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CEOs' early-life disaster experiences and corporate hedging activities

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Abstract

We study how traumatic experiences in childhood influence CEOs' risk preferences and corporate financial hedging decisions. Based on a sample of U.S. public firms 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 increase the gap between CEOs' and shareholders' risk preferences, potentially leading to conflicts of interest. Furthermore, our cross-sectional analysis shows that the positive relation between disaster experiences and financial hedging is more pronounced in firms with weaker corporate governance, fewer financial constraints, and higher firm-specific risk. Our findings suggest 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.

"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 posits that firms use financial hedging to enhance value by mitigating financial constraints (Stulz and Johnson, 1985; Purnanandam, 2008), improving credit access (Froot et al., 1993; Leland, 1998), and reducing information asymmetry (DeMarzo and Duffie, 1995; Dadalt et al., 2002). This classical framework assumes that managers are risk-neutral agents who hedge solely to maximize firm value. Empirical evidence supports this value-enhancing view (e.g., Allayannis and Weston, 2001), yet other studies argue that observed hedge positions are often too small to materially reduce firm risk or alter firm value (e.g., Guay and Kothari, 2003). Such mixed findings suggest that firm-level motives alone cannot fully explain hedging decisions and that managerial characteristics likely play an important role.

Agency-based perspectives challenge managerial risk-neutrality by noting that managers' wealth and careers are tied to firm outcomes, rendering them more risk-averse than shareholders (Stulz and Johnson, 1985; Smith and Stulz, 1985; Stulz, 1988). Under this view, hedging can reflect both firm-level incentives and personal preferences shaped by managerial traits. Prior research documents that compensation structures (Knopf et al., 2002; Bakke et al., 2016), age (Croci et al., 2017), and tenure (Bodnar et al., 2019) influence hedging behavior. Yet we know relatively little about whether formative life experiences–particularly those shaping long-term attitudes toward risk–affect corporate risk management policies.

Psychology and behavioral economics show that early-life experiences strongly influence individuals' perceptions of risk and control (e.g., Lichtenstein et al., 1978; Nisbett and Ross, 1980; Yechiam et al., 2005). Traumatic childhood events can leave lasting cognitive

and emotional imprints that shape behavior well into adulthood (e.g., Parry and Chesler, 2005; Cryder et al., 2006; Duran, 2013). Building on this literature, we study whether CEOs' exposure to major natural disasters during childhood or adolescence influences their firms' use of financial derivatives.

Behavioral theory offers competing predictions. The "hot-stove" effect suggests that individuals who have experienced severe losses become more cautious, avoiding risk to prevent similar negative outcomes (March, 1996; Denrell and March, 2001; Denrell, 2007). Applied to CEOs, disaster exposure may heighten sensitivity to downside risk and strengthen preferences for stability, leading to greater use of hedging to protect cash flows. Traumatic experiences may also alter neurological threat-processing mechanisms (Vogel and Bolino, 2020), producing persistent risk aversion and stronger demand for predictable outcomes. Accordingly, the "hot-stove" effect implies that CEOs with early-life disaster experiences tend to engage more actively in financial hedging to reduce volatility and safeguard cash flows.

Conversely, adversity can increase resilience, self-efficacy, and perceived control, fostering risk tolerance (e.g., Taylor and Lobel, 1989; Aldwin, 2009). Surviving a disaster may cultivate confidence in navigating uncertainty, encouraging risk-taking (e.g., Ben-Zur and Zeidner, 2009; Eckel et al., 2009; Hanaoka et al., 2018). Within an agency framework, such confidence may resemble managerial overconfidence, reducing hedging demand. Given these competing forces, whether early-life disaster exposure increases or decreases hedging is ultimately an empirical question.

Our study combines behavioral and agency perspectives to assess whether CEOs' formative experiences shape their firms' financial hedging policies. We focus on hedging rather than broader risk-taking outcomes, such as leverage or investment, because hedging offers a more direct measure of managerial preferences toward externally driven, quantifiable risks. Whereas corporate financing and investment choices may be influenced by strategic considerations, growth opportunities, or capital market conditions, hedging decisions are specifically designed to manage exposure to interest rate, currency, and commodity price

risks. As such, they provide a cleaner lens into CEOs' attitudes toward uncertainty and their desire for stability versus risk exposure.

To empirically test our predictions, we identify CEOs covered by the ExecuComp database between 1993 and 2020 and collect detailed information on their names, birth dates, and birthplaces. We then construct a comprehensive database of U.S. natural disaster events at the county level, including earthquakes, hurricanes, tornadoes, floods, and wildfires. By merging these datasets, we determine whether each CEO experienced a disaster during key developmental periods, defined as ages 1–5 or 5–15, which are commonly regarded as formative years (Nelson, 1993; Bernile et al., 2017; O'Sullivan et al., 2021). Our final sample includes 1,823 U.S.-born CEOs with identifiable early-life disaster exposure.

Next, we employ textual analysis of firms' annual reports from the EDGAR database to measure financial hedging activity. Using a Python web crawler, we extract keywords related to financial derivatives following prior studies (e.g., Hoberg and Moon, 2017; Alexandridis et al., 2021; Sun et al., 2022). We construct two binary indicators of financial hedging: (1) *IR/FX*, which equals one if a firm uses interest rate or foreign exchange derivatives, and (2) *Hedging*, which equals one if a firm uses at least one of interest rate, foreign exchange, or commodity derivatives.

Our baseline results indicate that firms led by CEOs who experienced natural disasters between ages 5 and 15 are 1.39 to 1.72 times more likely to engage in financial hedging. CEOs exposed before age 5 also show a roughly 1.5 times higher likelihood. These findings are consistent with the "hot stove" effect, suggesting that early-life adversity fosters greater caution and more conservative financial policies. The results are robust to various identification strategies, including difference-in-differences (DID) analyses exploiting exogenous CEO turnovers, propensity score matching (PSM), and entropy balancing (EB). We also control for CFO traits, governance structures, and corporate culture to mitigate omitted variable concerns.

Importantly, our supplementary analyses reveal that disaster-experienced CEOs' hedging decisions are associated with lower firm value, indicating potential costs of excessive

conservatism. These findings align with the agency view that managerial risk aversion can lead to value-destroying financial hedging (Tufano, 1996). Cross-sectional tests further show that the positive relation between early-life disaster exposure and hedging is stronger in firms with weaker governance, lower financial constraints, and higher firm-specific risk, contexts in which CEOs have greater discretion to imprint personal preferences on policy decisions.

Our study contributes to the literature in several ways. First, we extend research on managerial traits and corporate financial hedging by introducing early-life experiences as a fundamental and enduring determinant of risk management behavior. While prior studies emphasize incentive-based factors such as compensation, risk exposure, or governance structures (Tufano, 1996; Schrand and Unal, 1998; Knopf et al., 2002; Rogers, 2002), we show that formative traumatic events, specifically childhood exposure to natural disasters, shape CEOs' long-term attitudes toward financial risk. This finding highlights the role of stable psychological imprints, beyond incentives or market frictions, in explaining cross-firm heterogeneity in hedging decisions.

Second, we contribute to the growing literature on formative experiences and managerial behavior (e.g., Malmendier and Nagel, 2011; Bernile et al., 2017; O'Sullivan et al., 2021) by focusing on natural disasters, which are acute, exogenous shocks that evoke stronger psychological responses than gradual environmental or economic exposures. Our evidence shows that such experiences not only affect broad corporate risk-taking but also influence specific financial policies, such as the use of derivatives to hedge measurable risks.

Finally, we offer new insights into the value implications of behavioral conservatism. While classical theory predicts that hedging enhances value (Allayannis and Weston, 2001), our results suggest that experience-driven risk aversion can lead to suboptimal hedging and lower firm value, consistent with agency-based distortions (Tufano, 1996). Collectively, our findings suggest that CEOs' early-life disaster experiences leave enduring imprints on corporate risk management. By integrating behavioral psychology with agency models of hedging, this study advances our understanding of how personal history influences corpo-

rate policy and under what conditions such behavioral imprints create or destroy value.

2. Empirical predictions

Corporate hedging decisions reflect an interplay between firm fundamentals and managerial preferences. Traditional theories emphasize value-enhancing motives, arguing that hedging reduces expected financial distress costs (Smith and Stulz, 1985), mitigates underinvestment problems by stabilizing internal funds (Froot et al., 1993), and alleviates information asymmetry between insiders and external financiers (DeMarzo and Duffie, 1995). However, empirical evidence remains mixed. While some studies document substantial hedging premiums (e.g., Allayannis and Weston, 2001), others report more modest valuation effects (e.g., Guay and Kothari, 2003). Complementing these value-based arguments, agency-based theories highlight that managers are typically more risk-averse than diversified shareholders, implying that hedging may partly reflect personal preferences rather than strict value maximization (Tufano, 1996).

We examine whether CEOs' early-life disaster experiences shape their risk preferences and corporate hedging choices. Psychological research suggests that traumatic childhood events create persistent imprints on individuals' risk perception and economic behavior (Lichtenstein et al., 1978; Parry and Chesler, 2005; Cryder et al., 2006). Yet the directional effect is theoretically ambiguous. Behavioral psychology offers two competing perspectives on how severe adverse experiences influence risk attitudes, leading to opposing predictions regarding corporate hedging behavior.

2.1. The risk-aversion perspective

Disaster experiences increase hedging by inducing long-lasting risk aversion. Neuroscience research shows that childhood trauma produces persistent changes in brain regions responsible for threat detection, such as heightened amygdala activation and elevated cortisol levels (Boling et al., 2016; Vogel and Bolino, 2020). These physiological imprints

manifest as heightened vigilance, sustained anxiety, and strong preferences for stability (Malmendier and Nagel, 2011; Bucciol and Zarri, 2013). For CEOs, such trauma-induced traits may translate into greater sensitivity to firm-level risk and a preference for more comprehensive hedging programs.

Cognitive mechanisms may reinforce this prediction. The availability heuristic suggests that individuals vividly recall extreme events, leading them to overweight the probability and severity of adverse outcomes (Tversky and Kahneman, 1973; Lichtenstein et al., 1978). This experiential bias may prompt CEOs to hedge beyond what objective risk exposures warrant. The "hot-stove" effect provides additional support that individuals who experience severe negative outcomes develop generalized avoidance behaviors (March, 1996; Denrell and March, 2001). CEOs exposed to disasters, therefore, may systematically adopt conservative financial policies, even when some risk exposure is value-enhancing.

Empirical evidence is consistent with this view. Malmendier and Nagel (2011) show that Great Depression survivors maintain conservative financial behavior across the life cycle. Bernile et al. (2017) document that disaster-exposed CEOs take fewer corporate risks, including lower leverage and fewer acquisitions. Dittmar and Duchin (2016) find that managers who witnessed financial distress adopt more conservative policies in subsequent roles. Drawing on these mechanisms and findings, we expect firms led by disaster-experienced CEOs to be more likely to engage in financial hedging.

2.2. The risk-tolerance perspective

A contrasting view holds that disaster experiences decrease hedging by fostering resilience and confidence. Post-traumatic growth theory suggests that surviving trauma can enhance self-efficacy and reduce fear of future risks (Tedeschi and Calhoun, 2004; Aldwin, 2009). CEOs who endured disasters may perceive corporate risks as manageable relative to early-life adversity, reducing the appeal of hedging. "Downward comparison" effects similarly lead survivors to view later threats as minor (Taylor and Lobel, 1989). Disaster experiences can also shift risk perception and tolerance. Survivors often view normal

uncertainty as trivial compared to past extremes (Ben-Zur and Zeidner, 2009), making costly hedging seem unnecessary. Additionally, individuals who experience disasters and still rise to CEO positions may be positively selected for risk-taking tendencies, reinforcing lower hedging demand.

This perspective also received supports from empirical evidence. Eckel et al. (2009) find that Hurricane Katrina evacuees exhibited increased risk-seeking behavior in laboratory settings. Page et al. (2014) show that individuals facing large disaster losses subsequently take more financial risks. Hanaoka et al. (2018) document persistent increases in risk tolerance among earthquake survivors. Taken together, these mechanisms suggest that firms led by disaster-experienced CEOs may be less likely to engage in financial hedging.

2.3. Value implication

The two perspectives provide contrasting predictions. Disaster exposure may either increase hedging due to heightened risk aversion or decrease hedging due to resilience and recalibrated risk tolerance. Which effect dominates likely varies with disaster severity, timing, and individual heterogeneity, making this an empirical question.

Despite their differences, both perspectives imply value consequences when CEO preferences deviate from shareholder-optimal hedging. Over-hedging wastes resources, whereas under-hedging increases distress risk. Both outcomes reflect agency frictions. Thus, we expect disaster-induced hedging behavior to be negatively associated with firm value.

Our view contrasts with the traditional value-enhancing argument that hedging increases firm value by reducing financial frictions (e.g., Stulz, 1984; Allayannis and Weston, 2001) and with the limited-effects view that hedging has modest valuation impact due to small position sizes (e.g., Guay and Kothari, 2003). Instead, we argue that hedging may reflect CEOs' formative experiences and personal risk preferences. When these preferences diverge from shareholder interests, hedging can destroy value. We test this prediction by examining whether disaster-driven hedging reduces firm value.

3.   Sample, variables, and research design

3.1.   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.[1] 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. 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 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 9,430 firm–year observations with 1,191 unique firms.

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[1]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.

3.2. Measures for CEOs' early-life disaster experiences

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 1,596 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 3.1. 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 CEOs' early-life disaster experiences. 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.

3.3.   Financial hedging measures

To collect data on corporate financial hedging, we apply textual analysis to firms' annual reports, searching for keywords related to financial derivatives use. This approach 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. Following previous studies (e.g., Hoberg and Moon, 2017; Alexandridis et al., 2021; Sun et al., 2022), we use three lists of keywords and identify the use of IR, FX, and COMMD derivatives. Details of the keywords and identification process are provided in Appendix B.

We employ two indicator variables, *IR/FX* and *Hedging*, to measure firms' financial hedging activities (e.g., Allayannis and Weston, 2001; Graham and Rogers, 2002; Bartram et al., 2011; Manconi et al., 2018; Sun et al., 2022). *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.[2]

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. The standard replaced mandatory notional value reporting with fair value reporting, and hedges with positive notional values may have fair values near zero when the underlying asset's price matches the strike price.[3] Consequently, recent studies commonly use categorical hedging variables to proxy for derivatives usage.

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[2]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.

[3]While some firms voluntarily disclose the notional values of their hedging positions after 2000, the inconsistent nature of this information can result in sample selection bias and limit the sample size.

3.4.   Research design

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

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

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 tax function convexity, financial distress, investment spending, investment opportunities, risk exposure, economies of scale, business cycle, and information asymmetry. Specifically, we include 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, *Foreign Income* and *Sale Volatility* as control variables to account for corporate risk exposure, *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.

Previous study has highlighted the influence of CEO's equity-based incentives and personal attributes on corporate risk-taking activities (Coles et al., 2006; Gormley et al., 2013; Barsky et al., 1997; Huang and Kisgen, 2013).[4] We control for CEO characterisctics

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[4]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 a 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). Recent research posits that female managers tend to exhibit risk-averse tendencies and may engage in more hedging activities (Barsky et al., 1997; Huang and Kisgen, 2013). However, Schubert

in our baseline regression, including CEO vega, delta, gender, age and tenure. 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, *Firm Age*, *Female CEO*, *CEO Age*, and *CEO Tenure*. For detailed variable definitions, please refer to the Table A1 in Appendix A.

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 CEOs' 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.

4.   Main results

4.1.   Descriptive statistics

Table 1 presents the summary statistics of the variables used in our main empirical analysis. Our main sample consists of 9,430 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 0.691, with a standard deviation of 0.462, indicating that, on average, approximately 69.1% of firms in our sample utilize IR or FX derivatives. Similarly, for *Hedging*, the mean value is 0.740, with a standard deviation of 0.439, suggesting that approximately 74% 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 0.215, implying that, on average, about 21.5% of sample firms are managed by CEOs who experience at least one natural disaster between

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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.

the ages of 5 and 15 years. *Child Disaster* has a mean value of 0.142, indicating that, on average, 14.2% of CEOs in our sample have experienced a natural disaster before the age of 5 years.

Regarding the control variables, the sample firms report an average net operating loss of 4.4% and an average net worth of 26.9%. Research and development (R&D) expenses account for 20% of total assets, while the mean Tobin's Q is 1.82. On average, 1.8% of firm sales are derived from foreign income, and the sales volatility is 16.8%. The average firm size, measured by the natural logarithm of total assets, is 8.24, whereas the average firm age, also measured using the natural logarithm, is 3.29. Institutional investors hold, on average, 52.6% of firm stock ownership. These summary statistics are consistent with findings reported in previous studies (e.g., Disatnik et al., 2014; Hoberg and Moon, 2017). The mean values of CEOs' vega and delta are 0.03 and 0.233, respectively. Female CEOs account for 2.5% of the sample, while the average CEO age is 57 years, and the average tenure is 9.8 years.

4.2.   Baseline regression results

To investigate the relation between CEOs' 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 variable 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 and CEO characteristics, and the results remain consistent.[5]

Specifically, in column (3), the estimated coefficient on *Disaster* is 0.87, indicating

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[5]We also manually collected data on CFOs' early-life disaster experiences for firms in our sample from 1992 to 2020 and conducted baseline analyses. Our empirical results reveal no significant relationship between CFOs' early-life disaster experiences and corporate financial hedging decisions. This result reinforces prior survey and empirical evidence that hedging policy is primarily driven by CEOs rather than CFOs (Graham and Harvey, 2001; Rogers, 2002; Campello et al., 2011; Bodnar et al., 2019).

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 1.39 ($= exp(0.87) - 1$) times higher odds of utilizing IR or FX derivatives. Similarly, in column (4), the estimated coefficient on *Child Disaster* is 1.001, implying that firms managed by CEOs who experience at least one natural disaster before the age of 5 years exhibit 1.72 ($= exp(1.001) - 1$) times higher odds of using IR or FX derivatives. The coefficient for *Hedging* in column (7) is 0.921, suggesting that firms managed by CEOs who experience at least one natural disaster between the ages of 5 and 15 years have 1.51 (=exp(0.921)-1) times higher odds of employing IR, FX, or COMMD derivatives. In column (8), the coefficient for *Hedging* is 0.915, indicating that firms managed by CEOs who experience at least one natural disaster before the age of 5 years have 1.50 (=exp(0.915)-1) times higher odds of using IR, FX, or COMMD derivatives.[6] 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 presents evidence that financial hedging decisions are positively associated with sales volatility, net operating loss, firm size, firm age, and institutional ownership. In contrast, firms with greater net worth are less likely to engage in the use of financial derivatives. Additionally, financial hedging decisions are negatively related to CEOs' risk-taking propensity and positively related to CEO tenure. These findings are consistent with the results reported by Knopf et al. (2002) and Croci et al. (2017).[7]

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

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[6]The numbers of observation in Table 2 are less than 9,430 as reported in Table 1. This is because some independent variables and fixed effects perfectly predict the binary outcome.

[7]We also examine the potential non-monotonic relation between the intensity of CEOs' early-life disaster exposure and corporate hedging activities, as suggested by Bernile et al. (2017). Our findings indicate a consistent positive relation between the intensity of CEOs' early-life disaster exposure and their likelihood of adopting financial derivatives. Furthermore, we do not observe a significant relation between the fatality of disasters and the probability of CEOs using financial derivatives. The regression results supporting these conclusions are presented in Table A2 of Appendix A.

to adopt a more conservative approach to corporate activities. Moreover, our findings are consistent with Dittmar and Duchin (2016), who find 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. Our findings highlight the substantial role of CEOs' early-life experiences in shaping corporate risk management policies.[8]

4.3.   Identification tests

In this section, we conduct a series of identification tests to address potential endogeneity concerns regarding the relation between CEOs' early-life disaster experiences and corporate financial hedging. Specifically, we employ a stacked difference-in-differences (DID) approach, along with both t-tests and regression analysis, to tackle issues of reverse causality and unobservable factors influencing firms' decisions on derivative usage. Additionally, we apply propensity-score matching (PSM) and entropy balancing (EB) techniques to mitigate self-selection bias. Finally, we control for various other factors, including managerial characteristics, corporate governance, and corporate culture.

4.3.1.   Exogenous CEO turnover events

We use the difference-in-differences (DID) approach to address potential endogeneity concerns related to unobserved firm characteristics that may simultaneously influence both the likelihood of hiring CEOs with early-life disaster experiences and the firm's risk management policies. For instance, firms with a conservative corporate culture may prefer CEOs with disaster experiences and be more inclined to adopt hedging strategies. This introduces a potential bias in our baseline regression if some of these firm characteristics are not controlled for. To mitigate this concern, we leverage exogenous CEO turnover

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[8]To address regional risk differences, we use FEMA's National Risk Index and state-level disaster frequency data (FEMA website) to classify counties into high- and low-risk areas. The positive effect of CEOs' early-life disaster experiences on hedging remains significant in both groups, confirming that our results are driven by individual experiences rather than regional risk characteristics.

events identified by Gentry et al. (2021). CEO departure reasons are classified 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 corporate strategies, we choose departure reasons 1), 2), 5), and 6) as the exogenous CEO turnovers.[9]

We focus on 186 exogenous CEO turnovers within a four-year window around the event, excluding continuous CEO turnover observations. Among these exogenous 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 exogenous 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. For a detailed classification of the exogenous CEO turnovers, please refer to Table A3 of Appendix A.

Following the approach used by Bernile et al. (2017), for each exogenous CEO turnover event occurring in year t, we assess changes in firms' use of financial derivatives by comparing 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 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),

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[9]These events allow us to examine changes in a firm's financial hedging behavior before and after the CEO transition, isolating the effect of hiring a CEO with early-life disaster experiences. By focusing on these exogenous changes, the DID framework helps control for time-invariant firm characteristics and other unobservable factors that could otherwise confound the relation between CEO characteristics and hedging decisions.

we observe that the changes in the mean values of *IR/FX* and *Hedging* are negative 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 significant 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.[10]

While the sample of exogenous CEO turnovers is relatively small, this analysis provides critical identification evidence by exploiting changes in financial hedging around CEO transitions that involve differences in early-life disaster experiences. Small sample sizes are a common feature of CEO turnover-based studies in the corporate finance literature (e.g., Dittmar and Duchin, 2016; Bernile et al., 2017; Schoar and Zuo, 2017), yet the statistical significance of our findings indicates a robust underlying relationship. The consistent pattern–where firms increase hedging following the appointment of a CEO with disaster experience, and reduce hedging when transitioning away from such a CEO–provides compelling evidence of a causal link between early-life experiences on corporate financial hedging.

To further investigate the changes in corporate financial hedging policies around CEO turnovers, we conduct a stacked DID analysis using multivariate regressions. Recent econometrics studies (Cengiz et al., 2019; Sun and Abraham, 2021; Baker et al., 2022; Roth et al., 2023) suggest that the stacked DID method can address the challenges associated

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[10]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.

with heterogeneous treatment effects in DID analysis. This approach creates separate cohorts for each treatment year, each covering a fixed period before and after treatment. These cohorts are then "stacked" together to form a panel. This setup aligns the data according to the timing of the treatment rather than the calendar year, enhancing the accuracy of the DID analysis. Specifically, for each exogenous CEO turnover year, we construct a cohort (c) of treated and control firm–year observations within a five-year window around the year of treatment: two years before and two years after, including the event year. Each cohort must have non-missing data on financial hedging and accounting information over the five-year window. The stacked 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 stacked DID sample 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). Our stacked DID regression specification is:

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

where $Treat\_Disaster_i$ ($Treat\_Child\ Disaster_i$) is an indicator variable that equals to one if firm i experiences 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 the event year or after the turnover event and zero otherwise. Control variables are the same as those in our baseline regression Equation (1). We also control for the firm, year and cohort (τ_c) fixed effects in the DID regression model.[11]

Table 4 reports the results of the stacked DID tests. The estimated coefficients on the interacted terms, *Treat_Disaster×Post* and *Treat_Child Disaster×Post*, are positive and statistically significant, consistent with the view that firms managed by CEOs with

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[11] After controlling for the firm fixed effects, it is not necessary to include *Treat_Disaster* and *Treat_Child Disaster* separately in the DID regression model (Huang and Kisgen, 2013).

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early-life disaster experiences are more likely to use financial derivatives. These findings provide robust evidence of the impact of CEOs' early-life experiences on corporate risk management strategies.[12]

4.3.2. Propensity score matching and entropy balancing matching

While our stacked DID analysis helps address potential endogeneity concerns related to unobserved heterogeneity and reverse causality, it may not fully account for the fact that firms and CEOs are not randomly matched in the labor market. Firms may strategically select CEOs based on attributes that align with their risk management needs. For instance, firms with higher cash flow volatility might prefer risk-tolerant CEOs and be more likely to adopt financial hedging strategies, leading to biased estimates in our baseline regression. To mitigate the non-random matching between firms and CEOs, we employ two matching strategies: PSM and EB matching. These two matching approaches allow us to construct treatment groups consisting of firms managed by CEOs with early-life disaster experiences and control groups consisting of firms with similar firm-specific characteristics but managed by CEOs without disaster experiences.

First, we utilize the 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 firm 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.[13]

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[12]Our DID analysis utilize CEO exogenous turnover events. A potential limitation of this identification strategy is the relatively small sample size, which may constrain statistical power and the generalizability of the results. To address this concern, we conduct two robustness checks. First, we re-estimate Equation (2) using an expanded sample that includes all CEO turnover events (N = 243) and find results consistent with our baseline estimates. Second, we implement a placebo test by shifting the exogenous turnover dates one year earlier to create pseudo-events. We observe no significant effects around these placebo turnovers, reinforcing the validity of our DID results. Untabulted results are available upon request.

[13]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.

Our PSM sample includes 4,356 firm–year observations 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 using the same specification as the one estimating propensity scores. We find that in the post-match sample, 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. We find 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.

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 achieved through EB matching reduces approximation bias and minimizes model dependency in finite samples.

While there are significant differences in the mean, variance, and skewness of the matching variables between the treatment and control groups before matching, these differences vanish after the EB 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 CEOs' 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 selection biases and improving comparability between the treatment and control groups.

4.3.3. Additional controls

In our baseline regression, we follow previous studies on the determinants of corporate financial hedging and select a set of firm-level characteristics and CEO characteristics as control variables. However, recent studies suggest that CFOs play an important role in shaping corporate strategies 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.[14] Panel A of Table 6 shows that the positive relation between CEOs' early-life disaster experiences and the use of financial derivatives remains robust even after controlling for CFO characteristics.

Previous studies show that firms with weaker governance structures are more likely to use financial derivatives to align with managerial risk preferences and achieve greater

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

risk reduction (DeMarzo and Duffie, 1995; Dadalt et al., 2002). In contrast, firms with strong governance frameworks often use derivatives to hedge currency exposure and lower external financing costs (Froot et al., 1993; Lel, 2012). We adopt two proxies for corporate governance: *BLC* and *Risk Committee*. *BLC* is the total ownership of block holders who hold more than 5% of a firm's stocks (Edmans, 2014). *Risk Committee* equals one if the board has a risk committee, zero otherwise. Panel B of Table 6 shows that after controlling for corporate governance. The estimated coefficients on *Disaster* and *Child Disaster* are all positive and statistically significant, affirming the robustness of our main finding.[15]

Corporate culture may also be an omitted variable in our empirical analysis, potentially influencing both corporate risk management policies and the likelihood of appointing CEOs with early-life disaster experiences. We incorporate five dimensions of corporate culture based on earnings call transcripts: *Innovation*, *Quality*, *Integrity*, *Teamwork*, and *Respect*, constructed by Li et al. (2021). These dimensions relate to various corporate activities, including risk-taking, operational efficiency, and firm value.[16] Panel C of Table 6 shows that the positive relation between CEOs' 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.

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[15]We also control Gompers et al.'s (2003) governance measure (G-Index), the E-Index developed by Bebchuk et al. (2009), the hostile takeover index (Cain et al., 2017), and the fraction of co-opted directors in the corporate board (Coles et al., 2014). The coefficients of disaster proxies remain robust.

[16]We would like to thank Kai Li for sharing the data on corporate culture. The corporate culture data from Li et al. (2021) covers the period between 2001 and 2018.

5. Supplementary tests

5.1. CEOs' early-life disaster experiences, financial hedging, and firm value

Although financial derivatives are widely employed as essential risk management tools, empirical findings on 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 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-life disaster experiences and financial hedging results in higher or lower firm value. On one hand, 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 preferences align with those of shareholders. On the other hand, 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 for firm value (Peters and Taylor, 2017; Bartram et al., 2011), we use *Total Q* and *Growth* as proxies for

firm value, reflecting 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 7, we estimate the following regressions:

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

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 7 reports the results. In columns (1)–(4), the dependent variable is *Total Q*. The estimated coefficient on the financial hedging proxies and CEOs' 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 CEOs' 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* $\times$ *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-life disaster experiences, the use of financial derivatives reduces their firm value.

5.2. Cross-sectional analyses

Thus far, we find that CEOs with early-life disaster experiences are more likely to adopt derivatives as part of their corporate risk management strategies, although this choice may not always be optimal for firm value. To further investigate the underlying mechanisms behind these findings, we conduct cross-sectional analyses to explore the roles of corporate governance, financial constraints, and firm risk.

5.2.1. Corporate governance

In Section 5.1, our firm value tests suggest that CEOs' early-life disaster experiences widen the gap between CEOs' and shareholders' risk preferences, leading to suboptimal decisions in corporate financial hedging. If the use of financial derivatives by CEOs with disaster experiences is mainly driven by CEOs' personal risk preference rather than aligning with shareholders' interests, then we expect to observe a more pronounced relation between CEOs' early-life 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: *BLC*, *HOI*, and *COP*. A higher *BLC* value is associated with stronger corporate governance. *HOI* 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. *COP* is the fraction of co-opted directors in the corporate board. A higher proportion of such directors indicates weaker internal monitoring intensity (Coles et al., 2014). We divide our sample into two sub-samples based on the top and bottom quartiles of corporate governance proxies for each industry, following the Fama-French 48 industry classification, for each year. Firms in the sub-samples with lower *BLC* and *HOI*, or higher *COP*, are characterized by weaker corporate governance.

In Panels A and B of Table 8, the corporate governance proxies are *BLC* and *HOI*. 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 *BLC* or *HOI*. We conduct

seemingly unrelated regressions (SUR) and find that the differences in the coefficients of disaster experience proxies between the low and high corporate governance sub-samples are positive and significant. Our SUR tests indicate that the positive relation between CEOs' early-life disaster experiences and financial hedging is stronger in firms with weaker corporate governance.

In Panel C of Table 8, the corporate governance proxy is *COP*. We observe that 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), we observe a weak positive relation for firms with a low ratio of co-opted directors and this relation are insignificant in columns (6) and (8). The SUR tests show that the differences in the coefficients of disaster experience proxies between the low and high corporate governance sub-samples are all positive and significant, supporting our expectation that the positive relation between CEOs' early-life disaster experiences and financial hedging is stronger in firms with weaker corporate governance. This finding is consistent with our results reported in Panels A and B of Table 8.

5.2.2. Financial constraints

Next, we investigate whether the positive relation between CEOs' 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 for investment. Since financial hedging by CEOs with disaster experiences tends to decrease firm value, we interpret 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 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 top and bottom quartiles of *DTD* for each industry (Fama-French 48 industry classification) for each year. Panel D of Table 8 shows that the estimated coefficients on *Disaster* and *Child Disaster* are all 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 for columns (3) and (4). Our finding indicates that CEOs with disaster experiences are more likely to adopt financial hedging in firms with fewer financial constraints.

5.2.3. Firm risk

Our third cross-sectional analysis examines whether the positive relation between CEOs' 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.

Building on these findings, we expect that CEOs with early-life disaster experiences are more likely to employ financial derivatives when their firms face higher levels of risk. This increased propensity for hedging likely stems from these CEOs' enhanced risk awareness and sensitivity to potential downside scenarios. Personal experiences with catastrophic events may foster a deeper appreciation for proactive risk mitigation strategies. We propose

that CEOs who have witnessed the impact of unforeseen events firsthand during childhood may adopt a more conservative approach to risk management. This could manifest as a stronger inclination to protect their firms from unexpected shocks through the strategic use of financial derivatives. Their decision-making process may be influenced by a profound understanding of worst-case scenarios and a desire to insulate their organizations from similar vulnerabilities.

We adopt two proxies for firm-specific risk. Our first proxy is operating cash flow volatility ($CFsd$), measured as the average standard deviation of operating cash flows over a five-year period for firms with the same two-digit SIC codes (Bartram et al., 2011). Higher cash flow volatility generally indicates greater operational risks. Our second proxy is a firm's options trading volume (OTV). Previous research suggests that a higher level of options trading activities can stimulate innovation and development of new products (Blanco and Wehrheim, 2017; Hsu et al., 2021). However, such innovation may also potentially increase a firm's overall risk exposure. High options trading volume may also indicate that investors hold divergent opinions about a firm's future prospects, which could be driven by upcoming earnings announcements, regulatory changes, or other events that could significantly impact on the firm's stock price. We assign our sample firm–year observations into two sub-samples based on the top and bottom quartiles of $CFsd$ or OTV for each industry (Fama-French 48 industry classification) for each year. Firms with higher values of $CFsd$ or OTV are classified as having higher firm-specific risk.

Panels E and F of Table 8 show that the estimated coefficients on *Disaster* and *Child Disaster* are positive and statistically significant only in the sub-samples of firms with high firm-specific risk. Additionally, the estimated coefficients on the disaster proxies are larger in the high-risk sub-samples compared to those in the low-risk sub-samples. 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 CEOs' early-life disaster experiences are associated with more prudent financial hedging policy, especially for firms with higher firm-specific risk.

5.3. Business diversification and cash holdings

Corporate risk management literature indicates that, aside from financial hedging, firms may also employ other corporate strategies to mitigate their future financial risk. For example, firms may diversify business into different industries, utilize geographic diversification of production, and acquire their subsidiaries (Allayannis et al., 2001; Kim et al., 2006; Hankins, 2011). In addition, 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 CEOs' early-life disaster experiences affect firms' business diversification and cash holdings.

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

$$Y_{i,t} = \beta_0 + \beta_1 Disaster\ Experiences_{i,t} + B\ Controls_{i,t} + \mu_t + \theta_i + \varepsilon_{i,t} \qquad (4)$$

where i is firm index and t is year index. $Y_{i,t}$ refers to one of the following four variables: *#.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 are 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 9 reports the results of our operational hedging tests. In columns (1)–(8), all estimated coefficients on *Disaster* and *Child Disaster* are statistically insignificant, sug-

gesting that CEOs' early-life disaster experiences do not exert a direct influence on business diversification and cash holdings. 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, modifying 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 to be 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 other firms' risk mitigation strategies. However, we acknowledge the limitations of our operational risk mitigation strategies. Proper identification of operational hedging requires detailed firm-specific analysis beyond the scope of our study. For example, operational hedging can include customized arrangements, such as forward selling production at fixed prices in commodity businesses, which are difficult to identify systematically.

5.4.   CEOs raised in inherently higher-risk regions

A potential concern on our main findings is that CEOs raised in inherently higher-risk regions may exhibit greater risk aversion even without personally experiencing a disaster. To address this issue, we conduct additional robustness tests using the National Risk Index (NRI) published by FEMA and the annual number of disaster events by state. The NRI provides standardized county-level risk measures across 18 natural hazards, incorporating expected annual loss, social vulnerability, and community resilience[17].

We partition the sample into High-Risk and Low-Risk groups based on both the median NRI and the median number of disaster events. Untabulated results show that the positive association between CEOs' early-life disaster exposure and corporate hedging remains statistically significant in both subsamples. Moreover, coefficient equality tests

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[17]Please refer to the FEMA Technical Documentation.

reveal no significant differences across the risk groups, suggesting that our findings are not driven simply by CEOs growing up in high-risk locations rather than by personal disaster experience. To further ensure that our results are not driven by regional characteristics, we re-estimate the baseline regressions after excluding states with the highest NRI scores and those in the top quartile of disaster frequency. Untabulated results show that our main findings remain statistically and economically significant.

Taken together, these additional tests indicate that the positive association between CEOs' early-life disaster exposure and corporate financial hedging is attributable to individual formative experiences, rather than simply reflecting the risk profile of the regions in which CEOs grew up.

6.   Conclusion

A growing body of research highlights the influence of CEOs' past experiences on corporate policies. In this study, we focus on a specific aspect of CEOs' personal life histories—early-life disaster experiences—and examine how such formative events affect corporate financial hedging activities. We hypothesize that CEOs with early-life disaster experiences exhibit heightened sensitivity to the consequences of risk-taking. Therefore, we expect these CEOs to display greater risk aversion and to be more inclined to adopt financial derivatives as a risk-mitigation tool.

Using a sample of U.S. 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 CEOs' 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 though 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 experience-induced conservatism may drive CEOs' risk preferences away from those of shareholders, potentially creating an agency problem. Cross-sectional analysis further shows that this relationship is more pronounced in firms with weaker corporate governance, fewer financial constraints, and higher 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.

Despite the robustness of our findings, several limitations warrant consideration. First, our sample is limited to S&P 1500 firms, which may constrain the generalizability of our results to smaller firms or those operating in different institutional contexts. Second, although we manually collect data on CEOs' early-life disaster experiences, accurately measuring the intensity and psychological impact of such events remains challenging. Third, our textual analysis approach to identifying financial hedging activities, though consistent with prior literature, may not fully reflect the complexity of corporate risk management practices. Access to more detailed data on hedging positions could provide deeper insights into how CEOs' formative experiences influence specific risk management decisions. Finally, future research could extend our framework by exploring the influence of later-life experiences, such as military service, professional crises, or exposure to major corporate restructurings on financial risk management.

Appendix A

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Table A1. Variable definitions

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This table provides variable definitions and corresponding data sources. 10-Ks refer to firms' annual reports from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. s34 files refer to the Thomson Reuters 13F Database, LN refers to Lalitha Naveen's website, SM refers to Stephen McKeon's website, LMSY refers to Li et al. (2021), PT refers to Peters and Taylor's Total Q data from WRDS, and GH refers to Gerard Hoberg's website

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, and 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, and zero otherwise (Hoberg and Moon, 2017).	10-Ks
Disaster	A dummy variable equals to one if a CEO has early-life disaster experiences at the age of 5 to 15, and zero otherwise. (Bernile et al., 2017).	
Child Disaster	A dummy variable equals to one if a CEO has early-life disaster experiences before the age of 5, and zero otherwise. (Bernile et al., 2017).	
Extreme #.Disaster	A dummy variable equals to one if a CEO is in the top quintile of total disaster experiences encountered before the age of 15, and zero otherwise (Bernile et al., 2017).	
Medium #.Disaster	A dummy variable equals to one if a CEO has experienced some disasters but does not belong to the *Extreme #.Disaster* group, and zero otherwise (Bernile et al., 2017).	
No #.Disaster	A dummy variable equals to one if a CEO has not experienced any disasters, and zero otherwise (Bernile et al., 2017).	
Extreme Fatality	A dummy variable equals to one if a CEO is in the top quintile for the number of disaster-related fatalities per capita in their birth county, and zero otherwise (Bernile et al., 2017).	
Medium Fatality	A dummy variable equals to one if a CEO has experienced some disaster-related fatalities in their birth county but does not belong to the *Extreme Fatality* group, and zero otherwise (Bernile et al., 2017).	
No Fatality	A dummy variable equals to one if a CEO has experienced no disaster-related fatalities in their birth county, and zero otherwise (Bernile et al., 2017).	

Variable	Definition	Source
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
Foreign Income	The ratio of pre-tax income from a firm's foreign operations to sales (Géczy et al., 1997).	Compustat
Sale Volatility	The standard deviation of a firm's sales scaled by total assets over the past 10 years (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 a firm first appears in Compustat with nonmissing total assets (Bartram et al., 2011).	Compustat
Institutional Ownership	The percentage of a firm's institutional ownership (Purnanandam, 2008).	s34 files
CEO/CFO Vega	Vega is the change in the value of the CEO/CFO's option grant in a year, and any accumulated option holdings, for a 1% change in the annualized standard deviation of stock returns, scaled by the CEO/CFO's total compensation (Liu and Mauer, 2011).	ExecuComp
CEO/CFO Delta	Delta is the change in the value of the CEO/CFO's option or restricted stock grants in a year, shareholdings, and any accumulated restricted stock and option holdings, for a 1% change in the stock price, scaled by the CEO/CFO's total compensation (Liu and Mauer, 2011).	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 a CEO/CFO as reported in ExecuComp (Bernile et al., 2017).	ExecuComp
CEO/CFO Tenure	The number of years that the current CEO/CFO has served in that role as reported in ExecuComp (Beber and Fabbri, 2012).	ExecuComp
CEO Duality	A dummy variable equals to one when a CEO is the chairman of the board and zero otherwise (Croci et al., 2017).	BoardEx
COP	The percentage of directors hired after the current CEO assumes office (Coles et al., 2014).	LN
HOI	Firm-level hostile takeover index (Cain et al., 2017).	SM

Continued on next page

Variable	Definition	Source
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
DTD	The Hoberg and Maksimovic text-based measure of financial constraints, which is based on the discussions of capitalization and liquidity in firms' 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	Herfindahl-Hirschman index (HHI) based on sales to each major corporate business segment (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 A2. Non-monotonic impact of CEOs' early-life disaster experiences

This table presents the results of tests examining whether the intensity of CEOs' early-life disaster experiences has a non-monotonic impact on corporate financial hedging. The dependent variables are *IR/FX* in columns (1) and (2), and *Hedging* in columns (3) and (4). *Extreme #.Disaster* is an indicator variable that equals one if a CEO falls within the top quintile of total disaster experiences encountered before the age of 15, and zero otherwise. *Medium #.Disaster* is an indicator variable that equals one if a CEO has experienced some disasters but does not belong to the *Extreme #.Disaster* group, and zero otherwise. *No #.Disaster*, omitted in the regressions, is an indicator variable that equals one if a CEO has not experienced any disasters, and zero otherwise. *Extreme Fatality* is an indicator variable that equals one if a CEO is in the top quintile for disaster-related fatalities per capita in their birth county, and zero otherwise. *Medium Fatality* is an indicator variable that equals to one if a CEO has experienced some disaster-related fatalities in their birth county but does not belong to the *Extreme Fatality* group, and zero otherwise. *No Fatality*, omitted in the regressions, is an indicator variable that equals one if a CEO has experienced no disaster-related fatalities in their birth county, and zero otherwise. For brevity, we omit the estimated coefficients for control variables that are the same as those reported in Table 2. All models include the firm and year fixed effects. z-statistics based on standard errors clustered at the firm level are reported in brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	IR/FX_t		$Hedging_t$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Extreme #.Disaster	1.053*		1.756***	
	[1.87]		[2.78]	
Medium #.Disaster	-0.158		-0.180	
	[-0.75]		[-0.84]	
Extreme Fatality		-0.005		-0.400
		[-0.00]		[-0.21]
Medium Fatality		1.456		1.457
		[0.85]		[0.78]
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	7,227	6,914	6,763	6,455
Pseudo-R^2	0.276	0.277	0.283	0.283

Table A3. Classification of CEO turnovers

This table presents a detailed classification of CEO turnovers, including the total number of turnovers and those categorized as exogenous according to Gentry et al. (2021). The reasons for CEO departures are divided into eight categories: 1) CEO death, 2) CEO illness, 3) CEO dismissal for job performance, 4) CEO dismissal for personal reasons, 5) CEO retirement, 6) New opportunity, 7) Other, and 8) Missing. Turnovers due to reasons 1), 2), 5), and 6) are classified as exogenous CEO turnovers.

	$Disaster_t$	$Child\ Disaster_t$
Number	**(1)**	**(2)**
Total CEO turnovers	243	243
Exogenous CEO turnovers	186	186
No-Disaster to Disaster	18	15
Disaster to No-Disaster	22	14
No-Disaster to No-Disaster	143	155
Disaster to Disaster	3	2

Appendix B. Financial hedging measures

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 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. Following previous studies (e.g., Hoberg and Moon, 2017; Alexandridis et al., 2021; Sun et al., 2022), we compile three lists of keywords and specifically target 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 making 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.[18] 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 consider 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.[19] 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 all firm–year observations with annual reports in the EDGAR database during our sample period,

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[18]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.

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

and manually re-assess their annual reports. Among this randomly selected sample, the accuracy rates are 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).[20]

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[20]We manually validate firm–year observations in our merged sample for the years 1996 and 2003, covering a total of 1,074 cases. For both years, we cross-check all firms identified as hedgers and find no evidence of significant misclassification between hedgers and non-hedgers. These results provide strong support for the accuracy and reliability of our automated hedging identification process.

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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 9,430 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 left 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*, *Female CEO*, *CEO Age*, and *CEO Tenure*. All variables are defined in Table A1 of Appendix A.

Variable	Obs.	Mean	S.D.	p1	p25	Median	p75	p99
Dependent variables								
$Disaster_t$	9,430	0.215	0.411	0	0	0	0	1
$Child\ Disaster_t$	9,430	0.142	0.349	0	0	0	0	1
Dependent variables								
IR/FX_t	9,430	0.691	0.462	0	0	1	1	1
$Hedging_t$	9,430	0.740	0.439	0	0	1	1	1
Independent variables of interest								
$Disaster_t$	9,430	0.215	0.411	0	0	0	0	1
$Child\ Disaster_t$	9,430	0.142	0.349	0	0	0	0	1
Control variables								
NOL_t	9,430	0.044	0.147	0.000	0.000	0.000	0.011	1.058
$Networth_t$	9,430	0.269	0.206	-0.368	0.143	0.293	0.408	0.697
$Leverage/Equity_t$	9,430	1.159	2.503	-7.285	0.274	0.678	1.332	17.238
$R\&D_t$	9,430	0.020	0.043	0.000	0.000	0.000	0.019	0.237
$Tobin's\ Q_t$	9,430	1.825	1.163	0.819	1.123	1.412	2.030	7.461
$Foreign\ Income_t$	9,430	0.018	0.038	-0.047	0.000	0.000	0.022	0.190
$Sale\ Volatility_t$	9,430	0.168	0.152	0.004	0.066	0.128	0.223	0.810
$Firm\ Size_t$	9,430	8.237	1.901	4.275	6.871	8.198	9.503	13.205
$Firm\ Age_t$	9,430	3.290	0.672	1.386	2.833	3.466	3.850	4.205
$Institutional\ Ownership_t$	9,430	0.526	0.328	0.000	0.304	0.616	0.777	1.000
$CEO\ Vega_t$	9,430	0.030	0.038	0.000	0.008	0.019	0.038	0.252
$CEO\ Delta_t$	9,430	0.233	0.486	0.001	0.033	0.070	0.154	2.394
$Female\ CEO_t$	9,430	0.025	0.155	0	0	0	0	1
$CEO\ Age_t$	9,430	57.518	7.261	28	53	57	62	79
$CEO\ Tenure_t$	9,430	9.874	7.630	2	4	8	13	38

Table 2. Baseline regression: CEOs' early-life disaster experiences 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 A1 of Appendix A. z-statistics based on standard errors clustered at the firm level are reported in brackets. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	IR/FX_t				$Hedging_t$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Disaster_t$	0.924***		0.870***		0.861***		0.921***	
	[5.20]		[4.58]		[4.67]		[4.64]	
$Child\ Disaster_t$		0.997***		1.001***		0.783***		0.915***
		[5.10]		[4.73]		[3.99]		[4.27]
NOL_t			0.980**	0.952**			0.680	0.676
			[2.11]	[2.05]			[1.45]	[1.44]
$Networth_t$			-0.724**	-0.755**			-0.760**	-0.771**
			[-2.15]	[-2.24]			[-2.19]	[-2.22]
$Leverage/Equity_t$			0.006	0.006			0.012	0.012
			[0.29]	[0.27]			[0.50]	[0.49]
$R\&D_t$			4.397	4.541			3.275	3.393
			[1.52]	[1.56]			[1.13]	[1.17]
$Tobin's\ Q_t$			-0.013	-0.023			-0.062	-0.070
			[-0.22]	[-0.41]			[-1.12]	[-1.27]
$Foreign\ Income_t$			-2.524	-2.915			-2.524	-2.971
			[-1.27]	[-1.47]			[-1.15]	[-1.35]
$Sale\ Volatility_t$			1.289**	1.303**			1.108**	1.131**
			[2.54]	[2.56]			[2.11]	[2.15]
$Firm\ Size_t$			0.240**	0.243**			0.006	0.011
			[2.16]	[2.19]			[0.05]	[0.10]
$Firm\ Age_t$			2.075***	2.117***			2.326***	2.348***
			[5.67]	[5.77]			[6.11]	[6.17]
$Institutional\ Ownership_t$			0.872***	0.863***			1.322***	1.312***
			[3.20]	[3.16]			[4.44]	[4.41]
$CEO\ Vega_t$			-3.589***	-3.669***			-3.672***	-3.738***
			[-2.94]	[-3.00]			[-2.91]	[-2.97]
$CEO\ Delta_t$			0.043	0.047			0.054	0.057
			[1.02]	[1.13]			[1.24]	[1.32]
$Female\ CEO_t$			-0.028	0.012			0.401	0.428
			[-0.05]	[0.02]			[0.74]	[0.79]
$CEO\ Age_t$			0.002	0.004			0.007	0.009
			[0.15]	[0.29]			[0.53]	[0.65]
$CEO\ Tenure_t$			0.027**	0.027**			0.014	0.013
			[2.20]	[2.16]			[1.07]	[1.06]
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	6,684	6,684	6,898	6,898	6,234	6,234
Pseudo-R^2	0.270	0.270	0.303	0.303	0.276	0.275	0.310	0.310

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 a 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, we calculate the mean changes around exogenous CEO turnover events based on whether the CEO has any early-life disaster experience *at the age of 5 to 15*. Column (1) reports the mean change around exogenous CEO turnover events where the incoming CEO has an early-life disaster experience, 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 (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 A1 of Appendix A. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% 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. Stacked DID analyses: CEO turnovers and financial hedging

This table reports the results of stacked difference-in-differences (DID) tests. In columns (1) and (3), the DID sample 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). In columns (2) and (4), the DID sample includes treated firms with *No-Child Disaster to Child Disaster* CEO turnovers (N=15), and control firms with *No-Child Disaster to No-Child Disaster* CEO turnovers (N=155). 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, year and cohort fixed effects. All variables are defined in Table A1 of Appendix A. z-statistics based on standard errors clustered at the firm level are reported in brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	IR/FX		Hedging	
	(1)	(2)	(3)	(4)
Treat_Disaster $\times$ *Post$_t$*	2.310**		2.431*	
	[2.00]		[1.70]	
Treat_Child Disaster $\times$ *Post$_t$*		2.747*		3.010**
		[1.93]		[2.00]
Post$_t$	0.121	0.274	0.272	0.314
	[0.25]	[0.57]	[0.51]	[0.58]
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	805	850	805	850
Pseudo-R^2	0.606	0.603	0.651	0.658

Table 5. Propensity score matching and entropy balancing matching

This table reports the results our baseline regression estimated 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. 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 A1 of Appendix A. z-statistics based on standard errors clustered at the firm level are reported in brackets. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	PSM				EB matching			
	IR/FX_t		$Hedging_t$		IR/FX_t		$Hedging_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Disaster_t$	1.305***		1.430***		1.049***		1.171***	
	[4.23]		[4.68]		[4.88]		[5.23]	
$Child\ Disaster_t$		1.208***		1.193***		1.323***		1.291***
		[2.79]		[2.70]		[5.04]		[4.94]
Constant					-1.389	-1.897	-0.523	-0.664
					[-0.78]	[-0.99]	[-0.30]	[-0.34]
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	2,312	1,368	2,133	1,260	6,287	6,287	5,837	5,837
Pseudo-R^2/F-stat	0.304	0.376	0.309	0.374	2.342	2.348	2.346	2.399

Table 6. Additional controls

This table presents the results of our baseline regression with additional controls. Panel A reports the results with additional controls for CFO characteristics, including CFO vega, delta, female indicator, age, and tenure. Panel B reports the result with additional controls for corporate governance. The first 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 second corporate governance proxy is *Risk Committee*, equal to one if the board has a risk committee and zero otherwise. Panel C reports the results with additional controls for corporate culture, including *Innovation*, *Quality*, *Integrity*, *Teamwork*, and *Respect*, developed by Li et al. (2021). The dependent variable in columns (1) and (2) is *IR/FX* and the dependent variable in columns (3) and (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 A1 of Appendix A. z-statistics based on standard errors clustered at the firm level are reported in brackets. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. CFO characteristics

Variables	IR/FX_t		$Hedging_t$	
	(1)	(2)	(3)	(4)
$Disaster_t$	1.960***		2.202***	
	[4.29]		[4.70]	
$Child\ Disaster_t$		2.197***		2.254***
		[4.38]		[4.39]
$CFO\ Vega_t$	2.035	2.203	1.482	1.777
	[0.84]	[0.91]	[0.48]	[0.58]
$CFO\ Delta_t$	-1.856**	-2.048**	-2.088	-2.410
	[-2.00]	[-2.23]	[-1.20]	[-1.37]
$Female\ CFO_t$	-0.673	-0.685	-0.769*	-0.866**
	[-1.58]	[-1.61]	[-1.77]	[-2.00]
$CFO\ Age_t$	0.015	0.012	0.025	0.021
	[0.84]	[0.69]	[1.36]	[1.13]
$CFO\ Tenure_t$	-0.053*	-0.043	-0.072**	-0.059*
	[-1.66]	[-1.36]	[-2.17]	[-1.78]
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,227	2,227	2,093	2,093
Pseudo-R^2	0.333	0.334	0.343	0.341

Panel B. Corporate governance

Table 6 - continued from previous page

Variables	IR/FX$_t$		Hedging$_t$	
	(1)	**(2)**	**(3)**	**(4)**
Disaster$_t$	1.780***		2.319***	
	[2.78]		[2.90]	
Child Disaster$_t$		2.439***		2.274**
		[2.70]		[2.26]
Risk Committee$_t$	1.163	1.175	0.993	1.042
	[1.44]	[1.46]	[1.19]	[1.26]
BLC$_t$	2.464**	2.517**	1.749	1.866
	[2.06]	[2.11]	[1.32]	[1.41]
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,333	2,333	2,166	2,166
Pseudo-R^2	0.496	0.496	0.543	0.540

Panel C. Corporate culture

Variables	IR/FX$_t$		Hedging$_t$	
	(1)	**(2)**	**(3)**	**(4)**
Disaster$_t$	1.710***		3.018***	
	[3.04]		[3.74]	
Child Disaster$_t$		2.022***		2.688***
		[3.08]		[3.14]
Innovation$_t$	0.278**	0.248*	0.321**	0.293**
	[2.04]	[1.84]	[2.26]	[2.07]
Quality$_t$	-0.120	-0.107	-0.234	-0.203
	[-0.63]	[-0.56]	[-1.14]	[-0.99]
Integrity$_t$	-0.125	-0.138	-0.218	-0.221
	[-0.60]	[-0.66]	[-0.90]	[-0.92]
Teamwork$_t$	-0.402*	-0.395*	-0.478*	-0.497**
	[-1.75]	[-1.72]	[-1.94]	[-2.02]
Respect$_t$	0.158	0.144	0.193	0.187
	[1.06]	[0.97]	[1.22]	[1.18]
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,388	2,388	2,215	2,215
Pseudo-R^2	0.363	0.364	0.398	0.394

Table 7. CEOs' early-life disaster experiences, 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 A1 of Appendix A. t-statistics based on standard errors clustered at the firm level are reported in brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Total Q_t				Growth$_t$			
	(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 8. Cross-sectional analyses

This table presents the results of our cross-sectional analyses. We divide our sample into two sub-samples based on the top and bottom quartiles of six variables in Panels A–F for each industry, following the Fama-French 48 industry classification, for each year. The first three variables are proxies for corporate governance: *BLC* defined as the total ownership of blockholders (Edmans, 2014), *HOI* defined as the hostile takeover index (Cain et al., 2017), and *COP* defined as the fraction of co-opted board directors (Coles et al., 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 A1 of Appendix A. z-statistics based on standard errors clustered at the firm level are reported in brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Corporate governance: Blockholder ownership (BLC).

Variables	IR/FX_t				$Hedging_t$			
	High (1)	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**	**High (7)**	**Low (8)**
$Disaster_t$	-0.342	0.865***			-0.341	1.046***		
	[-0.51]	[3.20]			[-0.49]	[3.62]		
$Child\ Disaster_t$			-1.035	1.047***			-1.399	0.934***
			[-1.21]	[3.53]			[-1.53]	[3.14]
Coefficients equality test (χ^2)	3.13*		2.71*		2.12		2.86*	
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	910	2,613	910	2,613	813	2,377	813	2,377
Pseudo-R^2	0.338	0.289	0.339	0.291	0.406	0.282	0.409	0.280

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

Variables	IR/FX_t				$Hedging_t$			
	High (1)	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**	**High (7)**	**Low (8)**
$Disaster_t$	0.717	2.830***			0.813	2.627***		
	[1.01]	[3.46]			[1.13]	[3.19]		
$Child\ Disaster_t$			0.379	3.255***			0.396	2.363***
			[0.53]	[3.42]			[0.54]	[2.79]
Coefficients equality test (χ^2)	6.55**		9.54***		6.39**		5.72**	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Table 8 - continued from previous page

Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	587	993	587	993	562	913	562	913
Pseudo-R^2	0.331	0.320	0.330	0.322	0.333	0.301	0.331	0.297

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

	IR/FX_t				$Hedging_t$			
	High	Low	High	Low	High	Low	High	Low
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	4.708**	-0.222			4.405**	-0.083		
	[2.18]	[-0.35]			[2.09]	[-0.11]		
$Child\ Disaster_t$			4.678**	0.335			4.360**	0.036
			[2.16]	[0.53]			[2.06]	[0.05]
Coefficients equality test (χ^2)	5.35**		3.97**		4.32**		3.84*	
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	478	966	478	966	406	868	406	868
Pseudo-R^2	0.435	0.386	0.434	0.387	0.413	0.453	0.413	0.453

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)**
$Disaster_t$	-0.040	2.275***			-0.145	2.400***		
	[-0.06]	[2.93]			[-0.20]	[2.77]		
$Child\ Disaster_t$			0.047	2.122***			-0.412	2.349***
			[0.06]	[2.59]			[-0.52]	[2.68]
Coefficients equality test (χ^2)	3.65*		2.51		3.42*		3.48*	
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	244	476	244	476	194	392	194	392
Pseudo-R^2	0.416	0.509	0.416	0.518	0.536	0.432	0.536	0.443

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)**
$Disaster_t$	2.021***	0.337			4.460***	0.513		
	[2.70]	[0.71]			[3.56]	[0.98]		
$Child\ Disaster_t$			5.027***	0.416			6.183***	0.411
			[3.67]	[0.80]			[4.11]	[0.77]
Coefficients equality test (χ^2)	1.39		11.35***		3.17*		11.36***	
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	867	1,614	867	1,614	782	1,555	782	1,555

Table 8 - continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pseudo-R^2	0.338	0.397	0.355	0.397	0.401	0.411	0.407	0.411

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

	IR/FX_t				$Hedging_t$			
Variables	**High (1)**	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**	**High (7)**	**Low (8)**
$Disaster_t$	1.218***	-0.840			1.448***	-0.316		
	[2.66]	[-1.35]			[2.65]	[-0.53]		
$Child\ Disaster_t$			2.193***	-0.754			2.407***	-1.214*
			[3.70]	[-1.14]			[3.65]	[-1.65]
Coefficients equality test (χ^2)	3.64*		2.48		6.68***		11.29***	
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	990	1,462	990	1,462	920	1,354	920	1,354
Pseudo-R^2	0.345	0.340	0.357	0.340	0.392	0.347	0.406	0.350

Table 9. Business diversification and cash holdings

This table reports OLS regression estimates for examining the relation between CEO disaster experience and business diversification and the relation between disaster experience and corporate cash holdings. 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 A1 of Appendix A. t-statistics based on standard errors clustered at the firm level are reported in brackets. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	$\#.Segment_t$		$Bus.HHI_t$		$Cash_t$		$Net\ Cash_t$	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$Disaster_t$	0.043		0.014		0.004		0.012	
	[0.34]		[0.71]		[0.51]		[0.57]	
$Child\ Disaster_t$		0.100		0.013		0.003		0.001
		[0.67]		[0.57]		[0.43]		[0.07]
Constant	-0.481	-0.521	1.235***	1.236***	0.336***	0.336***	0.750***	0.755***
	[-0.58]	[-0.62]	[10.61]	[10.59]	[5.86]	[5.78]	[4.41]	[4.34]
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	7,766	7,766	7,766	7,766	9,430	9,430	9,430	9,430
Adjusted-R^2	0.225	0.225	0.126	0.126	0.288	0.288	0.259	0.259