CEOs' risk preference away from shareholders' risk preference, leading to sub-optimal decisions in corporate financial hedging. Second, we conduct cross-sectional analyses to help us further understand the mechanisms through which disaster experiences influence financial hedging. We find that the positive relation between disaster experiences and financial hedging is more pronounced among firms with weaker corporate governance, fewer financial constraints, and higher firm-specific risks. Third, we find no evidence that disaster experiences are related to corporate operational hedging, consistent with Petersen and Thiagarajan's (2000) view that CEOs' risk management decisions are influenced not only by their risk preferences but also by the fundamental characteristics of the firm and the costs associated with altering production.

Our study contributes to several strands of literature. First, we offer insights into the literature on the role of corporate managers in corporate financial hedging. Previous research in this domain has predominantly focused on managerial risk aversion driven by compensation incentives and its impact on corporate hedging decisions (Tufano, 1996; Schrand and Unal, 1998; Rogers, 2002; Knopf et al., 2002; Chernenko and Faulkender, 2011). Only a limited number of studies have explored the influence of managerial personal traits, such as CEO characteristics related to age, educational background, and work experience (Beber and Fabbri, 2012; Croci et al., 2017; Bodnar et al., 2019). To the best of our knowledge, our study stands as the first in the corporate risk management literature that directly examines how CEOs' early-child experiences affect their financial hedging choices. We find that CEO early-life disaster experiences can lead to a more risk-averse approach to corporate financial management, with an emphasis on using financial derivatives to mitigate risks. Unlike managerial risk aversion driven by compensation incentives, early-life disaster experiences do not change over time and are not subject to CEOs' decisions in the timing of exercising their option-based compensations. We also acknowledge that CEOs' risk preferences influenced by early-life disaster experiences and managerial compensation may interact in complex ways. For example, a CEO with a risk-averse disposition due to early-life experiences might still take on calculated risks if their compensation incentivizes stock price growth.

Second, our research contributes to the growing field of behavioral corporate finance, which studies managerial biases rooted in personal experiences. Previous studies in this area have categorized experiences into two main groups. The first group focuses on professional experiences, such as industry-specific expertise and innovation exposure (Custódio and Metzger, 2014), past career experiences (Schoar and Zuo, 2017), dismissal experience (Ellis et al., 2021), and corporate distress experience (Dittmar and Duchin, 2016; Faulkner and García-Feijóo, 2022). The other group emphasizes personal experiences, including growing up during significant historical economic events like the Great Depression (Malmendier et al., 2011; Malmendier and Nagel, 2011), enduring events like the Great Chinese Famine (Feng and Johansson, 2018), and early-life disaster experiences (Bernile et al., 2017; Chen et al., 2021; O'Sullivan et al., 2021). While studies in the second group have shed light on how these personal experiences affect various aspects of firms, including capital structure and investment policies, our research uniquely explores the impact of personal experiences on corporate risk management policies, particularly regarding the use of financial derivatives.

Third, our study provides novel evidence on the value implications of corporate hedging decisions. Existing theoretical literature has outlined various channels through which hedging can enhance firm value, such as mitigating bankruptcy losses (Smith and Stulz, 1985), leveraging tax convexity (Stulz, 1984; Graham and Smith, 1999), reducing underinvestment costs (Bessembinder, 1991; Froot et al., 1993), and mitigating information asymmetry (DeMarzo and Duffie, 1991, 1995). However, our empirical findings reveal that experience-driven conservatism, shaped by CEOs' early-life disaster experiences, can sometimes lead to financial hedging decisions that inadvertently diminish firm value. This observation aligns with the agency model proposed by Tufano (1996), which integrates manager-shareholder agency costs into the risk management model developed by Froot et al.'s (1993). Consequently, our study broadens our understanding of the intricate relation between corporate risk management and firm value.

2. Sample, variables, and research design

2.1. Data sources and sample

To construct our main sample, we start the data collection process with all firms covered by the ExecuComp database between 1993 and 2020. We choose 1993 as the starting year because it marks the commencement of electronic filings on the EDGAR database.[2] For the collection of financial hedging data, we conduct textual analyses on firms' annual financial reports available on the EDGAR database. The ExecuComp database mainly covers the public firms in the Standard & Poor's (S&P) 1500 index, including the S&P

[2] It's noteworthy that companies transitioned to EDGAR filing over a three-year phase ending on May 6, 1996. Our main finding remains robust over the sample period from 1997 to 2020, a period during which electronic filings on EDGAR became mandatory.

500, S&P MidCap 400, and S&P SmallCap 600 indexes. We identify firm CEOs by using the data item "CEOANN" in the ExecuComp database. CEO biographical details are hand-collected from sources such as Bloomberg, the Notable Names Database (NNDB), official company websites, university websites, and other reputable sources such as obituary and newspapers. Our dataset on disaster events is compiled from multiple sources, including the United States Geological Survey (USGS), the National Geophysical Data Center (NGDC), the NGDC website, the National Climatic Data Center (NCDC), the National Weather Service (NWS) of the National Oceanic and Atmospheric Administration, and Wikipedia pages. We obtain financial accounting data from the Compustat database, institutional ownership data from the Thomson Reuters s34 files, board co-option data from Lalitha Naveen's website (Coles et al., 2014), anti-takeover index data from Stephen McKeon's website, and text-based financial constraint data from Gerard Hoberg's website (Hoberg and Maksimovic, 2015). After merging data from different sources, our effective sample comprises 10,352 firm–year observations with 1,293 unique firms.

2.2. CEO early-life disaster measures

Following Bernile et al. (2017), we define CEOs with early-life disaster experience as those who encountered a natural disaster between the ages of 5 and 15 within their childhood county. This specific age range is considered pivotal for shaping enduring childhood memories and early-adolescent development (e.g., Nelson, 1993; Gathercole et al., 2004). As a robustness check, we also define CEOs with child disaster experience as those who encountered a natural disaster before the age of 5 within their childhood county. Using data from the ExecuComp database, we identify 8,808 unique CEOs who serve during the period spanning from 1992 to 2020. We then manually collect each CEO's biographical information, including birthplace, birth year, childhood location, and education from various sources. This process allows us to confirm the precise childhood location for 1,685 CEOs. For CEOs with unconfirmed childhood locations, we follow the approach outlined by Bernile et al. (2017) and use their birthplace as a proxy. After excluding foreign-born

CEOs and firm–year observations with missing data for our analysis, we identify 1,823 CEOs with either confirmed childhood locations or birthplaces in our sample period.

Subsequently, we identify natural disaster events that occurred within each CEO's childhood county during their formative years. These disaster events encompass earthquakes, volcanic eruptions, tsunamis, hurricanes, tornadoes, severe storms, floods, landslides, extreme temperatures, and wildfires (Bernile et al., 2017; O'Sullivan et al., 2021; Chen et al., 2021). To ensure the accuracy of our data, we manually collect disaster-related information from reputable sources mentioned in Section 2.1. We also conduct cross-verification through additional Google searches. Our data on natural disasters spans from 1900 onwards, as all CEOs in our sample were born after that year.

We construct two proxy variables for CEO early-life disaster experience. The first proxy, labeled as *Disaster*, equals one if a CEO experienced at least one of the specified natural disasters in their childhood county between ages 5–15 and zero otherwise. Our second proxy, labeled as *Child Disaster*, equals one if a CEO experienced at least one of these disasters in their childhood county before the age of 5 years old and zero otherwise.

2.3. Financial hedging variables

To gather data on corporate financial hedging, we employ textual analysis to examine firms' annual financial reports and search for keywords related to the use of financial derivatives. This approach, inspired by Nguyen et al. (2019) and Andreou et al. (2020), allows us to expand our sample size while reducing sample selection bias. Our textual analysis encompasses various types of annual financial reports, including 10-K, 10-K405, 10-K/A, and 10-K405/A. Specifically, we develop a Python web crawler program and utilize it to assess these reports stored in the EDGAR database. We compile three lists of keywords based on prior financial hedging literature, specifically targeting the use of IR, FX, and COMMD derivatives. List A consists of keywords identifying underlying assets, such as "foreign exchange", "currency exchange", "interest rate", "loan rate", and "commodity". List B comprises keywords denoting the type of financial derivatives, such as "future", "forward", "option", "put", "call", "swap", "cap", and "collar". List C contains keywords confirming financial hedging positions, such as "derivative", "hedge", "agreement", "contract", "instrument", "transaction", "position", and "strategy".

We classify a firm as a derivatives user in a given year if its annual financial report contains at least one word or its plural form from each of these three lists within a paragraph. In many instances, firms disclose their financial hedging positions using multiple sentences. To reduce the risk of false discoveries, we extract keywords from entire paragraphs rather than single sentences. Additionally, we impose a condition that the distance between any two keywords from Lists A, B, and C must be less than 30 words within a paragraph.[3] Our automated identification process involves several steps. First, we search for keywords from List B to pinpoint specific paragraphs. Then, we define a window of 15 words before and after each keyword identified in List B. Within this window, we search for underlying asset keywords from List A and hedging position keywords from List C. If both List A and List C keywords are found within this window, we considered it a "hit". For each firm-year observation, we count the number of such "hits" for each type of financial derivatives and hedging position. A firm is classified as a derivatives user in a given year if the number of "hits" is positive and a non-user otherwise.[4] To enhance the accuracy of our identification process, we exclude "hits" containing false-positive terms such as "do not/don't use", "do not/don't enter", "do not/don't cover", or their past tense forms. To verify the reliability of our classification, we randomly selected 2% of our sample firm–year observations and manually re-assess their annual reports. Among this randomly selected sample, the accuracy rates is of 80% for IR derivatives, 87% for FX derivatives, and 78% for COMMD derivatives, which are comparable to the accuracy ranges reported in Hoberg and Moon (2017) and Sun et al. (2022).

Following the recent financial hedging studies (e.g., Allayannis and Weston, 2001; Graham and Rogers, 2002; Bartram et al., 2011; Manconi et al., 2018; Sun et al., 2022), we

[3]We adopt different distance thresholds, including 5, 15, 25, and 50 words, as suggested by Hoberg and Moon (2017). Untabulated tests show that our finding remains robust.

[4]A similar identification process is used in Hoberg and Moon (2017) and Sun et al. (2022).

employ two indicator variables, *IR/FX* and *Hedging*, to measure firms' financial hedging activities. *IR/FX* equals one if a firm uses at least one of IR and FX derivatives, and zero otherwise. *Hedging* equals one if a firm uses at least one of IR, FX, and COMMD derivatives and zero otherwise.[5] In this study, we refrain from using the notional value of financial derivatives to gauge financial hedging activities due to the changes in reporting requirements after the implementation of SFAS No.133 in 2000. SFAS No.133 replaces the mandatory reporting of notional values with the fair value of derivatives positions. Although many firms voluntarily disclose the notional values of their hedging positions post-2000, this information can be noisy and may introduce sample selection bias. Hedging positions with positive notional values would have fair values close to zero if the underlying asset's market price closely matches the strike price of the hedging position. Consequently, recent financial hedging studies commonly employ categorical hedging variables to represent the use of specific types of financial derivatives.

2.4. Research design

To explore the empirical relation between CEO early-life disaster experiences and corporate financial hedging activities, we estimate the following baseline regression model:

$$Hedging_{i,t} = \beta_0 + \beta_1 Disaster\ Experiences_{i,t} + B\,Controls_{i,t} + \theta_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

where i is firm index, t is year index, $Hedging_{i,t}$ is either $IR/FX_{i,t}$ or $Hedging_{i,t}$, $Disaster\ Experiences_{i,t}$ is either $Disaster_{i,t}$ or $Child\ Disaster_{i,t}$. To account for various determinants of corporate financial hedging, we incorporate a set of control variables in line with existing literature on the use of financial derivatives (e.g., Géczy et al., 1997; Allayannis et al., 2001; Allayannis and Weston, 2001; Graham and Rogers, 2002; Kim et al., 2006; Purnanandam, 2008; Bartram et al., 2011; Disatnik et al., 2014), including factors such as risk exposure, tax function convexity, financial distress, investment spending, investment opportunities,

[5] We conduct sensitivity analyses by replacing *IR/FX* and *Hedging* with individual indicator variables for IR, FX, and COMMD derivatives. Our main finding remains qualitatively the same.

economies of scale, business cycle, and information asymmetry. Specifically, we include *Foreign Income* and *Sale Volatility* as control variables to account for corporate risk exposure, net operating loss carry-forwards (*NOL*) to capture tax function convexity, *Networth* and *Leverage/Equity* to control for financial distress, *R&D* to control for investment spending, Tobin's Q to capture future growth opportunities, *Firm Size* to account for economies of scale, *Firm Age* to control for a firm's business life cycle, and *Institutional Ownership* to control for risk management incentives resulting from information asymmetry between managers and shareholders. All dollar-denominated accounting variables are adjusted for inflation to 2020 dollars. To mitigate the effect of outliers, we apply winsorization to the top and bottom 1% of continuous variables' distributions, except for indicator variables and *Firm Age*. For detailed variable definitions, please refer to Table A of the Appendix.

We control for the firm fixed effects (θ_i) in our baseline regression to account for time-invariant unobserved firm-specific heterogeneity, such as firm culture or management quality, which can affect corporate risk management policy. We also include the year fixed effects (μ_t) to isolate the effect of CEO early-life disaster experiences on corporate financial hedging from time-specific factors that can influence a firm's financial hedging decisions, such as the development of derivatives markets and regulation changes.

3. Main results

3.1. Descriptive statistics

Table 1 presents the summary statistics of the variables used in our main empirical analysis. Our main sample consists of 10,352 firm–year observations spanning fiscal years 1993 to 2020, all with complete data for our baseline regressions. The primary dependent variables are *IR/FX* and *Hedging*. The mean value for *IR/FX* is 0.684, with a standard deviation of 0.465, indicating that, on average, approximately 68.4% of firms in our sample utilize IR and/or FX derivatives. Similarly, for *Hedging*, the mean value is 0.733, with a standard deviation of 0.443, suggesting that approximately 73.3% of sample firms employ IR, FX, or COMMD derivatives for financial hedging purposes. As for our two independent variables of interest, *Disaster* has an average value of 0.211, implying that, on average, about 21.1% of sample firms are managed by CEOs who experience at least one natural disaster between the ages of 5 and 15 years. *Child Disaster* has a mean value of 0.138, indicating that, on average, 13.8% of CEOs in our sample have experienced a natural disaster before the age of 5 years.

In terms of the control variables, our sample firms generate an average of 1.8% of their sales from foreign income, and the average sales volatility stands at 16.8%. The average net operating loss is 4.3%, while the average net worth is 26.7%. R&D expenses account for roughly 20% of total assets for an average firm in our sample. The mean Tobin's Q is 1.82, and the average firm size, measured by the natural logarithm of total assets, is 8.20. On average, firms in our sample have a 3-year age, with institutional investors representing 50.6% of firm stock ownership. The summary statistics of these firm characteristics align with those reported in prior studies (e.g., Disatnik et al., 2014; Hoberg and Moon, 2017).

3.2. Baseline regression results

To investigate the relation between CEO early-life disaster experiences and corporate financial hedging, we employ a logistic regression model and estimate Equation (1). The results of our regression analysis are presented in Table 2. The dependent varaible is *IR/FX* in columns (1)–(4) and *Hedging* in columns (5)–(8). In columns (1)–(2) and (5)–(6), we conduct univariate tests while controlling for the firm and year fixed effects. All the estimated coefficients on *Disaster* and *Child Disaster* are positive and statistically significant at the 1% level. In columns (3)–(4) and (7)–(8), we introduce control variables representing firm characteristics, and the results remain consistent.

Specifically, in column (3), the estimated coefficient on *Disaster* is 0.928, indicating that firms managed by CEOs who experience at least one natural disaster in their early life between the ages of 5 and 15 years are associated with 1.53 ($= exp(0.928) - 1$) times higher odds of utilizing IR or FX derivatives. Similarly, in column (4), the estimated coefficient on *Child Disaster* is 1.05, implying that firms managed by CEOs who experience at least one natural disaster before the age of 5 years exhibit 1.86 ($= exp(0.105) - 1$) times higher odds of using IR or FX derivatives. The coefficient for *Hedging* in column (7) is 0.875, suggesting that firms managed by CEOs who experience at least one natural disaster between the ages of 5 and 15 years have 1.40 ((=exp(0.875)-1)) times higher odds of employing IR, FX, or COMMD derivatives. In column (8), the coefficient for *Hedging* is 0.836, indicating that firms managed by CEOs who experience at least one natural disaster before the age of 5 years have 1.31 (=exp(0.836)-1) times higher odds of using IR, FX, or COMMD derivatives.

The coefficients of our control variables are consistent with prior studies Géczy et al. (1997) and Disatnik et al. (2014), which examine the determinants of derivatives usage and the relation between corporate financial hedging and liquidity policies. Table 2 shows that financial hedging decisions are positively associated with sale volatility, net operating loss, firm size, firm age, and institutional ownership. Conversely, firms with more net worth are less likely to use financial derivatives.

Overall, our findings suggest that firms managed by CEOs with early-life disaster experiences are more likely to engage in financial hedging. This observation aligns with Denrell and March's (2001) "Hot-Stove" view that CEOs with disaster experiences tend to adopt a more conservative approach to corporate activities. Moreover, our findings are consistent with existing literature, indicating that direct exposure to a bankruptcy event in the financial market can significantly influence a manager's risk preference, leading to more conservative decisions to mitigate unfavorable outcomes (Dittmar and Duchin, 2016). Our findings highlight the substantial role of CEO early-life experiences in shaping corporate risk management policies.

3.3. Identification tests

In this section, we conduct a battery of identification tests to establish a causal link between CEO early-life disaster experiences and corporate financial hedging.

3.3.1. Exogenous CEO turnover events

First, certain firm characeristics not being controlled for in our baseline regression may influence both the likelyhood of a firm hiring CEOs with early-life disaster experiences and corporate risk management policies. For example, firms with conservative corporate culture may choose to hire CEOs with early-life disaster experiences and adopt the use of financial hedging. To mitigate this concern, we utilize exogenous CEO turnover events classified by Gentry et al. (2021) and examine the changes in the likelihood of financial hedging around these events. Gentry et al. (2021) classify the CEO departure reasons into eight categories: 1)CEO death, 2) CEO illness, 3) CEO dismissed for job performance, 4) CEO dismissed for personal issues, 5) CEO retired, 6) New opportunity, 7) Other, and 8) Missing. To ensure that the CEO turnovers we select are not related to firm performance and corproate strategies, we choose department reasons 1), 2), 5), and 6) as the exogenous CEO turnovers.[6]

We focus on 186 exogenous CEO turnovers within a four-year window around the event, excluding continuous CEO turnover observations. Among these turnovers, 40 transitions involve a change in the CEOs' early-life disaster experiences according to *Disaster*: 18 transitions from CEOs without disaster experiences to those with disaster experiences and 22 transitions from CEOs with disaster experiences to those without disaster experiences. We also classify turnover events based on *Child Disaster*. We find that among 29 transitions with a change in CEOs' disaster experiences, 15 transitions are categorized as from without disaster experiences to with disaster experiences and 14 are classified as from with disaster experiences to without disaster experiences.

Following the approach used by Bernile et al. (2017), for each CEO turnover event occurring in year t, we assess changes in firms' use of financial derivatives by comparing the mean values of *IR/FX* or *Hedging* over years $[t-2, t]$ to years $[t+1, t+2]$. In Panel A of Table 3, we use *Disaster* to define CEOs' disaster experiences. Columns (1) and (2) present the

[6] Our finding remains robust if we use all CEO turnovers regarless of departure reasons.

changes in the mean values of financial hedging indicator variables from $[t-2, t]$ to $[t+1, t+2]$. In column (1), we observe that the changes in the mean values of *IR/FX* and *Hedging* are positive in the "No-Disaster to Disaster" groups, suggesting that when outgoing CEOs do not have disaster experiences and incoming CEOs have disaster experiences, firms are more likely to use financial derivatives. In column (2), we observe that the changes in the mean values of *IR/FX* and *Hedging* are positive in the "Disaster to No-Disaster" groups, indicating that when outgoing CEOs have disaster experiences and incoming CEOs do not have disaster experiences, firms are less likely to use financial derivatives. Columns (3) and (4) report the differences in these changes between the "No-Disaster to Disaster" groups and the "Disaster to No-Disaster" groups, as well as the corresponding t-statistics for the null hypothesis that the difference is equal to zero. Panel A shows that the differences in the changes between these two groups are statistically signficant at the 1% level, suggesting that firms are more likely to adopt financial hedging when the outgoing CEOs do not have disaster experiences and the incoming CEOs have disaster experiences than when the outgoing CEOs have disaster experiences and the incoming CEOs do not have disaster experiences. In Panel B, we use *Child Disaster* to define CEOs' disaster experiences and find consistent results with those in Panel A.[7]

To further explore the changes in corproate financial hedging policies around CEO turnovers, we conduct a difference-in-differences (DID) analysis using the multivaraite regressions. The DID sample classified by *Disaster* includes treated firms with *No-Disaster to Disaster* CEO turnovers (N=18) and control firms with *No-Disaster to No-Disaster* CEO turnovers (N=143). The DID subsample classified by *Child Disaster* includes firms with *No-Child Disaster to Child Disaster* CEO turnovers (N=15) and *No-Child Disaster to No-Child Disaster* CEO turnovers (N=155). For both treated and control firms, the DID sample covers firm–year observations two years before and after the turnover events, including the event year. We also require that firms have available accounting data in

[7]We also test the differences in the changes between the "No-Disaster to Disaster" groups and the "Disaster to No-Disaster" groups, using all CEO turnover events (N=243) in our sample. The results are quantitatively consistent.

Compustat for at least two years before the event year. Our DID regression specification is:

$$\begin{aligned} Hedging_{i,t} = \beta_0 + \beta_1\, Treat\_Disaster_i(or\;\; Treat\_Child\ Disaster_i) \times Post_{i,t} \\ + \beta_2 Post_{i,t} + B\, Controls_{i,t} + \mu_t + \theta_i + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $Treat\_Disaster_i$ ($Treat\_Child\ Disasteri$) is an indicator variable that equals one if firm i experience a *No-Disaster to Disaster* (*No-Child Disaster to Child Disaster*) CEO turnover in the event year and zero otherwise. $Posti, t$ is an indicator variable that equals to one if year t is either the event year or after the turnover event and zero otherwise. Control variables remain the same as those in our baseline regression Equation (1). We also control for the firm and year fixed effects in the DID regression model.

Table 4 reports the results of the DID tests. The estimated coefficients on the interacted terms, $Treat\_Disaster \times Post$ and $Treat\_Child\ Disaster \times Post$, are positive and statistically significant, consistent with the view that firms managed by CEOs with early-life disaster experiences are more likley to use financial derivatives. These findings provide robust evidence of the impact of CEO early-life experiences on corporate risk management strategies.[8]

3.3.2. Propensity score matching and entropy balancing matching

While our DID analysis helps address potential endogeneity concerns related to unobserved heterogeneity in firm and CEO characteristics, we also need to account for potential biases stemming from the endogenous matching problem. Firms and CEO candidates are not randomly matched in the labor market. If firms strategically appoint CEOs based on specific attributes aligned with their risk management strategies and firm characteristics, the estimated coefficients in our baseline regression could be biased. For example, firms with higher cash flow volatility may be more inclined to hire risk-tolerant CEOs and adopt

[8] The results remain robust when we re-estimate the Equation 2 based on the DID samples extracted from all CEO turnover events (N=243) in our sample.

financial hedging for risk management. To mitigate non-random matching between firms and CEOs, we employ two matching strategies: propensity-score matching (PSM) and entropy balancing (EB) matching. Through these two matching approaches, we construct treatment groups in which firms are managed by CEOs with early-life disaster experiences and control groups in which firms share similar firm-specific characteristics with those in the treatment groups but are managed by CEOs without disaster experiences.

First, we utilize a PSM method proposed by Rosenbaum and Rubin (1983). We employ a probit model to estimate the probabilities (propensity scores) of firms hiring CEOs with early-life disaster experiences. The dependent variables in the probit models are *Disaster* and *Child Disaster*, while the independent variables include the control variables in Equation (1). Based on the estimated propensity scores, we match the firm–year observations in the treatment groups with those in the control groups, using a one-to-one nearest-neighbor matching without replacement and with a caliper width of 0.005.[9] Our PSM sample includes 4,356 firm–year for the indicator variable *Disaster* and 2,848 firm–year observations for the indicator variable *Child Disaster*.

To validate the efficiency of our PSM procedure, we conduct two diagnostic tests. The first one is a post-match diagnostic regression based on the propensity score matched samples. Panel A of Table B of the Appendix presents the pre-match that all estimated coefficients on the matching variables are statistically insignificant. The F-statistics of the Hotelling test indicate that we fail to reject the null hypothesis of equal means between the treatment and control groups. Our second diagnostic test is the univariate comparison of the matching variables between the treatment and control groups. Panel B of Table B of the Appendix shows that all the differences in the mean values of the matching variables between the treatment and control groups are statistically insignificant. Both diagnostic tests suggest that firms in the treatment and control groups are comparable in terms of observable firm characteristics.

[9] Our finding remains robust if we adopt a one-to-one nearest-neighbor matching with the caliper width of 0.001 or a one-to-three nearest-neighbor matching with the caliper width of 0.005.

Next, we re-estimate Equation (1) using the propensity score matched samples. Columns (1)-(4) of Table 5 present the results. The estimated coefficients on *Disaster* and *Child Disaster* are all positive and statistically significant. The magnitude of these coefficients is comparable to those reported in Table 2. The evidence from the PSM tests reinforces our earlier conclusion regarding the significant role that CEOs' early-life disaster experiences play in affecting corporate financial hedging.

In our PSM procedure, we match firm–year observations between the treatment and control groups based on their respective propensity scores. The application PSM leads to the exclusion of more than half of the observations in the pre-match sample. To enhance the robustness of our findings, we also employ an EB matching procedure, which recalibrates the observation weights by imposing constraints that adjust the moments of the covariate distributions to achieve tight covariate balance. We assign firm–year observations to the treatment and control groups based on *Disaster* or *Child Disaster*. Our EB matching ensures that the treatment and control groups closely mirror each other in terms of mean, variance, and skewness. Unlike PSM, EB matching retains all observations, avoiding the need to discard "unmatched" data points. Furthermore, EB matching is not contingent on specific research designs for achieving covariate balance, thus addressing concerns regarding potential model specification dependencies (DeFond et al., 2017). Hainmueller (2012) argue that the improved balance attained through EB matching reduces approximation bias and minimizes model dependency in finite samples.

Panel C of Table B of the Appendix illustrates the efficiency of our EB matching. While there exist significant differences in the mean, variance, and skewness of the matching variables between the treatment and control groups before matching, these differences vanish after matching. Columns (5)–(8) of Table 5 present the results of Equation (1) based on the EB matching sample. The estimated coefficients on *Disaster* and *Child Disaster* remain positive and statistically significant at the 1% level, suggesting that the positive impact of CEO's early-life disaster experiences on the use of financial derivatives remains robust when utilizing the EB matching method. The adoption of EB matching further enhances the credibility of our findings by mitigating potential biases and improving comparability between the treatment and control groups.

3.3.3. Additional controls for CEO and CFO characteristics

In our baseline regression, we follow previous studies on the determinants of corporate financial hedging and select a set of firm-level characteristics as the control variables. However, corporate risk management policies can depend on the characteristics and preferences of CEOs and CFOs. First, previous research has established a link between CEO equity-based incentives and corporate risk taking. Delta and Vega, common proxies for managers' equity-based incentives, represent option values' sensitivity to stock performance and to stock volatility, respectively (Core et al., 1999). Several studies document an empirical relation between equity-based incentives and corporate risk taking activities, such as increased leverage, greater investment in R&D, and more acquisitions (Rajgopal and Shevlin, 2002; Coles et al., 2006; Gormley et al., 2013). Some empirical studies also offer evidence of the causal effect of equity-based incentives on firms' hedging behavior (Rogers, 2002; Bakke et al., 2016), while others do not support such a relation (e.g., Géczy et al., 1997; Haushalter, 2000; Allayannis and Ofek, 2001; Knopf et al., 2002).

Second, recent research also highlights the influence of top managers' personal attributes on corporate risk management policy, including gender, age, and tenure, on corporate risk-taking. Barsky et al. (1997) and Huang and Kisgen (2013) posit that female managers tend to exhibit risk-averse tendencies and may engage in more hedging activities. However, Schubert et al. (1999) and Atkinson et al. (2003) find no significant correlation between risk aversion and gender. Other studies by Yim (2013) and Serfling (2014) suggest that younger CEOs tend to take more risks. In line with this finding, Croci et al. (2017) demonstrate that older CEOs are more inclined to hedge, with those close to retirement favoring linear hedging instruments. Additionally, Berger et al. (1997) argue that CEOs with longer tenures seek entrenchment and avoid risk. Supporting this argument, Croci et al. (2017) provide empirical evidence that a CEO holding both the CEO and chairman positions signals entrenchment, which leads to less financial hedging as CEO duality reduces CEOs' risk of getting replaced during financial distress.

To account for the possibility that our main finding is influenced by manager-level characteristics, we first introduce CEO equity-based incentives, CEO gender, CEO age, CEO tenure, and CEO duality as additional control variables in our baseline regression model. In columns (1)–(2) and columns (5)–(6) of Table 6, we present the regression results after controlling for these CEO characteristics. We observe that the estimated coefficients on *Disaster* and *Child Disaster* remain positive and statistically significant at the 1% level. Second, recent studies suggest that CFOs play an important role in shaping corporate strategy and actively engage in risk management decisions due to their responsibilities and expertise (Tufano, 1996; Datta and Iskandar-Datta, 2014; Florackis and Sainani, 2018). We further include additional controls for CFO characteristics, including CFO equity-based incentives, CFO gender, CFO age, and CFO tenure.[10] Columns (3)–(4) and (7)–(8) of Table 6 show that the positive relation between CEO early-life disaster experiences and the use of financial derivatives remains robust even after controlling for both CEO and CFO characteristics.

3.3.4. Additional controls for corporate governance

The existing body of literature has offered several explanations regarding how the strength of corporate governance can influence firms' use of financial derivatives (e.g., Stulz, 1984; Smith and Stulz, 1985; DeMarzo and Duffie, 1995). First, corporate governance affects firms' choices regarding the use of derivatives for either hedging or speculation purposes. A survey study on derivatives usage among US firms by Géczy et al. (2007) reveals that firms with weaker governance structures are more inclined to engage in speculative activities. Second, firms with less robust monitoring mechanisms may turn to financial derivatives as a means to accommodate managerial risk preferences and achieve

[10] Managerial characteristic data is sourced from ExecuComp over our entire sample period from 1993 to 2020. However, CFO characteristic data is only available from ExecuComp starting in 2007, resulting in a reduced sample size after incorporating these control variables.

more substantial risk reduction (DeMarzo and Duffie, 1995; Dadalt et al., 2002). Third, firms with sound governance frameworks may incorporate financial derivatives as part of their risk management policies to hedge against currency exposure and reduce external financing costs (Froot et al., 1993; Lel, 2012).

Given the potential influence of corporate governance on corporate financial hedging, we extend our analysis to control for firm-level governance mechanisms. We adopt three proxies for corporate governance. The first proxy is *COP*, which is the fraction of co-opted directors in the corporate board. Co-opted directors are those appointed after the current CEO takes office. A higher proportion of such directors indicates weaker internal monitoring intensity (Coles et al., 2014). The second proxy is *HOI*, which is the hostile takeover index (Cain et al., 2017). A higher *HOI* index value signifies a greater likelihood of a hostile takeover and stronger corporate governance. This index considers a firm's legal environment along with other exogenous factors influencing takeover vulnerability, providing a robust measure of exogenous shifts in the threat of takeovers. The third proxy is *BLC*, which is the total ownership of block holders who hold more than 5% of a firm's stocks (Edmans, 2014). Previous studies indicate that blockholder ownership is a major corporate governance mechanism that helps control agency problems and strengthen the governance environment (Kaplan and Minton, 1994; Edmans, 2014). A higher *BLC* value is associated with stronger corporate governance.[11] Columns (1)–(12) in Table 7 present regression results after controlling for three additional proxies for corporate governance. The estimated coefficients on *Disaster* and *Child Disaster* are all positive and statistically significant, except in column (8), affirming the robustness of our main finding.

3.3.5. Additional controls for corporate culture

Corporate culture could also be an omitted variable in our empirical analysis which simultaneously affects corporate risk management policy and the likelihood of appointing CEOs with early-child disaster experiences. In this section, we directly control for corporate

[11] We also control for Gompers et al.'s (2003) governance measure (G-Index) and the E-Index developed by Bebchuk et al. (2009). The coefficients of disaster proxies remain positive and statistically significant.

culture in our baseline regression. Li et al. (2021) develop a new semisupervised machine learning approach and construct five dimensions of corporate culture measures based on earnings call transcripts: *Innovation*, *Quality*, *Integrity*, *Teamwork*, and *Respect*. Li et al. (2021) provide empirical evidence that these five culture measures are associated with various corporate activities, such as risk-taking, operational efficiency, and firm value.

The corporate culture data from Li et al. (2021) covers the period between 2001 and 2018.[12] We merge this data with our main sample and include the five corporate culture measures as additional control variables in our baseline regression. The results are presented in Table 8. The dependent variable is *IR/FX* in columns (1)–(2) and *Hedging* in columns (3)–(4). We observe that the positive relation between CEO early-life disaster experiences and the use of financial derivatives remains robust. The estimated coefficients on *Innovation* are all positive and statistically significant, while the estimated coefficients on *Teamwork* are all negative and statistically significant.

4. Supplementary tests

4.1. CEO early-life disaster experiences, financial hedging, and firm value

Although financial derivatives have been widely employed as essential risk management tools, empirical findings concerning the relation between corporate financial hedging and firm value remain inconclusive. For instance, Allayannis et al. (2001) document a positive correlation between the use of foreign currency derivatives and firm value in a sample of U.S. non-financial corporations exposed to foreign currency risks. Similarly, Carter et al. (2006) report a significantly positive hedging premium among a sample of U.S. airline firms that actively engage in jet fuel hedging. However, Guay and Kothari (2003) present evidence indicating that the cash flows generated by hedging are relatively

[12] We would like to thank Kai Li for sharing the data on corporate culture.

modest and insufficient to account for a substantial increase in firm value. Focusing on oil and gas producers, Jin and Jorion (2006) do not find a significant impact of financial hedging on firm value.

In this section, we examine whether the positive relation between CEO early-like disaster experiences and financial hedging results in higher or lower firm value. On one side, As CEOs with early-life disaster experiences tend to be more conservative in their risk management policies, the use of financial derivatives can create firm value if CEOs' risk preference is consistent with shareholders' risk preference. On the other side, managers' personal wealth is closely tied to their firm performance, but shareholders can diversify their portfolios by holding many different stocks. Therefore, in many economic and finance models, it is often assumed that managers are risk-averse, while shareholders are risk-neutral. If CEOs' early-life disaster experiences induce an overly conservative corporate risk management policy, the use of financial derivatives may destroy firm value given the substantial costs of financial hedging.

Following prior studies on the implication of corporate financial hedging on firm value (Peters and Taylor, 2017; Bartram et al., 2011), we use *Total Q* and *Growth* as the proxy for firm value reflected by future growth opportunities. *Total Q* is a new Tobin's Q proxy that accounts for intangible capital. Peters and Taylor (2017) show that *Total Q* is a superior proxy for both physical and intangible investment opportunities. As an alternative measure of firm growth options, we follow Bartram et al. (2011) and adopt *Growth* measured by capital expenditures to sales. Géczy et al. (1997) show that firms with a higher level of growth options are more likely to use financial derivatives. In Table 9, we estimate the following regressions:

$$\begin{aligned} Firm\ Value_{i,t} = {} & \beta_0 + \beta_1 Disaster\ Experiences_{i,t} \times Hedging_{i,t} + \beta_2 Hedging_{i,t} \\ & + \beta_3 Disaster\ Experiences_{i,t} + B\,Controls_{i,t} + \theta_i + \mu_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where i is firm index, t is year index, $Firm\ Value_{i,t}$ refers to either *Total Q* or *Growth*, $Disaster\ Experiences_{i,t}$ refers to either *Disaster* or *Child Disaster*, $Hedging_{i,t}$ refers to either

IR/FX or *Hedging*, and $Controls_{i,t}$ refers to the control variables used in Equation (1). We include both the firm (θ_i) and year (μ_t) fixed effects in Equation (3).

Table 9 reports the results. In columns (1)–(4), the dependent variable is *Total Q*. The estimated coefficient on the financial hedging proxies and CEO early-life disaster experience proxies are positive but statistically insignificant. However, the estimated coefficients on the interaction terms between the financial hedging proxies and disaster experience proxies are negative and statistically significant. In columns (5)–(8), the dependent variable is *Growth*. We observe that financial hedging proxies and CEO early-life disaster experience proxies have a positive and statistically significant impact on firm value in columns (5) and (7). The estimated coefficients on *Disaster Experiences* × *Hedging* remain negative and statistically significant in columns (5)–(7). These findings align with Allayannis et al. (2001) and Bartram et al. (2011), suggesting that the use of financial derivatives can enhance firm value. More importantly, our findings highlight that when CEOs have early-child disaster experiences, the use of financial derivatives reduces their firm value.

4.2. Cross-sectional analyses

To help us further understand the mechanisms through which CEO early-life experiences in shaping corporate risk management policies, we conduct three cross-sectional analyses.

4.2.1. Corporate governance

In Section 4.1, our firm value tests suggest that CEOs' early-child disaster experiences increase the gap between CEOs' and shareholders' risk preferences so that CEOs make sub-optimal decisions in corporate financial hedging. If the use of financial derivatives by CEOs with disaster experiences is mainly driven by CEOs' personal risk preference and not aligned with shareholders' interests, then we expect to observe a more pronounced relation between CEOs' disaster experiences and financial hedging in firms with weaker corporate governance and more severe agency problems. To examine this possibility, we employ three proxies for corporate governance mechanisms: *COP*, *HOI*, and *BLC*. We divide our sample into two sub-samples based on the annual median value of our corporate governance proxies. Firms in the sub-samples with a lower *COP*, *HOI*, or *BLC* tend to have weaker corporate governance.

We then re-estimate our baseline regression Equation (1) in each sub-sample. In Panel A of Table 10, the corporate governance proxy is *COP*. In the odd-numbered columns, the estimated coefficients on *Disaster* and *Child Disaster* are positive and statistically significant for firms with a high ratio of co-opted directors. In columns (2) and (4), the estimated coefficients on *Disaster* and *Child Disaster* remain positive and statistically significant for firms with a low ratio of co-opted directors. But in columns (6) and (8), the estimated coefficients on *Disaster* and *Child Disaster* are statistically insignificant for firms with a low ratio of co-opted directors. We conduct seemingly unrelated tests (SUR) and find that the positive differences in the coefficients of disaster experience proxies between the high and low *COP* sub-samples are all statistically significant, supporting our expectation that the positive relation between CEO early-life disaster experiences and financial hedging is stronger in firms with weaker corporate governance.

In Panels B and C of Table 10, the corporate governance proxies are *HOI* and *BLC*. We find that the estimated coefficients on *Disaster* and *Child Disaster* are positive and only statistically significant in the sub-samples of firms with low *HOI* or *BLC*. The differences in the coefficients of disaster experience proxies between the low and high corporate governance sub-samples are all positive. Our SUR tests indicate that most of these differences are statistically significant, consistent with our finding in Panel A of Table 10.

4.2.2. Financial constraints

Next, we investigate whether the positive relation between CEO early-life disaster experiences and financial hedging is contingent on firms' financial conditions. Froot et al. (1993) argue that financial hedging adds firm value if it helps ensure that a firm has sufficient internal funds available to investment. Since financial hedging by CEOs with disaster experiences tends to decrease firm value, we may take the positive relation between CEOs' disaster experiences and financial hedging as an agency problem. Firms with financial constraints have fewer resources to engage in financial hedging activities, which naturally mitigates the agency problem. Therefore, we posit that the positive relation between CEOs' disaster experiences and financial hedging is stronger in firms with low financial constraints than in firms with high financial constraints. To measure financial constraints, we utilize the debt-focused financial constraints measure (*DTD*) which is constructed by Hoberg and Maksimovic (2015) through a textual analysis of discussions about debt financing issues discussed in firms' annual reports. Firms with a higher value of *DTD* have more severe financial constraints.

After dividing our sample into two sub-samples based on the annual median value of *DTD*, we re-estimate Equation (1) for each sub-sample. Panel D of Table 10 shows that the estimated coefficients on *Disaster* and *Child Disaster* are positive and statistically significant in the sub-samples of firms with low financial constraints, while the estimated coefficients are statistically insignificant in the sub-samples of firms with high financial constraints. Our SUR tests show that the differences in the estimated coefficients between the low and high financial constraint sub-samples are statistically significant, except between columns (5) and (6). Our finding indicates that the agency problem that CEOs with disaster experiences tend to adopt financial hedging is more severe in firms with fewer financial constraints.

4.2.3. Firm risk

Our third cross-sectional analysis explores whether the positive relation between CEO early-life disaster experiences and financial hedging varies with firm-specific risk. Prior research consistently shows that the use of financial derivatives can effectively mitigate firms' risk exposure. For example, Guay (1999) finds that firms experience reductions in total risk, idiosyncratic risk, and interest rate risk after adopting financial hedging. Similarly, Allayannis and Weston (2001) and Allayannis and Ofek (2001) demonstrate that the use of financial derivatives significantly reduces firms' exposure to exchange rate risk. In a study encompassing 47 countries, Bartram et al. (2011) provides international evidence that firms utilizing derivatives exhibit lower risk.

We adopt two proxies for firm-specific risk. Our first proxy for firm risk is operating cash flow volatility (*CFsd*), measured as the average standard deviation of operating cash flows over a five-year period for firms within the same two-digit SIC codes (Bartram et al., 2011). Higher operating cash flow volatility typically indicates greater operational risks. Our second measure of firm-specific risk is a firm's options trading volume (OTV). Previous research suggests that more options trading activities can stimulate a firm's innovation and development of new products (Blanco and Wehrheim, 2017; Hsu et al., 2021). However, such actions may also potentially increase a firm's overall risk exposure. High options trading volume may also indicate that investors hold strong opinions about a firm's future prospects, which could be driven by upcoming earnings announcements, regulatory changes, or other events perceived as having a significant impact on the firm's stock price. We assign our sample firm–year observations into two sub-samples based on the annual median of *CFsd* or OTV. Firms with a high value of *CFsd* or OTV tend to have high firm-specific risk.

Panels E and F of Table 10 show that the estimated coefficients on *Disaster* and *Child Disaster* are positive and statistically significant in the sub-samples of firms with high firm-specific risk. The estimated coefficients on *Disaster* and *Child Disaster* are statistically insignificant in the sub-samples of firms with low firm-specific risk. The estimated coefficients on the disaster proxies are larger in the sub-samples of firms with high firm-specific risk than those in the sub-sample of firms with low firm-specific risk. Our SUR tests show that most of the differences in these coefficients between the two sub-samples are statistically significant. Overall, our third cross-sectional analysis suggests that CEO early-life disaster experiences are associated with more prudent financial hedging policy, especially for firms with higher firm-specific risk.

4.3. CEO early-life disaster experience and operational hedging

The literature on corporate risk management indicates that aside from financial hedging, firms may employ operational hedging to reduce their future cash flow risk. Operational hedging includes actions, such as diversifying business into different industries, geographic diversification of production, and acquisitions of subsidiaries (Allayannis et al., 2001; Kim et al., 2006; Hankins, 2011). Moreover, corporate cash holdings are also recognized as a risk management tool to protect firms from future uncertainty (Acharya et al., 2007; Haushalter et al., 2007). In this section, we examine whether CEO early-life disaster experiences affect firms' operational hedging activities.

In line with prior research, we employ three proxies to assess a firm's operational hedging activities: the number of business segments (*#.Segment*), business concentration (*Bus.HHI*), cash holdings (*Cash*), and net cash reserves (*Net Cash*). We estimate the following regression:

$$Operational\ Hedging i,t = \beta 0 + \beta_1 Disaster\ Experiences i,t + B\,Controls i,t + \mu_t + \theta_i + \varepsilon_{i,t} \tag{4}$$

where i is firm index and t is year index. $Operational\ Hedging_{i,t}$ refers to one of the following four varaibles: *#.Segment* defined as the number of business segments (Dittmar and Shivdasani, 2003), *Bus.HHI* defined as a Herfindahl-Hirschman index based on major corporate business segment sales (Villalonga, 2004), *Cash* defined as the ratio of cash and short-term investments scaled by total assets (Haushalter et al., 2007), and *Net Cash* defined as the ratio of cash and short-term investments scaled by net assets, where net assets is total assets minus cash and short-term investments (Bates et al., 2009). $Disaster\ Experiences_{i,t}$ refers to either *Disaster* or *Child Disaster*. $Controls_{i,t}$ refers to the control variables used in Equation (1).

Table 11 reports the results of our operational hedging tests. In columns (1)–(8), all estimated coefficients on *Disaster* and *Child Disaster* are statistically insignificant, suggesting that CEO early-life disaster experiences do exert a direct influence on operational hedging activities. As discussed by Petersen and Thiagarajan (2000), managers' decisions regarding risk management are contingent on the firm's fundamental characteristics and the costs associated with altering production or diversification. Compared to the use of financial derivatives, the modification of a firm's operations can be relatively costly, particularly in response to short-term fluctuations in risk exposures. Furthermore, the use of financial derivatives is less likely monitored by the board of directors and shareholders compared to diversifying a firm's operations. Therefore, although we document a positive relation between CEOs' early-life disaster experiences and financial hedging, we do not find any evidence that such experiences are associated with operational hedging.

5. Conclusion

A growing body of research highlights the influence of CEOs' past experiences on corporate policies. In our study, we focus on a specific aspect of CEOs' personal life experiences, that is early-life disaster experiences, and study how such experiences may affect corporate financial hedging activities. We hypothesize that CEOs with early-life disaster experiences would exhibit heightened sensitivity to the consequences of risk-taking. Consequently, we expect these CEOs to lean towards risk aversion and, as a result, to be more inclined to adopt financial derivatives as a risk-mitigation tool.

Using a sample of US public firms between 1993 and 2020, our empirical findings support our hypothesis, revealing that CEOs with early-life disaster experiences are more likely to engage in corporate financial hedging, compared to CEOs without such experiences. Our finding aligns with prior research, which demonstrates the enduring impact of CEO's early-life experiences on their risk preferences (Malmendier and Tate, 2005; Malmendier et al., 2011; Feng and Johansson, 2018). The positive relation between CEOs' early-life disaster experiences and financial hedging remains robust to DID tests based on exogenous CEO turnovers, two matching methods, and the inclusion of additional controls for managerial attributes, corporate governance, and corporate culture. We also find that the interactive impact of CEOs' early-life disaster experiences and financial hedging on firm value is negative, suggesting that such disaster experiences drive CEOs' risk preferences away from shareholders' risk preferences, potentially creating an agency problem. Furthermore, our cross-sectional analysis shows that the positive relation is more pronounced in firms with weaker corporate governance, fewer financial constraints, and more firm-specific risk. Overall, our study calls for a proactive approach from regulators and corporate boards to ensure that corporate risk management strategies align with the best interests of stakeholders, taking into account CEOs' unique personal experiences and risk preferences.

Appendix

Table A. Variable definitions

This table provides variable definitions and corresponding data sources. s34 files refer to the Thomson Reuters 13F Database, ISS refers to the Institutional Shareholder Services (formerly RiskMetrics), LN refers to Lalitha Naveen's website, SM refers to Stephen McKeon's website, GH refers to Gerard Hoberg's website, LMSY refers to Li et al. (2021), and PT refers to the WRDS Peters and Taylor Total Q dataset.

Variable	Definition	Source
IR/FX	A dummy variable equals to one if a firm uses at least one of interest rate and foreign currency derivatives, zero otherwise (Campello et al., 2011).	10-Ks
Hedging	A dummy variable equals to one if a firm uses at least one of interest rate, foreign currency, and commodity derivatives, zero otherwise (Hoberg and Moon, 2017).	10-Ks
Disaster	A dummy variable equals to one if the CEO has an early-life disaster experience at the age of 5 to 15, otherwise zero. (Bernile et al., 2017).	
Child Disaster	A dummy variable equals to one if CEO the CEO has an early-life disaster experience before the age of 5, otherwise zero. (Bernile et al., 2017).	
Foreign Income	The ratio of pretax income from the firm's foreign operations to sales (Géczy et al., 1997).	Compustat
Sale Volatility	The standard deviation of firm sales scaled by total assets over the past 10 years (Disatnik et al., 2014).	Compustat
NOL	Net operating loss, measured by the portion of prior and current year net operating losses applied as a reduction of taxable income scaled by total assets (Géczy et al., 1997).	Compustat
Networth	The ratio of total assets minus cash minus total liabilities to total assets (Disatnik et al., 2014).	Compustat
Leverage/Equity	The ratio of total debt to common equity (Disatnik et al., 2014).	Compustat
R&D	The ratio of R&D expenses to total assets (Disatnik et al., 2014).	Compustat
Tobin's Q	The ratio of the sum of total assets and market value of common equity minus the sum of common equity and deferred taxes, to total assets (Disatnik et al., 2014).	Compustat
Firm Size	The natural logarithm of total assets (Allayannis et al., 2001).	Compustat
Firm Age	The natural logarithm of the number of years since the firm first appeared on Compustat with nonmissing total assets (Bartram et al., 2011).	Compustat

Continued on next page

Table A1 - continued from previous page

Variable	Definition	Source
Institutional Ownership	The percentage institutional ownership in the firm (Purnanandam, 2008).	s34 files
CEO/CFO Vega	The ratio of vega of shares and stock options held by a CEO/CFO to total compensation, where total compensation includes salary, bonus, restricted stock and option grants, long-term incentive payouts, and any other compensation (Beber and Fabbri, 2012).	ExecuComp
CEO/CFO Delta	The ratio of delta of shares and stock options held by a CEO/CFO to total compensation, where total compensation includes salary, bonus, restricted stock and option grants, long-term incentive payouts, and any other compensation(Beber and Fabbri, 2012).	ExecuComp
Female CEO/CFO	A dummy variable equals one if a CEO/CFO is female and zero otherwise (Bernile et al., 2017).	ExecuComp
CEO/CFO Age	The age of the CEO/CFO as reported in the ExecuComp database (Bernile et al., 2017).	ExecuComp
CEO/CFO Tenure	The number of years that the current CEO/CFO has served in that capacity as reported in the ExecuComp database (Beber and Fabbri, 2012).	ExecuComp
CEO Duality	A dummy variable equals one when the CEO is the chairman of the board and zero otherwise (Croci et al., 2017).	BoardEx
COP	Fraction of director after the CEO assumed office (Coles et al., 2014).	LN
HOI	Firm-level hostile takeover index (Cain et al., 2017).	SM
BLC	Total ownership of blockholders who hold more than 5% of a firm's stocks (Edmans, 2014).	s34 files
Innovation	Weighted-frequency count of innovation-related words in the earnings call conference transcripts over three years (Li et al., 2021). LMSY	
Quality	Weighted-frequency count of quality-related words in the earnings call conference transcripts over three years (Li et al., 2021).	LMSY
Integrity	Weighted-frequency count of integrity-related words in the earnings call conference transcripts over three years (Li et al., 2021).	LMSY
Teamwork	Weighted-frequency count of teamwork-related words in the earnings call conference transcripts over three years (Li et al., 2021).	LMSY
Respect	Weighted-frequency count of respect-related words in the earnings call conference transcripts over three years (Li et al., 2021).	LMSY
Total Q	Total Q measured by Peters and Taylor (2017), which is a new Tobin's Q proxy that accounts for intangible capital.	PT
Growth	A firm's growth option, measured by capital expenditures to sales (Bartram et al., 2011).	Compustat

Continued on next page

Table A1 - continued from previous page

Variable	Definition	Source
DTD	The Hoberg and Maksimovic text-based measures of financial constraints are based on firm disclosures in the capitalization and liquidity discussion of firm 10-Ks (Hoberg and Maksimovic, 2015).	GH
CFsd	The average of the standard deviations of operating cash flows over five years for firms with the same two-digit SIC codes (Bartram et al., 2011).	Compustat
OTV	The average daily trading volume of options(Hung et al., 2019).	OptionMetrics
#.Segment	The number of business segment (Dittmar and Shivdasani, 2003).	Compustat
Bus.HHI	Business Herfindahl-Hirschman index (HHI), a HHI based on major corporate business segment sales (Villalonga, 2004).	Compustat
Cash	The ratio of cash and short-term investments scaled by total assets (Haushalter et al., 2007).	Compustat
Net Cash	The natural logarithm of the ratio of cash and short-term investments scaled by net assets, where net assets is total assets minus cash and short-term investments (Bates et al., 2009).	Compustat

Table B. First-stage regression of PSM and matching efficiency of PSM and EB matching

Panel A. First-stage regression of PSM. This panel reports the post-match diagnostic regressions using a probit model. The dependent variable is $Disaster_t$ in column (1) and $Child\ Disaster_t$ in columns (2). The independent variables are the matching variables included in Equation (1). We conduct a Hotelling test (F-statistic) to examine whether the vectors of the means of the matching variables are equal between the treatment and control groups. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\boldsymbol{Disaster_t}$	$\boldsymbol{Child\ Disaster_t}$
Variables	**(1)**	**(2)**
$Foreign\ Income_t$	0.190	-0.183
	[0.18]	[-0.14]
$Sale\ Volatility_t$	0.046	0.101
	[0.16]	[0.29]
NOL_t	-0.087	-0.211
	[-0.30]	[-0.73]
$Networth_t$	-0.096	0.138
	[-0.46]	[0.57]
$Leverage/Equity_t$	0.002	-0.007
	[0.15]	[-0.42]
$R\&D_t$	0.060	-0.116
	[0.05]	[-0.09]
$Tobin's\ Q_t$	-0.001	0.008
	[-0.02]	[0.18]
$Firm\ Size_t$	-0.002	0.006
	[-0.06]	[0.14]
$Firm\ Age_t$	0.004	0.038
	[0.06]	[0.46]
$Institutional\ Ownership_t$	0.038	0.003
	[0.27]	[0.02]
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Hotelling F-stat.	0.203	0.791
Observations	4,356	2,848
Pseudo-R^2	0.003	0.004

Panel B. Matching efficiency of PSM. This panel reports the univariate comparisons of the matching varibles between the treatment and control groups in the propensity score matched samples. In columns (1)–(2) and (4)–(5), we report the mean values of the matching variables. In columns (3) and (6), we report the t-statistics of the univariate comparisons between the treatment and control groups. All variables are defined in Table A of the Appendix. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Disaster **(4,356 Obs.)**			***Child Disaster*** **(2,848 Obs.)**		
Variables	**Treatment (1)**	**Control (2)**	**t-stat. (3)**	**Treatment (4)**	**Control (5)**	**t-stat. (6)**
$Foreign\ Income_t$	0.019	0.019	0.30	0.019	0.019	0.02
$Sale\ Volatility_t$	0.179	0.178	0.16	0.174	0.172	0.32
NOL_t	0.040	0.041	-0.42	0.049	0.062	-2.01
$Networth_t$	0.281	0.287	-0.91	0.280	0.267	1.59
$Leverage/Equity_t$	1.079	1.045	0.47	1.052	1.154	-1.09
$R\&D_t$	0.021	0.021	0.11	0.022	0.024	-0.89
$Tobin's\ Q_t$	1.898	1.900	-0.05	1.887	1.882	0.10
$Firm\ Size_t$	8.089	8.064	0.43	8.172	8.145	0.37
$Firm\ Age_t$	3.208	3.205	0.13	3.256	3.227	1.12
$Institutional\ Ownership_t$	0.514	0.507	0.76	0.509	0.506	0.28

Panel C. Matching efficiency of EB matching. This panel reports the mean, variance, and skewness of the matching variables between the treatment and control groups. All variables are defined in Table A of the Appendix.

Disaster									
	Treatment			**Control (before-weighting)**			**Control (after-weighting)**		
Variables	**Mean (1)**	**Variance (2)**	**Skewness (3)**	**Mean (4)**	**Variance (5)**	**Skewness (6)**	**Mean (7)**	**Variance (8)**	**Skewness (9)**
$Foreign\ Income_t$	0.019	0.002	2.433	0.018	0.001	2.417	0.019	0.002	2.433
$Sale\ Volatility_t$	0.179	0.025	1.647	0.165	0.023	1.835	0.179	0.025	1.647
NOL_t	0.039	0.018	5.234	0.044	0.022	5.164	0.039	0.018	5.234
$Networth_t$	0.282	0.047	-0.489	0.261	0.048	-1.098	0.282	0.047	-0.491
$Leverage/Equity_t$	1.078	6.167	4.108	1.154	6.362	3.018	1.077	6.168	4.107
$R\&D_t$	0.021	0.002	2.686	0.020	0.002	3.027	0.021	0.002	2.686
$Tobin's\ Q_t$	1.904	1.550	2.373	1.803	1.346	2.807	1.904	1.550	2.373
$Firm\ Size_t$	8.089	3.872	0.243	8.227	3.641	0.235	8.089	3.872	0.243
$Firm\ Age_t$	3.206	0.456	-0.695	3.299	0.467	-0.910	3.206	0.456	-0.695
$Institutional\ Ownership_t$	0.515	0.106	-0.490	0.521	0.107	-0.502	0.515	0.106	-0.490

Child Disaster									
	Treatment			**Control (before-weighting)**			**Control (after-weighting)**		
Variables	**Mean (1)**	**Variance (2)**	**Skewness (3)**	**Mean (4)**	**Variance (5)**	**Skewness (6)**	**Mean (7)**	**Variance (8)**	**Skewness (9)**
$Foreign\ Income_t$	0.019	0.002	2.489	0.018	0.001	2.413	0.019	0.002	2.489
$Sale\ Volatility_t$	0.174	0.027	1.869	0.167	0.023	1.771	0.174	0.027	1.868
NOL_t	0.051	0.024	4.447	0.042	0.021	5.335	0.051	0.024	4.447
$Networth_t$	0.281	0.047	-0.449	0.263	0.048	-1.052	0.281	0.047	-0.451
$Leverage/Equity_t$	1.050	5.648	4.335	1.152	6.428	3.091	1.050	5.649	4.335
$R\&D_t$	0.023	0.002	2.527	0.019	0.002	3.028	0.023	0.002	2.527
$Tobin's\ Q_t$	1.885	1.575	2.463	1.815	1.361	2.747	1.885	1.575	2.463
$Firm\ Size_t$	8.166	3.932	0.188	8.203	3.655	0.243	8.166	3.932	0.188
$Firm\ Age_t$	3.254	0.423	-0.679	3.284	0.472	-0.887	3.254	0.423	-0.679
$Institutional\ Ownership_t$	0.508	0.113	-0.404	0.521	0.106	-0.515	0.508	0.113	-0.404

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Table 1. Summary statistics

This table reports the summary statistics of the variables used in our baseline regression. Our main sample includes 10,352 firm–year observations spanning from year 1993 to 2020, with non-missing data for our baseline regressions. For each variable, we provide the following statistics, listed from lef to right: the number of observations, mean, standard deviation, 1st percentile, 25th percentile, median, 75th percentile, and 99th percentile. All dollar-denominated accounting variables are adjusted for inflation to 2020 dollars. We winsorize all continuous variables at the 1% and 99% levels, except for *Firm Age*. All variables are defined in Table A of the Appendix.

Variable	**Obs.**	**Mean**	**S.D.**	**p1**	**p25**	**Median**	**p75**	**p99**
Dependent variables								
IR/FX_t	10,352	0.684	0.465	0.000	0.000	1.000	1.000	1.000
$Hedging_t$	10,352	0.733	0.443	0.000	0.000	1.000	1.000	1.000
Independent variables of interest								
$Disaster_t$	10,352	0.211	0.408	0.000	0.000	0.000	0.000	1.000
$Child\ Disaster_t$	10,352	0.138	0.345	0.000	0.000	0.000	0.000	1.000
Control variables								
$Foreign\ Income_t$	10,352	0.018	0.039	-0.047	0.000	0.000	0.021	0.193
$Sale\ Volatility_t$	10,352	0.168	0.153	0.004	0.065	0.128	0.224	0.810
NOL_t	10,352	0.043	0.145	0.000	0.000	0.000	0.010	1.058
$Networth_t$	10,352	0.267	0.208	-0.367	0.135	0.292	0.408	0.702
$Leverage/Equity_t$	10,352	1.138	2.514	-7.899	0.264	0.672	1.326	17.238
$R\&D_t$	10,352	0.020	0.043	0.000	0.000	0.000	0.018	0.237
$Tobin's\ Q_t$	10,352	1.822	1.167	0.817	1.121	1.406	2.023	7.499
$Firm\ Size_t$	10,352	8.198	1.921	4.209	6.809	8.148	9.480	13.214
$Firm\ Age_t$	10,352	3.282	0.674	1.386	2.833	3.466	3.829	4.205
$Institutional\ Ownership_t$	10,352	0.506	0.320	0.000	0.266	0.598	0.757	0.916

Table 2. Baseline regression: CEO Early-Life Disaster Experience and Corporate Financial Hedging

This table reports logistic regression estimates for the relation between CEO disaster experience and corporate financial hedging behaviour. The dependent variable in Columns (1) to (4) is *IR/FX*, a dummy variable equals to one if a firm uses at least one of IR and FX derivatives, zero otherwise (Campello et al., 2011). The dependent variable in Columns (5) to (8) is *Hedging*, a dummy variable equals to one if a firm uses at least one of IR, FX, and COMMD derivatives, zero otherwise (Hoberg and Moon, 2017). All models include the firm and year fixed effects.All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IR/FX_t				$Hedging_t$			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	0.924***		0.928***		0.861***		0.875***	
	[5.20]		[5.18]		[4.67]		[4.68]	
$Child\ Disaster_t$		0.997***		1.050***		0.783***		0.836***
		[5.10]		[5.30]		[3.99]		[4.20]
$Foreign\ Income_t$			-2.698	-3.134			-2.270	-2.678
			[-1.41]	[-1.63]			[-1.07]	[-1.26]
$Sale\ Volatility_t$			1.222***	1.249***			0.998**	1.022**
			[2.63]	[2.69]			[2.07]	[2.12]
NOL_t			1.484***	1.476***			1.252***	1.257***
			[3.33]	[3.31]			[2.80]	[2.80]
$Networth_t$			-0.718**	-0.747**			-0.813**	-0.824***
			[-2.33]	[-2.42]			[-2.56]	[-2.60]
$Leverage/Equity_t$			0.002	0.002			0.007	0.006
			[0.08]	[0.08]			[0.30]	[0.29]
$R\&D_t$			1.925	1.991			1.089	1.141
			[0.70]	[0.72]			[0.39]	[0.41]
$Tobin's\ Q_t$			0.010	0.003			-0.036	-0.041
			[0.20]	[0.06]			[-0.69]	[-0.79]
$Firm\ Size_t$			0.201**	0.206**			0.022	0.027
			[2.01]	[2.07]			[0.21]	[0.27]
$Firm\ Age_t$			1.841***	1.879***			1.982***	2.007***
			[5.61]	[5.72]			[5.85]	[5.92]
$Institutional\ Ownership_t$			0.879***	0.878***			1.276***	1.270***
			[3.48]	[3.47]			[4.67]	[4.65]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,355	7,355	7,295	7,295	6,898	6,898	6,838	6,838
Pseudo-R^2	0.270	0.270	0.286	0.286	0.276	0.275	0.293	0.293

Table 3. Financial Hedging around Exogenous CEO Turnover Events

This table presents the mean changes in the adoption of financial hedging, measured by *IR/FX* and *Hedging*, for firms that experience exogenous CEO turnover events. The sample of exogenous CEO turnovers is sourced from Gentry et al. (2021). Following the approach used in Bernile et al. (2017), we calculate the change in the firm's financial hedging variable for each turnover event occurring in year t by subtracting the average value of *IR/FX* or *Hedging* over years [t–2,t] from the average value over years [t+1,t+2]. In Panel A, Column (1) reports the mean change around exogenous CEO turnover events where the incoming CEO has a early-life disaster experience *at the age of 5 to 15*, while the outgoing CEO has no such disaster experience (No-Disaster to Disaster turnovers). Column (2) reports the mean change around exogenous CEO turnover events where neither the incoming nor outgoing CEO has any early-life disaster experience at the age of 5 to 15 (Disaster to No-Disaster turnovers). Column (3) reports the difference in the mean change in financial hedging between the two samples of exogenous CEO turnover events, and Column (4) reports the corresponding t-statistic for the null hypothesis of no difference in means. Similarly, in Panel B, we calculate the mean changes around exogenous CEO turnover events based on whether the CEO has any early-life disaster experience *before the age of 5*. All variables are defined in Table A of the Appendix. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Exogenous CEO turnover events classified by *Disaster*				
	No-Disaster to Disaster (N=18)	**Disaster to No-Disaster (N=22)**	**Diff.**	**t-stat.**
	(1)	**(2)**	**(3)**	**(4)**
$\Delta IR/FX_t$	0.102	-0.098	0.200	3.641***
$\Delta Hedging_t$	0.120	-0.106	0.226	4.426***

Panel B. Exogenous CEO turnover events classified by *Child Disaster*				
	No-Child Disaster to Child Disaster(N=15)	**Child Disaster to No-Child Disaster(N=14)**	**Diff.**	**t-stat.**
	(1)	**(2)**	**(3)**	**(4)**
$\Delta IR/FX_t$	0.122	-0.143	0.265	4.170***
$\Delta Hedging_t$	0.144	-0.095	0.240	4.010***

Table 4. DID analyses: CEO Turnovers and Financial Hedging

This table reports the results of difference-in-differences (DID) tests. In columns (1) and (3), the DID sample includes treated firms with *No-Disaster to Disaster* CEO turnovers, and control firms with *No-Disaster to No-Disaster* CEO turnovers. In columns (2) and (4), the DID sample includes treated firms with *No-Child Disaster to Child Disaster* CEO turnovers, and control firms with *No-Child Disaster to No-Child Disaster* CEO turnovers. For both treated and control firms, the sample covers firm–year observations two years before and after the turnover events, including the event years. $Treat\_Disaster_i$ ($Treat\_Child\ Disaster_i$) is an indicator variable that equals to one if firm i has a *No-Disaster to Disaster* (*No-Child Disaster to Child Disaster*) CEO turnover in the event year and zero otherwise. $Post_{i,t}$ is an indicator variable that equals to one if year t is either an event year or after the event and zero otherwise. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IR/FX		*Hedging*	
Variables	**(1)**	**(2)**	**(3)**	**(4)**
$Treat\_Disaster \times Post_t$	2.207*		3.551**	
	[1.86]		[2.16]	
$Treat\_Child\ Disaster \times Post_t$		2.174*		3.631**
		[1.81]		[2.19]
$Post_t$	-0.716	-0.696	0.220	0.242
	[-1.63]	[-1.60]	[0.44]	[0.49]
$Foreign\ Income_t$	10.050	12.347	9.471	13.438
	[0.70]	[0.92]	[0.51]	[0.75]
$Sale\ Volatility_t$	0.572	1.501	-2.395	-1.955
	[0.13]	[0.35]	[-0.51]	[-0.42]
NOL_t	12.970	12.101	-9.438	-9.099
	[0.81]	[0.75]	[-0.28]	[-0.27]
$Networth_t$	6.921*	8.054**	2.104	2.198
	[1.73]	[2.02]	[0.53]	[0.55]
$Leverage/Equity_t$	2.790***	2.763***	2.040***	2.017***
	[4.28]	[4.32]	[3.16]	[3.16]
$R\&D_t$	4.306	4.952	-0.658	1.540
	[0.12]	[0.14]	[-0.02]	[0.04]
$Tobin's\ Q_t$	-0.327	-0.387	-0.142	-0.148
	[-1.22]	[-1.47]	[-0.37]	[-0.39]
$Firm\ Size_t$	0.144	0.195	1.895*	1.897*
	[0.15]	[0.20]	[1.84]	[1.84]
$Firm\ Age_t$	8.607	9.116	17.268***	17.773***
	[1.48]	[1.58]	[2.59]	[2.65]
$Institutional\ Ownership_t$	3.761*	3.069*	3.623	3.298
	[1.82]	[1.69]	[1.64]	[1.59]
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	375	395	360	375
Pseudo-R^2	0.411	0.425	0.496	0.513

Table 5. Propensity Score Matching and Entropy Balancing Matching

This table reports the results our baseline regression estimtated in the PSM sample and the EB matching sample. Columns (1)–(4) present the estimated results in the PSM sample. The matching sample is constructed using a nearest-neighbor PSM with a caliper width of 0.005 and without replacement. The propensity scores are calculated by a probit model, with the dependent variable being *Disaster* or *Child Disaster*. Columns (5)–(8) present the estimated results in the EB matching sample. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	PSM				**EB matching**			
	IR/FX_t		$Hedging_t$		IR/FX_t		$Hedging_t$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	1.373***		1.237***		0.978***		0.984***	
	[4.75]		[4.00]		[4.53]		[4.38]	
$Child\ Disaster_t$		1.328***		0.920**		1.162***		1.012***
		[3.23]		[2.16]		[4.50]		[3.92]
$Foreign\ Income_t$	-0.802	-0.128	0.454	4.576	-1.042	-0.274	0.314	1.234
	[-0.26]	[-0.03]	[0.13]	[0.92]	[-0.47]	[-0.11]	[0.13]	[0.48]
$Sale\ Volatility_t$	2.007***	1.866*	1.433*	1.732	1.813***	2.451***	1.551**	2.325***
	[2.63]	[1.84]	[1.86]	[1.63]	[2.91]	[3.80]	[2.35]	[3.36]
NOL_t	0.723	0.342	0.473	0.431	0.879	0.364	0.452	0.205
	[0.97]	[0.36]	[0.63]	[0.44]	[1.37]	[0.56]	[0.74]	[0.32]
$Networth_t$	-0.470	-0.875	-0.710	-1.203*	-0.387	-0.793	-0.594	-0.955*
	[-0.95]	[-1.24]	[-1.42]	[-1.68]	[-0.93]	[-1.61]	[-1.39]	[-1.86]
$Leverage/Equity_t$	0.014	-0.026	0.020	-0.066	0.012	-0.007	0.011	-0.015
	[0.38]	[-0.57]	[0.53]	[-1.16]	[0.46]	[-0.19]	[0.35]	[-0.34]
$R\&D_t$	1.852	12.177**	1.532	10.395*	2.030	2.033	1.397	0.800
	[0.42]	[2.19]	[0.36]	[1.90]	[0.59]	[0.50]	[0.42]	[0.21]
$Tobin's\ Q_t$	0.080	-0.060	0.035	-0.122	0.038	0.078	-0.021	0.031
	[1.00]	[-0.55]	[0.45]	[-1.08]	[0.56]	[0.96]	[-0.32]	[0.39]
$Firm\ Size_t$	-0.120	-0.244	-0.254	-0.499**	-0.019	-0.138	-0.201	-0.333**
	[-0.74]	[-1.13]	[-1.56]	[-2.22]	[-0.13]	[-0.87]	[-1.40]	[-2.07]
$Firm\ Age_t$	2.294***	2.843***	2.434***	2.670***	2.702***	2.724***	2.787***	2.804***
	[4.28]	[3.78]	[4.40]	[3.44]	[4.92]	[4.67]	[4.93]	[4.72]
$Institutional\ Ownership_t$	0.015	-1.342**	0.425	-0.855	-0.009	-0.221	0.440	0.198
	[0.04]	[-2.45]	[0.94]	[-1.49]	[-0.03]	[-0.59]	[1.22]	[0.48]
Constant					0.122	-0.244	0.087	-0.118
					[0.08]	[-0.16]	[0.06]	[-0.08]
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,515	1,485	2,344	1,353	6,881	6,881	6,422	6,422
Pseudo-R^2	0.292	0.333	0.292	0.336	2.459	2.441	2.429	2.479

Table 6. Additional Controls for CEO and CFO Characteristics

This table presents the results of our baseline regression with additional controls for CEO and CFO Characteristics. CEO characteristics include CEO vega, delta, female indicator, age, tenure, and duality. CFO characteristics variables include CFO vega, delta, female indicator, age, and tenure. The dependent variable in columns (1)–(4) is *IR/FX* and the dependent variable in columns (5)–(8) is *Hedging*. For brevity, we omit the estimated coefficients on the control variables that are the same as those reported in Table 2. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IR/FX_t				$Hedging_t$			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	0.885***		1.942***		0.934***		2.217***	
	[4.66]		[4.26]		[4.70]		[4.74]	
$Child\ Disaster_t$		1.011***		2.135***		0.920***		2.241***
		[4.76]		[4.26]		[4.28]		[4.36]
$CEO\ Vega_t$	-3.600***	-3.680***	-1.054	-0.936	-3.674***	-3.743***	0.767	1.073
	[-2.94]	[-3.01]	[-0.39]	[-0.35]	[-2.91]	[-2.97]	[0.28]	[0.39]
$CEO\ Delta_t$	0.041	0.045	-0.006	-0.015	0.053	0.056	-0.026	-0.040
	[0.96]	[1.07]	[-0.06]	[-0.15]	[1.21]	[1.30]	[-0.25]	[-0.38]
$Female\ CEO_t$	-0.041	-0.000	-2.972*	-2.982**	0.376	0.404	-2.449	-2.415
	[-0.08]	[-0.00]	[-1.93]	[-1.97]	[0.69]	[0.74]	[-1.32]	[-1.34]
$CEO\ Age_t$	0.004	0.006	-0.052*	-0.036	0.010	0.011	-0.031	-0.015
	[0.31]	[0.45]	[-1.76]	[-1.19]	[0.70]	[0.82]	[-0.99]	[-0.47]
$CEO\ Tenure_t$	0.032***	0.032**	0.042*	0.022	0.018	0.017	0.021	0.002
	[2.58]	[2.52]	[1.73]	[0.91]	[1.37]	[1.34]	[0.82]	[0.07]
$CEO\ Duality_t$	-0.277**	-0.268**	-0.639***	-0.608***	-0.239**	-0.227*	-0.437**	-0.393*
	[-2.37]	[-2.30]	[-3.04]	[-2.90]	[-1.97]	[-1.87]	[-1.99]	[-1.82]
$CFO\ Vega_t$			1.998	2.129			1.414	1.708
			[0.81]	[0.86]			[0.45]	[0.55]
$CFO\ Delta_t$			-1.774*	-1.933**			-2.026	-2.346
			[-1.93]	[-2.10]			[-1.16]	[-1.33]
$Female\ CFO_t$			-0.627	-0.653			-0.757*	-0.869**
			[-1.45]	[-1.51]			[-1.72]	[-1.98]
$CFO\ Age_t$			0.016	0.013			0.026	0.022
			[0.93]	[0.76]			[1.42]	[1.17]
$CFO\ Tenure_t$			-0.053*	-0.043			-0.072**	-0.058*
			[-1.65]	[-1.34]			[-2.15]	[-1.74]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,684	6,684	2,227	2,227	6,234	6,234	2,093	2,093
Pseudo-R^2	0.304	0.304	0.339	0.339	0.310	0.310	0.346	0.344

Table 7. Additional Controls for Corporate Governance

This table presents the results of our baseline regression with additional controls for corporate governance. The first corporate governance proxy is *COP*, defined as the fraction of co-opted directors (Coles et al., 2014). The second corporate governance proxy is *HOI*, defined as the hostile takeover index (Cain et al., 2017). The third corporate governance proxy is *BLC*, defined as the total ownership of blockholders who hold more than 5% of a firm's stocks (Edmans, 2014). The dependent variable in columns (1)–(6) is IR/FX and the dependent variable in columns (6)–(12) is *Hedging*. For brevity, we omit the estimated coefficients on the control variables that are the same as those reported in Table 2. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IR/FX_t						$Hedging_t$					
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$Disaster_t$	0.530**		0.915***		0.914***		0.429*		0.777***		0.852***	
	[2.20]		[4.01]		[5.10]		[1.68]		[3.35]		[4.56]	
$Child\ Disaster_t$		0.494*		0.860***		1.039***		0.359		0.623**		0.819***
		[1.88]		[3.48]		[5.25]		[1.31]		[2.52]		[4.12]
COP_t	0.812**	0.855**					0.974**	1.008**				
	[2.11]	[2.23]					[2.36]	[2.45]				
HOI_t			0.410	0.299					1.983	1.847		
			[0.24]	[0.18]					[1.12]	[1.04]		
$Blockholder_t$					2.550***	2.569***					2.760***	2.782***
					[4.70]	[4.73]					[4.80]	[4.85]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,295	4,295	4,240	4,240	7,295	7,295	4,007	4,007	4,014	4,014	6,838	6,838
Pseudo-R^2	0.257	0.257	0.179	0.177	0.290	0.290	0.264	0.264	0.164	0.163	0.298	0.297

Table 8. Additional Controls for Corporate Culture

This table presents the results of our baseline regression with additional controls for corporate governance. Corporate culture variables include *Innovation*, *Quality*, *Integrity*, *Teamwork*, and *Respect*, developed by Li et al. (2021). The dependent variable in columns (1)–(2) is *IR/FX* and the dependent variable in columns (3)–(4) is *Hedging*. For brevity, we omit the estimated coefficients on the control variables that are the same as those reported in Table 2. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IR/FX_t		$Hedging_t$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**
$Disaster_t$	1.525***		2.229***	
	[3.06]		[3.78]	
$Child\ Disaster_t$		1.679***		2.043***
		[2.96]		[3.14]
$Innovation_t$	0.241*	0.217*	0.320**	0.296**
	[1.86]	[1.69]	[2.36]	[2.20]
$Quality_t$	-0.233	-0.216	-0.340*	-0.310*
	[-1.34]	[-1.25]	[-1.81]	[-1.66]
$Integrity_t$	-0.064	-0.072	-0.125	-0.129
	[-0.32]	[-0.37]	[-0.56]	[-0.58]
$Teamwork_t$	-0.399*	-0.397*	-0.471**	-0.470**
	[-1.85]	[-1.84]	[-2.03]	[-2.03]
$Respect_t$	0.050	0.041	0.034	0.025
	[0.36]	[0.30]	[0.25]	[0.18]
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,528	2,528	2,355	2,355
Pseudo-R^2	0.332	0.332	0.362	0.358

Table 9. CEO Early-life Disaster Experience, Financial Hedging and Firm Value

This table reports the results of OLS regressions examining the impact of CEOs' disaster experience and corporate financial hedging on firm value. In columns (1)-(4), the dependent variable is *Total Q* (Peters and Taylor, 2017). In columns (5)–(8), the dependent variable is *Growth*, representing a firm's growth option measured by capital expenditures to sales (Géczy et al., 1997; Bartram et al., 2011). The variables of interest are the interaction terms between CEO disaster experience proxies and financial hedging proxies. For brevity, we omit the estimated coefficients on the control variables that are the same as those reported in Table 2, apart from dropping *Tobin's Q*. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Total Q_t				***$Growth_t$***			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t \times IR/FX_t$	-0.277*				-0.015***			
	[-1.95]				[-2.66]			
$Disaster_t \times Hedging_t$		-0.269*				-0.009*		
		[-1.72]				[-1.65]		
$Child\ Disaster_t \times IR/FX_t$			-0.401**				-0.017**	
			[-2.31]				[-2.53]	
$Child\ Disaster_t \times Hedging_t$				-0.384**				-0.008
				[-2.04]				[-1.20]
IR/FX_t	0.103		0.100		0.007**		0.007**	
	[1.45]		[1.43]		[2.31]		[2.21]	
$Hedging_t$		0.054		0.050		0.004		0.003
		[0.63]		[0.60]		[1.11]		[0.91]
$Disaster_t$	0.176	0.184			0.013*	0.009		
	[0.83]	[0.81]			[1.73]	[1.24]		
$Child\ Disaster_t$			0.260	0.260			0.017**	0.011
			[0.99]	[0.94]			[2.16]	[1.40]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,682	7,682	7,682	7,682	8,650	8,650	8,650	8,650
Adjusted-R^2	0.195	0.195	0.196	0.195	0.037	0.036	0.037	0.036

Table 10. Cross-sectional Analyses

This table presents the results of our cross-sectional analyses. We divide our sample into two sub-samples based on the annual median of six variables in Panels A–F. The first three variables are proxies for corporate governance: *COP* defined as the fraction of co-opted board directors (Coles et al., 2014), *HOI* defined as the hostile takeover index (Cain et al., 2017), and *BLC* defined as the total ownership of blockholders (Edmans, 2014). The fourth variable is a proxy for financial constraints: *DTD* defined as text-based delay debt (Hoberg and Maksimovic, 2015). The last two variables are proxies for firm risk: *CFsd* defined as the average of the standard deviations of operating cash flows over five years for firms with the same two-digit SIC codes (Bartram et al., 2011) and *OTV* defined as the average daily trading volume of options (Hung et al., 2019). In each sub-sample, we estimate our baseline regression Equation (1). The p-value of the Chi2-statistic corresponds to a test of equality of the estimated coefficients on disaster experience proxies between two sub-samples. For brevity, we omit the estimated coefficients on the control variables. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. z-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Corporate governance: Co-opted director ratio (**COP*****).***

	IR/FX_t				$Hedging_t$			
Variables	**High (1)**	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**	**High (7)**	**Low (8)**
$Disaster_t$	2.586***	0.616*			1.925***	0.463		
	[3.48]	[1.65]			[2.78]	[1.14]		
$Child\ Disaster_t$			2.958***	0.753*			2.085**	0.478
			[3.27]	[1.93]			[2.47]	[1.16]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,629	1,525	1,629	1,525	1,488	1,385	1,488	1,385
Pseudo-R^2	0.298	0.297	0.297	0.298	0.295	0.317	0.294	0.317
p-value (Chi2-statistic)	0.049**		0.075*		0.093*		0.067*	

Panel B. Corporate governance: Hostile takeover index (**HOI*****).***

	IR/FX_t				$Hedging_t$			
Variables	**High (1)**	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**	**High (7)**	**Low (8)**
$Disaster_t$	0.281	1.735***			0.235	1.722***		
	[0.84]	[3.40]			[0.69]	[3.36]		
$Child\ Disaster_t$			0.094	1.595***			-0.014	1.383***
			[0.26]	[3.11]			[-0.04]	[2.79]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,826	1,627	1,826	1,627	1,736	1,521	1,736	1,521
Pseudo-R^2	0.223	0.190	0.223	0.189	0.206	0.175	0.206	0.172
p-value (Chi2-statistic)	0.087*		0.120		0.089*		0.138	

Panel C. Corporate governance: Blockholder ownership (*BLC*).

	IR/FX$_t$				***Hedging***$_t$			
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Disaster$_t$	-0.174	1.532***			-0.124	1.419***		
	[-0.52]	[4.68]			[-0.36]	[4.23]		
Child Disaster$_t$			-0.219	1.604***			-0.273	1.420***
			[-0.58]	[4.72]			[-0.70]	[4.15]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,525	2,234	2,525	2,234	2,356	2,104	2,356	2,104
Pseudo-R^2	0.295	0.311	0.295	0.312	0.313	0.308	0.313	0.308
p-value (Chi2-statistic)	0.029**		0.038**		0.050**		0.042**	

Panel D. Financial constraints: Text-based delay debt (*DTD*).

	IR/FX$_t$				***Hedging***$_t$			
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Disaster$_t$	-0.382	1.946***			-0.322	2.132***		
	[-0.67]	[2.97]			[-0.56]	[2.82]		
Child Disaster$_t$			-0.864	1.817***			-1.056	2.097***
			[-1.33]	[2.62]			[-1.64]	[2.73]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	939	983	939	983	780	830	780	830
Pseudo-R^2	0.219	0.282	0.220	0.278	0.209	0.270	0.213	0.269
p-value (Chi2-statistic)	0.091*		0.087*		0.133		0.096*	

Panel E. Firm risk: Cash flow volatility (*CFsd*).

	IR/FX$_t$				***Hedging***$_t$			
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Disaster$_t$	1.366***	0.362			1.511***	0.167		
	[4.06]	[1.23]			[4.18]	[0.53]		
Child Disaster$_t$			1.594***	0.356			1.269***	0.074
			[3.96]	[1.11]			[3.20]	[0.22]

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Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,524	2,900	2,524	2,900	2,350	2,702	2,350	2,702
Pseudo-R^2	0.319	0.307	0.320	0.329	0.319	0.307	0.315	0.329
p-value (Chi2-statistic)	0.161		0.161		0.099*		0.196	

Panel F. Firm risk: Option trading volume (*OTV*).

	IR/FX$_t$				***Hedging***$_t$			
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Disaster$_t$	1.516***	-0.217			1.646***	-0.089		
	[4.77]	[-0.54]			[4.69]	[-0.21]		
Child Disaster$_t$			1.658***	-0.180			1.682***	-0.387
			[4.70]	[-0.40]			[4.55]	[-0.83]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,646	2,380	2,646	2,380	2,473	2,224	2,473	2,224
Pseudo-R^2	0.321	0.277	0.321	0.277	0.344	0.283	0.343	0.284
p-value (Chi2-statistic)	0.046**		0.077*		0.075*		0.049**	

Table 11. CEO Early-life Disaster Experience and Operational Hedging

This table reports OLS regression estimates for examining the relationship between CEO disaster experience and corporate operational hedging behaviour. In Columns (1) and (2), the dependent variable is the number of business segments (*#.Segment*), which reflects the extent of diversification in the firm's business operations. In Columns (3) and (4), the dependent variable is the business Herfindahl-Hirschman index (*Bus.HHI*), a measure based on major corporate business segment sales (Villalonga, 2004). The *Bus.HHI* captures the concentration of the firm's business operations, with higher values indicating a more focused business portfolio. In Columns (5) and (6), the dependent variable is cash holdings (*Cash*), defined as the ratio of cash and short-term investments scaled by total assets (Haushalter et al., 2007). In Columns (7) and (8), the dependent variable is net cash holdings (*Net Cash*), defined as the natural logarithm of the ratio of cash and short-term investments scaled by net assets, where net assets is total assets minus cash and short-term investments (Bates et al., 2009). These two variable represents the level of cash reserves a firm holds as a risk management strategy to buffer against adverse events. The control variables are the same as those reported in Table 2. All models include the firm and year fixed effects. All variables are defined in Table A of the Appendix. t-statistics based on standard errors clustered at the firm level are reported in brackets. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\#.Segment_t$		$Bus.HHI_t$		$Cash_t$		$Net\ Cash_t$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	0.073		0.009		0.002		0.096	
	[0.63]		[0.48]		[0.20]		[0.90]	
$Child\ Disaster_t$		0.096		0.011		-0.000		0.112
		[0.71]		[0.54]		[-0.04]		[1.20]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,483	8,483	8,483	8,483	10,352	10,352	10,319	10,319
Adjusted-R^2	0.215	0.215	0.119	0.119	0.285	0.285	0.183	0.183