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Industry tournament incentives and corporate hedging policies

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Abstract

This paper examines how a tournament among CEOs to progress within the CEO labor market influences their corporate hedging policies. We employ a textual analysis of 10-Ks to generate corporate hedging proxies, finding that the likelihood and intensity of hedging grow as the CEO labor market tournament prizes increase. We also explore the mitigating impact of corporate hedging on the adverse effects of risk-inducing industry tournament incentives (ITIs) on the cost of debt and stock price crash risk, noting that these could be possible reasons behind the relation. Additionally, we observe that the relationship between ITIs and corporate hedging is less pronounced for firms that demonstrate more financial distress and for firms whose CEOs are the founders of the company or are of retirement age. We identify a causal relation between ITIs and corporate hedging using an instrumental variable approach and an exogenous shock sourced from changes in the enforceability of noncompetition agreements across states.

KEYWORDS
corporate hedging, executive compensation, FX hedging, pay gap, risk management, risk-taking, tournament incentives

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1 INTRODUCTION

The use of financial derivatives as hedging tools has been increasing worldwide, even though active corporate risk management is irrelevant under the perfect market assumption of Modigliani and Miller (1958). Bartram et al. (2009) report that, based on a sample of 7319 firms from 50 countries, around 60% of the firms use derivative instruments, around 45% use foreign exchange (FX), around 33% use interest rate (IR), and around 10% use commodity (CMD) derivatives. According to the Bank for International Settlements (BIS), the notional value of outstanding FX, IR, and CMD derivatives held by nonfinancial customers has increased in the period between 2000 and 2018: from \$3.3 trillion (FX), \$6.1 trillion (IR), and \$0.6 trillion (CMD), to \$11.8 trillion, \$14.4 trillion, and \$2.1 trillion, respectively. One of the main reasons for hedging is to flatten a firm's performance in order to stabilize its net income and cash flows. For example, Bartram et al. (2011) find that derivative users experience lower cash-flow volatility, lower idiosyncratic volatility, and lower systematic risk.[1]

This study aims to examine how industry tournament incentives (ITIs) affect corporate hedging policies. ITIs can be defined as an external job-market setting in which CEOs aim to assume a CEO position in their industry's leading firm (Coles et al., 2017). These CEOs, therefore, are competing with one another; they are likely to compete for the highest-paid CEO position in their industry. Their performance is relatively evaluated, and the CEO with the highest performance moves up and wins the tournament. The winner of the tournament earns the difference between the highest-paid compensation in the industry and the winner's original compensation. Our results suggest that a CEO motivated by external job markets is more likely to engage in hedging activities. This finding is robust to the instrumental approach and natural experiment implementation, using different ITIs measures and industry classifications.

Coles et al. (2017) find that ITIs induce CEOs to exert greater effort and to increase the firm's risk level, resulting in a positive association between ITIs and both firm performance and risky corporate policies.[2] Promotion-based tournaments may also be considered an option; in these, the winner is given the entire tournament prize, whereas the others get nothing. Such tournaments provide CEOs with a convex payoff (Kini & Williams, 2012). These option-like and convex tournament compensation schemes might induce CEOs to pursue riskier corporate policies in order to increase the probability that they will win, or in an attempt to catch up with the leading firms (Coles et al., 2017; Goel & Thakor, 2008; Hvide, 2002; Kini & Williams, 2012). Therefore, our *risk incentive hypothesis* predicts that the risk-increasing incentives of ITIs might induce CEOs to refrain from engaging in hedging activities.

On the other hand, according to our *risk management hypothesis*, CEOs might be induced to use hedging tools as a buffer against the side effects of ITIs. ITIs are documented to have a positive association with the cost of borrowing (Kubick et al., 2020) and with stock price crash risk (Kubick & Lockhart, 2021), both of which can hurt a firm's performance. This negative effect can damage a CEO's reputation, thereby curtailing the probability of moving up.[3] Levine (2005) claims that financial derivatives make it possible to pursue high-risk–high-return projects. Hence, the *risk management hypothesis* requires a higher level of hedging activities to mitigate the adverse effects of undertaking the risky corporate policies incentivized by ITIs.

Following Coles et al. (2017), we define ITIs as the difference between the total compensation of the second-highest-paid CEO in the industry and the compensation of the CEO under consideration.[4] Industry classifications are determined using the Fama–French 30 (henceforth FF30) and size-median Fama–French 30 (henceforth FF30 size-median). Following the practice in recent corporate hedging literature, we develop our hedging measures based on a

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[1] The other motivations to hedge are tax convexity (Smith & Stulz, 1985; Graham & Smith, 1999), reduction in bankruptcy cost (Smith & Stulz, 1985), lowering the cost of debt (Smith & Stulz, 1985, Campello et al., 2011; Chen & King, 2014), agency problems (Nance et al., 1993; Kumar & Rabinovitch, 2013; Huang et al., 2013), managerial incentives (Smith & Stulz, 1985; Bakke et al., 2016), lower information asymmetry (DeMarzo & Duffie, 1991), and financial flexibility (Francis & Gao, 2018; Graham & Rogers, 2002).

[2] Other studies note that ITIs increase the level and marginal value of cash holdings (Huang et al., 2019), influence corporate innovation strategies (Kong et al., 2019), and motivate tax aggressiveness (Kubick & Lockhart, 2016).

[3] Firm performance is considered by outsiders to be one of the major indicators of CEO capability (Fee & Hadlock, 2003).

[4] The compensation of the second-highest-paid CEO, instead of that of the highest-paid CEO, is used in the literature to mitigate the outlier effect.

textual analysis of 10-K statements (e.g., Almeida et al., 2017; Hoberg & Moon, 2017; Manconi et al., 2017; Qiu, 2019). We apply three keyword lists related to foreign exchange (FX), interest rate (IR), and commodity (CMD) hedging to generate binary variables to measure the likelihood to hedge. We also use the number of words related to financial hedging in 10-K statements to measure hedging intensity. The assumption we make here regarding the hedging proxy, which is generated by counting words, is that the more intensely a firm expresses its hedging policies, the more actively it manages them.

Consistent with the *risk management hypothesis*, we find a positive association between ITIs and hedging practices, suggesting that a CEO who is motivated by higher visibility and status, a larger compensation package, and a greater span of control is more likely to engage in hedging activities. This result is consistent with findings by Graham and Rogers (2002), Knopf et al. (2002), and Kumar and Rabinovitch (2013), which find a CEO with an incentive-based compensation including more option delta hedges more.[5]

We also explore the possible reasons why a CEO motivated by the external CEO labor market might hedge more. Findings by Kubick et al. (2020) and Kubick and Lockhart (2021) suggest that the corporate policies of a CEO who is motivated by ITIs lead to a higher cost of borrowing and a higher stock price crash risk. Hedging, however, can lower financing costs by alleviating cash flow variability (Smith & Stulz, 1985). Furthermore, it is shown that firms can reduce their stock return exposure to exchange rate shocks through hedging (e.g., Allayannis & Ofek, 2001; Bartram et al., 2010; Chang et al., 2013). Thus, we test the impact of hedging tools on the effects of ITIs on both the cost of debt and the stock price crash risk. We find that hedging has a mitigating role on the amplifier impacts of ITIs on both the cost of debt and the stock price crash risk. Consistent with Levine's (2005) arguments, these results suggest that a CEO incentivized by ITIs uses hedging instruments as a buffer, thereby alleviating the anticipated negative impacts of their riskier corporate policies.

In this study, we use the instrumental variable approach to identify the causal association between ITIs and corporate hedging. Also, following Huang et al. (2019), we utilize the change in the enforceability of noncompetition employment agreements within states as an exogenous shock. By implementing the difference-in-differences (DID) method, we find that the increase in enforceability lessens ITIs' positive effect on corporate hedging as the number of competitors increases; this is consistent with Huang et al. (2019).

Our study contributes to the literature in the following ways. First, to the best of our knowledge, this paper is the first to examine the effects of ITIs on hedging behavior. Bakke et al. (2016) investigate the causal effect of the risk-taking incentives stemming from option compensation on corporate risk management policy; in comparison, we focus on convex payoffs that are driven by the external CEO labor market instead of those driven by options in a CEO's compensation package. Second, most of the previous studies examine a specific industry or a few industries (e.g., the oil and gas industries), investigating their corporate risk management policies using a limited sample (Carter et al., 2006; Gilje & Taillard, 2017; Haushalter, 2000; Jin & Jorion, 2006; Kumar & Rabinovitch, 2013; Mackay & Moeller, 2007; Tufano, 1996). Our sample contains data from a relatively larger number of firms from various different industries; this enables us to deduce the general implications of firms' hedging attitudes and how they are influenced by ITIs.

We also contribute to the literature by finding another channel through which a CEO who is influenced by ITIs may impact firm performance. Allayannis and Weston (2001), Carter et al. (2006), Mackay and Moeller (2007), Smith and Stulz (1985), and Gilje and Taillard (2017) detect a positive relation between hedging and firm performance. Thus, CEOs might be induced to hedge more in order to increase the probability that they will move up in the tournament by improving their firm's performance. Lastly, we explore the possible reasons behind the positive association between ITIs and hedging, namely, the need to mitigate the amplifying impact of risk-inducing ITIs on the cost of debt and stock price crash risk.

The rest of this paper is organized as follows. In Section 2, we discuss our hypotheses before describing our sample and the construction of our variables in Section 3. In Section 4, we examine the relation between ITIs and corporate hedging; we then investigate the effect of ITIs on different types of hedging and search for possible reasons behind the

[5] However, Bakke et al. (2016) find that a reduction in option pay may actually result in an increase in hedging intensity.

association between ITIs and corporate hedging. In Section 5, we examine the heterogeneities in the relation, whereas Section 6 contains the conclusions to our findings. Appendices A, B, C, and D provide more detailed information about our variables, including their definitions and how they are calculated.

2 | LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Hedging is a risk management tool used by firms to shield against unpredicted shocks, which can have a potentially harmful impact on contingent firm values. The primary benefit of hedging is to secure adequate and stable internal cash flows and to protect a firm from the inefficient liquidation of its investment. In perfect capital markets, which form the neoclassical view of risk management, risk management does not have any real impact on firm economics (Modigliani & Miller, 1958). However, more recent hedging theories, which take into account market imperfections, support the idea that hedging has real effects on firms. The major real benefits of hedging are enhancing firm value (Allayannis & Weston, 2001; Carter et al., 2006; Mackay & Moeller, 2007), mitigating the underinvestment problem (Froot et al., 1993; Geczy et al., 1997), and lowering the cost of capital (Campello et al., 2011; Chen & King, 2014; Gay et al. 2011; Smith & Stulz, 1985). Furthermore, corporate hedging also provides financial benefits, such as improving financial flexibility (Francis & Gao, 2018), reducing financial distress (Mayers & Smith, 1982; Smith & Stulz, 1985), and lowering contracting costs (Mayers & Smith, 1987).

Motivations behind corporate hedging that go beyond its real and financial benefits have also been investigated. These include engaging in tax reduction (Dionne & Garand, 2003; Graham & Smith, 1999; Smith & Stulz, 1985), addressing agency problems (Huang et al., 2013; Kumar & Rabinovitch, 2013; Nance et al., 1993), taking advantage of economies of scale (Mian, 1996), and dealing with information asymmetry (DeMarzo & Duffie, 1991). Managerial incentives also play an essential role in corporate hedging; for example, Bakke et al. (2016) find a significantly negative relation between CEO vega and hedging intensity.[6] However, the effect of ITIs (which are also viewed as managerial incentives) on corporate hedging has not yet been scrutinized.

Initiated by Lazear and Rosen (1981), promotion-based tournament theory suggests that if it is costly to monitor and measure the efforts and outputs of employees, compensating them based on their positions in the firm can be an optimal compensation scheme inducing them to expend a greater effort. Compensating high-level employees based on their ordinal ranks promotes competition among them; this may influence their policy choices, including how they deal with riskier firm activities (Coles et al., 2017; Goel & Thakor, 2008; Hvide, 2002; Kini & Williams, 2012), the acquisition policies (Nguyen and Phan, 2015), the aggressiveness of their approach to taxes (Kubick & Lockhart, 2016), their innovation strategies (Kong et al., 2019; Shen and Zhang, 2018), and their incrementation of cash holdings (Huang et al., 2019).[7]

2.1 | Risk incentive hypothesis

In this study, we focus on tournaments among CEOs, in which they compete for a CEO position in their industry's leading firm. The winning CEO moves up, eventually assuming the position of CEO in the leading firm. CEOs compete for such a position because it includes a larger compensation scheme, an enlarged span of control, higher visibility, and higher status (Coles et al., 2017). Tournaments have been theoretically and empirically shown to serve as a risk incentive (Coles et al., 2017; Goel & Thakor, 2008; Hvide, 2002; Kini & Williams, 2012). That is, CEOs tend to engage

[6] The findings of Bakke et al. (2016) are consistent with those of Coles et al. (2006), who show a positive association between CEO vega (which is mainly driven by option pay) and firm risk level.

[7] We focus on CEOs' impact on risk management policies because the extant literature shows that CEOs significantly influence firms' financial policies (Tufano, 1996; Coles et al., 2006; Chava & Purdanandam, 2010).

in riskier activities in an attempt to catch up with the leading firm and in order to increase the probability that they will win the tournament. Thus, CEOs are expected to be less risk averse as they are induced by more ITIs. However, Smith and Stulz (1985) claim that managers are risk averse due to being undiversified (compared to shareholders); as such, they are likely to hedge in order to diminish their exposure to the firm (Giambona et al., 2018). Because ITIs act as risk-seeking incentives, they discourage a CEO from engaging in corporate hedging.

Further, tournament incentives are option-like because the winner of the tournament earns the tournament prize, whereas the other participants receive nothing; thus, they provide a convex managerial payoff (Kini & Williams, 2012). The risk incentives of managerial option pay have been shown to have a negative impact on corporate hedging (Bakke et al., 2016; Haushalter, 2000; Smith & Stulz, 1985; Tufano, 1996). Consequently, the convexity inherent in option-like tournaments can discourage CEOs from corporate hedging. All these arguments support the idea of a negative relation between ITIs and corporate hedging; we refer to this hypothesis as the *risk incentive hypothesis*.

2.2 | Risk management hypothesis

There are several reasons why CEOs are likely to hedge more while experiencing higher ITIs (henceforth, we will refer to this as the *risk management hypothesis*). First, hedging can facilitate an increase in firm value and mitigate the unfavorable effects of ITIs on the cost of borrowing and stock price crash risk. CEOs induced by higher ITIs are empirically shown to exert more effort to improve their firm's standings (Coles et al., 2017). The reason for the positive relation between ITIs and firm value can be that firm performance is considered by outsiders to be one of the major indicators of CEO capability (Fee & Hadlock, 2003). Several studies support the idea that corporate hedging has a positive effect on firm value (e.g., Allayannis & Weston, 2001; Carter et al., 2006; Mackay & Moeller, 2007). Therefore, a CEO induced by ITIs might be more inclined to use hedging instruments to enhance firm value in order to increase the probability of moving up in the tournament. ITIs have been shown to increase stock price crash risk (Kubick & Lockhart, 2021) and the cost of debt (Kubick et al., 2020), both of which can negatively affect firm value. At the same time, however, hedging derivatives have been shown to reduce stock price crash risk (Kim et al., 2021) and the cost of external financing (Campello et al., 2011; Chen & King, 2014). Therefore, CEOs may hedge more as a means of alleviating the adverse impact of ITIs on firm value.[8]

Second, hedging makes the application of riskier policies by a CEO motivated by ITIs more possible. The *risk management hypothesis* is also consistent with Levine (2005), who observes that financial derivatives facilitate the pursuance of high-risk–high-return projects. Because ITIs are likely to motivate CEOs to choose riskier projects (Coles et al., 2017), hedging can enable them to implement said projects without harming firm value. Third, CEOs might prefer hedging, treating it as a means of positively influencing the labor market's perception of their managerial ability (DeMarzo & Duffie, 1995; Froot et al., 1993) or as a way to separate themselves from lower-ability managers (Breeden & Viswanathan, 2016). In addition, CEOs can hedge to satisfy shareholders; Campbell and Kracaw (1987) note that, because shareholders expect hedging to enhance managerial productivity, they want managers to hedge observable and unsystematic risks.

Lastly, Smith and Stulz (1985) indicate that, because managers have concave utility, they are risk averse, which induces them to hedge. The convexity in managerial payoff mitigates the risk aversion that discourages CEOs from hedging. However, Carpenter (2000) and Ross (2004) provide evidence that the convexity in managerial compensation might not afford sufficient risk-seeking incentives, which can deter them from hedging. Hence, the *risk management hypothesis* predicts a positive association between ITIs and corporate hedging.

Overall, the relation between ITIs and corporate hedging is likely to depend on CEOs' incentives to induce risk, preferences, and career concerns. On the one hand, if a CEO is not too risk averse, the *risk incentive hypothesis* suggests

[8] Similarly, findings by Francis and Gao (2018) provide some evidence that the reduction in the cost of debt through hedging is because firms can stabilize their cash flows through hedging, thus enabling them to use internal cash flows as an alternative to costly external capital financing.

that a CEO motivated by ITIs, which are also risk incentives, can refrain from using hedging instruments. On the other hand, the *risk management hypothesis* can dominate (i) if the positive effect of hedging on firm value attracts a CEO to hedging; (ii) if they prefer to hedge as a buffer against unpredicted adverse shocks; (iii) if they want to improve outsiders' perceptions of their ability; (iv) if they need to differentiate themselves from managers with only limited ability; or (v) if they are so highly risk averse that ITIs cannot induce them to engage in risky activities.

Furthermore, this paper is similar in some aspects to the study by Bakke et al. (2016), which examines the impacts of options pay on corporate hedging. However, there are differences in the samples, factors, and hedging measures used. First, they focus on practices in the oil and gas industry; because earnings in this industry are exposed to commodity prices, commodity hedging is very common. Although the literature indicates that commodity price exposure is a significant risk factor for the oil and gas industry, it does not have a significant impact on an aggregate level (Bartram, 2005; Nelson et al., 2005).[9] Second, the incentives arising from the tournaments are different from the performance-based executive incentives (delta and vega) that arise from CEO compensation structures. The basic difference is that performance-based incentives tie an executive's future earnings to their current performance (Becker & Stigler, 1974), whereas tournament prizes are promised in advance (Lazear & Rosen, 1981). The probability of moving up to a leading firm has been extensively proven to incentivize CEOs and to impact firm policies (e.g., Coles et al., 2017; Kini & Williams, 2012). CEOs place more importance on upward mobility in their labor market than on their current compensation schemes in influencing their corporate decisions (Graham et al., 2005). Moreover, in order to test the impact of ITIs on corporate hedging, we control for the performance-based and risk-taking incentives (CEO delta and CEO vega) that arise from their holdings and grants of stocks and options. Third, textual analysis enables us to obtain a much larger sample, covering a longer period of time.[10]

3 | DATA SOURCES, VARIABLE CONSTRUCTION, AND SAMPLE DESCRIPTIONS

3.1 | Data sources

Our sample is constructed from the intersection of 10-K filings, Compustat, and ExecuComp databases starting from the fiscal year 1997 up to 2016.[11] CEO compensation data are taken from ExecuComp, stock returns from CRSP, and firm characteristics from Compustat. Following the convention in the finance literature, we exclude financial (SIC codes 6000–6999) and utility firms (SIC codes 4900–4999). We obtain 10-K statements from the U.S. Securities and Exchange Commission (SEC) EDGAR filings to compute the text-based hedging measures.[12] The FF30 industry classification is taken from the Fama–French data library.[13]

Additionally, we gather information on loans from the Loan Pricing Corporation's (LPC) DealScan. We require that loans are U.S. dollar denominated. Following Bharath et al. (2009) and Kubick et al. (2020), we merge lagged variables from Compustat and ExecuComp with DealScan loan contracts and ensure that lenders observe firm characteristics and compensation variables prior to loan origination.[14] We use loan-spread information to examine the channels through which ITIs influence corporate hedging.

[9] Similarly, we could not find a significant difference in the percentage of firm-year observations of oil-and-gas firms that choose to hedge versus those of non-oil-and-gas firms. This is because we also include FX and IR hedging along with CMD hedging.

[10] Bakke et al. (2016) have a sample of 154 firm-year observations from 2003 to 2006, whereas our sample includes 19,705 firm-year observations from 1997 to 2016. The large sample enhances the generality and power of our results. Moreover, in their analysis, Huang et al. (2013) detect a high correlation between the notional values of hedging derivatives and hedging proxies based on the number of hedging-related words in the 10-K.

[11] SEC EDGAR filings started in 1994, but the full coverage of public firms was not available until 1997. Thus, we start our sample period from 1997 in order to obtain full coverage.

[12] We use an R package to download and parse 10-Ks provided by Lonare et al. (2020).

[13] The data are available at Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/Siccodes30.zip.

[14] We thank Michael Roberts for sharing the linking table (Chava & Roberts, 2008).

The details about stock price crash risk variables are defined in Appendix C, whereas the computation of expected default frequency (EDF) is provided in Appendix D. Changes in state-level noncompetition enforceability laws are obtained from Garmaise (2011), Jeffers (2019), and Huang et al. (2019).[15] We also extend these data to cover the 2014–2016 period.

3.2 | Measures of ITIs

We follow Coles et al. (2017) to measure ITIs as the total compensation difference (ExecuComp data item *TDC1*) between the CEO under consideration and the second-highest-paid CEO in the same industry.[16] Following Coles et al. (2017), we use FF30 industry group and FF30 size-median industry group to compute the CEO industry pay gap.[17] We denote the CEO industry pay gap as *INDGAP1* for the FF30 industry group and as *INDGAP2* for the FF30 size-median industry group. Specifically, ITIs are computed as follows:

$$\begin{aligned} INDGAP1 \ \ (\text{or } INDGAP2) = & \text{ Total compensation of the second highest-paid CEO in the same FF30} \\ & (\text{or FF30 size-median}) \ \ \text{industry} - \text{Total compensation of the CEO under consideration.} \end{aligned}$$

We also use the natural logarithm of *INDGAP1* (*INDGAP2*), denoted as *LN_INDGAP1* (*LN_INDGAP2*), in our regression tests to mitigate the influence of outliers. The higher value of *LN_INDGAP1* (*LN_INDGAP2*) for a CEO-year observation indicates that the CEO is facing higher ITIs.

3.3 | Hedging measures

Financial Accounting Standard (FAS) 133, implemented on June 15, 2000, requires firms to disclose the fair market value of derivatives, but not notional values. Without any information on the notional values of hedging instruments, any measurement of the extent of corporate derivative holdings could be undermined (Graham & Roger, 2002). Thus, we generate a general proxy for corporate hedging that can be used across all industries. Being aware of the limitations of corporate hedging measures, we develop our hedging measures based on a textual analysis of 10-K statements following the recent corporate hedging literature (Almeida et al., 2017; Hoberg & Moon, 2017; Manconi et al., 2017; Qiu, 2019, among others).

We first downloaded 10-K (and its variants) filings from the SEC EDGAR server and searched for hedging-related keywords. We applied three keyword lists related to FX, IR, and CMD hedging to generate binary variables (proxies for the likelihood to hedge) and the number of counts (proxies for hedging intensity). A binary variable is set to 1 if a firm mentions the use of related hedging instruments in its 10-K. We also generate the count variables for each hedging type. We then combine binary or count variables to form aggregated hedging variables. The binary variable *HEDGE* takes a value of 1 if a firm mentions the use of any hedging activity (FX hedge, CMD hedge, or IR hedge) in its 10-K for a given year; it is set to 0 otherwise. *HEDGE count* is a count of the total number of times a firm mentions the use of any hedging instruments in its 10-K. Following the hedging literature, we use the natural logarithm of one plus hedge count, *ln(1+ HEDGE count)*, as a measure of hedging intensity in our regression tests.

[15] As Compustat backfills headquarters state based on the most recent business address, we use the Loughran–McDonald augmented 10-X header data to identify a firm's headquartered state at any given fiscal year. These data are available at https://sraf.nd.edu/data/augmented-10-x-header-data.

[16] As discussed in Coles et al. (2017), we consider the second highest-paid CEO in the industry when computing ITIs for each year in order to eliminate the outlier effect of any abnormally highest-paid CEOs in the industry.

[17] Firm size is considered in the literature when benchmarking compensation (e.g., Faulkender & Yang, 2010; Bizjak et al., 2011; Coles et al., 2017). Following Coles et al., 2017, we partition each FF30 industry-year sample into two groups: below median firm size and above median firm size (here, firm size is measured by net sales).

While employing our text-based hedging variables, we assume that firms expressing their hedging policies more intensely in their 10-Ks manage them more actively. It is then possible that the external job market motivates a CEO to mislead their investors by discussing hedging activities more intensely. This concern is mitigated by Huang et al. (2013), who detect a high correlation (between 42% and 67%) between the notional values of hedging derivatives and text-based hedging variables. Additionally, Francis and Gao (2018) attribute their use of text-based binary hedging variables to inconsistencies in the notional amount of derivative usage.[18] A detailed discussion about hedging-related word lists and the formation of our hedging variables is provided in Appendix B.

3.4 | Instrumental variables

ITIs are recognized as endogenous in the tournament incentives literature. We use instruments for the industry pay gap from Coles et al. (2017) and Huang et al. (2019). Our first instrumental variable is the sum of total compensation received by all other CEOs in the same industry, except the highest-paid CEO. As discussed in Coles et al. (2017), total industry CEO compensation reflects an industry's ability to pay its CEOs; it is expected to be highly correlated with the industry pay gap. However, this industry-level total compensation variable is unlikely to be correlated with firm-level corporate hedging activities. Following Huang et al. (2019), our second instrument is the number of higher-paid CEOs in the same industry group in a given year: *#Higher paid ind CEOs*. An increase in the number of higher-paid CEOs in the same industry is likely to increase the pay gap between the CEO under consideration and the highest-paid CEO in the industry. Thus, using the number of higher-paid CEOs in the same industry as an instrument for ITIs is likely to satisfy the relevance condition. In our regression models, we mainly use the natural logarithms of *Ind CEO comp* and *#Higher paid ind CEOs* as instruments for our ITIs variable in order to minimize any problems associated with outliers.

Following Coles et al. (2017), we use another instrument—the average total compensation received by all other CEOs who work at firms that are in different industries but that are headquartered within a 250-km radius of the firm under consideration: *Geo CEO mean*. We use *Geo CEO mean* and *#Higher paid ind CEOs* variables alternately in our instrumental variable estimations.

3.5 | Control variables

Kale et al. (2009) and Kini and Williams (2012) show that the pay gap between the CEO and other executives is positively related to firm riskiness and performance. Thus, following the literature (Kale et al., 2009; Coles et al., 2017; Huang et al., 2019; Kini & Williams, 2012), we control for firm-level internal promotion–based incentives. We compute *Firm gap*, the proxy of firm-level internal promotion–based incentives, as the difference between the CEO's total compensation and the median of vice presidents' total compensation. CEO incentives have been documented as being determinants of corporate risk management (e.g., Bakke et al., 2016; Smith & Stulz, 1985; Tufano, 1996). Thus, we also include *CEO delta* and *CEO vega* in the regression, where *CEO delta* is defined as the change in executive wealth per \$1000 change in stock price, and *CEO vega* indicates the change in the value of a CEO's wealth when the annualized standard deviation of stock returns changes by 0.01.[19] We also control for CEO age and tenure, as these factors can

[18] We find an 85% correlation between the binary *HEDGE* measure and the binary corporate hedging variable used by Chen and King (2014). Additionally, effective in 2001, FAS 133 requires that unrealized holding gains and losses from changes in the fair value of the cash flow hedge are to be reported in the accumulated other comprehensive income data (Campbell et al., 2015; Bonaimé et al., 2014). This information is reported in Compustat (Item *AOCIDERGL*), which has full coverage starting from 2004. We categorize a firm as a hedging firm if *AOCIDERGL* is nonmissing, finding a 94% correlation with our binary *HEDGE* measure.

[19] Following Coles et al. (2006, 2013), we use the Black–Scholes option-valuation model modified by Merton (1973) to account for dividends, and use the estimates in Bettis et al. (2005) to model how the holding period of stock options varies with volatility. We use the SAS code provided by Coles et al. (2013) to compute both CEO delta and CEO vega.

affect a firm's hedging strategies (Croci et al., 2017). Following Coles et al. (2017), we also control for the number of CEOs (firms) in the industry each year.

Following corporate hedging literature, we include firm-level control variables that affect corporate risk management. We control for firm size, investment in R&D expenditures scaled by total assets, book leverage scaled by total assets, growth opportunities (Tobin's *Q*), investment in fixed assets (capital expenditures scaled by total assets), profitability (return on assets [ROA]), asset tangibility (net property, plant, and equipment scaled by total assets), cash holdings scaled by total assets, leverage, cash flow volatility, financial distress (*Z*-score), and firm age. Following Almeida et al. (2017), we also control for inventory (inventory divided by the costs of goods sold) and trade credit (account payables divided by total assets). Additionally, following Purnanandam (2008), we control for *Nondebt Tax Shield*, which is the depreciation and amortization scaled by total assets. Detailed variable definitions and data sources are provided in Appendix A.

Following Kale et al. (2009) and Coles et al. (2017), we require the firm-year observations to have *Firm gap* and *INDGAP1 (INDGAP2)* variables greater than 0. In all our regression models, as hedging behavior is industry specific, we include both year and industry fixed effects. We also show that our results are consistent by using year and CEO-firm fixed effects in Table 4. All dollar amounts are CPI-adjusted to the 2006 dollar value.

3.6 | Summary statistics

Table 1 shows summary statistics for our variables: binary and count hedging variables (Panel A), incentive variables (Panel B), firm characteristics (Panel C), CEO characteristics (Panel D), industry and instrument variables (Panel E), crash risk measures and related controls (Panel F), bank loan characteristics (Panel G), and macroeconomic controls (Panel H).

As shown in Table 1, the mean values of the binary variables *HEDGE*, *FX hedge*, *IR hedge*, and *CMD hedge* are 0.692, 0.505, 0.448, and 0.140, respectively. As the proxies of ITIs (using the second-highest CEO pay within FF30 industry classifications as the benchmark), the mean (median) of the industry pay gap, *INDGAP1*, is $25 million ($17.7 million), whereas the size-median industry pay gap, *INDGAP2*, is $14.5 million ($8.1 million). The internal pay gap, *Firm gap*, has a mean (median) value of $3.1 million ($2 million), which is smaller than *INDGAP1*. The sizes of *INDGAP1*, *INDGAP2*, and *Firm gap* are similar to the sizes reported in Coles et al. (2017). The means (medians) of *CEO delta* and *CEO vega* are $800 ($198) and $123 ($48), respectively. The means (medians) of *CEO tenure* and *Ind # CEOs* are 7.85 (5.67) and 110.4 (81), respectively. The median CEO age is 55.

Finally, the means of the measures of stock price crash risk, *CRASH*, *NCSKEW*, and *DUVOL*, are 0.356, 0.656, and 0.239, respectively, whereas the mean (median) of *Loan spread* is 179 (150) basis points.

4 | RESULTS

4.1 | ITIs and corporate hedging

In this section, we examine the relation between ITIs and corporate hedging. We use two different corporate hedging variables. The first proxy for corporate hedging is the binary *HEDGE* variable, which is equal to 1 if a firm engages in hedging activity (either FX, IR, or CMD) in a given fiscal year, and set to 0 otherwise. The second dependent variable is *HEDGE count*, which is the number of hedging-related words. The formation of these two variables is based on a textual analysis of 10-K statements. A detailed discussion of hedging and all other variables is given in Appendices A and B.

We perform ordinary least squares (OLS), Probit, two-stage least squares (2SLS), and instrumental variable (IV) Probit estimations. We employ Probit, 2SLS, and IV Probit models for regressions where the dependent variable is the binary variable *HEDGE*, and use OLS and 2SLS models for regressions where the dependent variable is *HEDGE count*.

TABLE 1 Descriptive statistics

	N	Mean	SD	25th percentile	Median	75th percentile
A. Hedging variables						
HEDGE	19,705	0.692	0.462	0.000	1.000	1.000
HEDGE count	19,705	13.934	19.238	0.000	6.000	21.000
FX hedge	19,705	0.505	0.500	0.000	1.000	1.000
FX count	19,705	6.439	10.605	0.000	1.000	10.000
IR hedge	19,705	0.448	0.497	0.000	0.000	1.000
IR count	19,705	5.875	10.378	0.000	0.000	8.000
CMD hedge	19,705	0.140	0.347	0.000	0.000	0.000
CMD count	19,705	1.264	4.747	0.000	0.000	0.000
Scaled HEDGE count	19,688	0.048	0.061	0.000	0.026	0.075
FRWD HEDGE	19,688	0.035	0.078	0.000	0.000	0.043
BCWD HEDGE	19,688	0.596	0.729	0.000	0.339	0.955
B. Incentives variables						
INDGAP1 ($000)	19,705	24,997.486	26,506.094	10,271.997	17,669.775	29,627.477
INDGAP2 ($000)	19,402	14,508.217	20,316.610	4000.878	8126.845	17,353.416
LN_INDGAP1	19,705	9.754	0.865	9.237	9.780	10.296
LN_INDGAP2	19,402	8.833	1.767	8.333	9.022	9.772
Firm gap ($000)	19,705	3107.064	3388.223	859.562	2005.303	4084.390
CEO delta ($000)	19,705	800.005	7593.010	75.889	197.679	523.493
CEO vega ($000)	19,705	123.054	225.854	13.112	47.867	135.808
C. Firm characteristics						
Total assets ($000,000)	19,705	5291.627	16,204.687	469.233	1226.968	3646.080
R&D/Assets	19,705	0.035	0.058	0.000	0.005	0.048
Leverage	19,705	0.203	0.169	0.036	0.192	0.318
Tobin's Q	19,705	2.013	1.291	1.207	1.614	2.329
CAPX/Assets	19,705	0.053	0.050	0.020	0.036	0.066
ROA	19,705	0.136	0.096	0.091	0.134	0.185
MTB	19,705	2.040	1.284	1.239	1.641	2.348
Cash/Assets	19,705	0.164	0.176	0.031	0.097	0.241
PPE/Assets	19,705	0.261	0.216	0.096	0.195	0.364
Cashflow vol	19,705	0.047	0.040	0.022	0.036	0.057
Z-score	19,705	1.819	1.608	1.158	1.922	2.691
Merton EDF (%)	16,502	0.259	2.354	0.000	0.000	0.000
Naive EDF (%)	16,502	0.210	1.775	0.000	0.000	0.000
Firm age (years)	19,705	27.870	19.169	13.000	22.000	40.000
Nondebt tax shield	19,705	0.044	0.026	0.027	0.039	0.055

(Continues)

TABLE 1 (Continued)

	N	Mean	SD	25th percentile	Median	75th percentile
Inventory	19,705	0.189	0.181	0.038	0.159	0.272
Trade credit	19,705	0.076	0.066	0.032	0.058	0.098
Asset maturity	19,692	7.764	5.684	3.708	6.177	10.319
Rated dummy	13,822	0.672	0.469	0.000	1.000	1.000
D. CEO characteristics						
CEO founder	19,705	0.074	0.263	0.000	0.000	0.000
CEO retire	19,705	0.071	0.257	0.000	0.000	0.000
CEO tenure (years)	19,705	7.849	7.250	2.701	5.671	10.674
CEO age (years)	19,705	55.442	7.178	51.000	55.000	60.000
E. Industry and instrument variables						
Ind # CEOs	19,705	110.406	75.866	44.000	81.000	185.000
Ind CEO comp ($000)	19,705	485,622.942	358,818.902	157,455.906	454,482.375	792,448.813
Geo CEO mean ($000)	19,705	5208.993	1715.009	4172.117	4972.411	5946.660
#Higher paid ind CEOs	19,705	52.953	50.446	15.000	34.000	77.000
F. Crash risk measures and related controls						
CRASH	15,449	0.356	0.479	0.000	0.000	1.000
NCSKEW	15,449	0.656	1.736	−0.387	0.276	1.115
DUVOL	15,449	0.239	0.600	−0.127	0.131	0.445
DTURN	15,449	0.000	0.004	−0.001	0.000	0.002
SIGMA	15,449	0.058	0.037	0.034	0.047	0.068
RET	15,449	−0.002	0.009	−0.005	−0.001	0.003
OPAQUE	15,449	0.220	0.111	0.182	0.223	0.254
G. Bank loan characteristics						
Loan spread (bps)	13,822	179.076	136.246	75.000	150.000	250.000
Loan maturity (months)	13,822	48.799	21.934	36.000	60.000	60.000
Covenant count	13,822	1.532	1.419	0.000	2.000	3.000
Loan Secured	13,822	0.449	0.497	0.000	0.000	1.000
Performance pricing	13,822	0.498	0.500	0.000	0.000	1.000
No. of Lenders	13,822	9.753	8.728	4.000	7.000	13.000
Loan amount ($000,000)	13,822	511.807	1034.501	100.000	250.000	525.000
Term loan	13,822	0.262	0.440	0.000	0.000	1.000
Revolver loan	13,822	0.708	0.455	0.000	1.000	1.000
Bridge loan	13,822	0.021	0.145	0.000	0.000	0.000
General purpose loan	13,822	0.428	0.495	0.000	0.000	1.000
Takeover/recap loan	13,822	0.127	0.333	0.000	0.000	0.000
Working capital loan	13,822	0.155	0.362	0.000	0.000	0.000

(Continues)

TABLE 1 (Continued)

	N	Mean	SD	25th percentile	Median	75th percentile
H. Macroeconomic controls						
Credit spread	13,822	0.011	0.006	0.008	0.010	0.012
Term spread	13,822	0.023	0.013	0.010	0.023	0.036
Crisis dummy	13,822	0.095	0.293	0.000	0.000	0.000
Postcrisis dummy	13,822	0.356	0.479	0.000	0.000	1.000

Note: This table presents summary statistics for ExecuComp firms that have information on all the required variables, excluding financials and utility firms, from the period 1997 to 2016. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity in a given year and set to 0 otherwise. *HEDGE* count is a count of the number of times a firm mentions the use of any hedging instruments in its 10-K statement. The details on the hedging variables are discussed in Appendix B. All the other variables are defined in Appendix A. All the continuous variables are winsorized at 1% and 99%.

We cluster standard errors by firms. All regressions incorporate year and industry fixed effects so as to control for heterogeneity by year and industry. The reason why we control for industry fixed effects is that each industry has its own risk management characteristics. Additionally, following Coles et al. (2017) and Huang et al. (2019), we check the robustness of the relation between ITIs and corporate hedging using CEO-firm and year-fixed effects in Table 4.

Coles et al. (2017) discuss that the analysis of ITIs is unlikely to be contaminated by an endogeneity issue because board members are unlikely to control the external job market. However, because ITIs are defined as endogenous variables by both Coles et al. (2017) and Huang et al. (2019), we perform both instrumental and lagged variable analyses. The instruments used to examine the relation between ITIs and corporate hedging are *ln(Ind CEO comp)* (the natural logarithm of the sum of the total compensation paid to all other CEOs in the same FF30 or FF30 size-median industry classifications) and *ln(#Higher paid ind CEOs)* (the natural logarithm of the total number of CEOs who are paid a higher compensation within the same FF30 or FF30 size-median industry classifications).

We report our findings regarding Probit, OLS, 2SLS, and IV Probit regressions in Table 2, where the industry pay gap is based on the FF30 industry classification. The coefficients shown in the Probit and IV Probit models (Columns 1 and 6) are marginal effects at means. Columns 1, 4, and 6 show the results when using binary *HEDGE* as the dependent variable, and Columns 2 and 5 present the results when using *HEDGE count* as the dependent variable. Columns 1 and 2 show the results relating to the Probit model and the OLS model, respectively, whereas Columns 3–5 illustrate the results relating to the 2SLS model, and Column 6 presents the results relating to the IV Probit model. The exogeneity tests in the 2SLS and IV Probit regressions in columns 4, 5, and 6 reject the null hypothesis of exogeneity at the 5% or 10% significance level, which validates the endogeneity of the variable *LN_INDGAP1*. Column 3 illustrates the results related to the first stage of the 2SLS regression. The significance of the coefficients on the two IVs and the significance of the *F*-statistics indicate that the relevance criterion has been satisfied by the instrumental variables. We also test the validity of the instruments through the overidentification test: Hansen's *J*-test *p*-values are 0.315 and 0.836 for the dependent variables *HEDGE* and *HEDGE count*, respectively, which suggest that the instruments used are unlikely to influence firm-level corporate hedging policy directly. We have similar results for *LN_INDGAP2*, based on the FF30 size-median industry classification in Table 3.

The coefficients on *LN_INDGAP1* in Table 2 and *LN_INDGAP2* in Table 3 are positive and statistically significant for all the Probit (Column 1), OLS (Column 2), 2SLS (Columns 4 and 5), and IV Probit (Column 6) regressions at the 1% significance level.[20] The positive effect of ITIs on corporate hedging activity is also economically significant. For instance, for the FF30 industry classification, in Table 2 (Column 5), a one standard deviation increase in *LN_INDGAP1* is associated with a 14% (0.865×0.164) increase in *HEDGE count* in the next year.[21] When we account for the fact that Huang

[20] Except the coefficient on *HEDGE* variable for the Probit model in Table 3, which is significant at the 5% level.

[21] Similarly, for the FF30 size-median industry classification, in Table 3 (Column 5), a one standard deviation increase in *LN_INDGAP2* is associated with a 17% (1.767×0.099) increase in *HEDGE count* in the next year.

TABLE 2 Industry tournament incentives and corporate hedging (based on FF30 industry)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$LN\_INDGAP1_t$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$HEDGE_{t+1}$
Predicted $LN\_INDGAP1_t$				**0.059*****	**0.164*****	**0.201*****
$LN\_INDGAP1_t$	**0.042*****	**0.096*****				
	(4.656)	(3.806)				
$ln(Firm\ gap_t)$	0.025***	0.069***	0.056***	0.026***	0.077***	0.082***
	(3.871)	(3.878)	(9.700)	(4.155)	(4.256)	(4.216)
$ln(CEO\ delta_t)$	0.005	0.003	0.005	0.004	0.003	0.015
	(0.724)	(0.170)	(1.505)	(0.629)	(0.147)	(0.698)
$ln(CEO\ vega_t)$	−0.005	−0.008	0.004	−0.003	−0.007	−0.015
	(−1.077)	(−0.571)	(1.391)	(−0.654)	(−0.524)	(−1.020)
$ln(CEO\ tenure_t)$	−0.012	−0.036	0.003	−0.011	−0.036	−0.036
	(−1.524)	(−1.642)	(0.634)	(−1.460)	(−1.625)	(−1.515)
$ln(CEO\ age_t)$	0.010	−0.133	−0.037	0.005	−0.131	0.032
	(0.163)	(−0.757)	(−1.251)	(0.088)	(−0.749)	(0.173)
$ln(Total\ assets_t)$	0.062***	0.282***	0.001	0.056***	0.287***	0.189***
	(6.332)	(10.515)	(0.127)	(6.768)	(10.789)	(6.490)
$R\&D_t/Assets_t$	0.359*	1.120**	−0.131	0.411**	1.142**	1.089**
	(1.905)	(2.105)	(−1.610)	(2.256)	(2.162)	(1.961)
$Leverage_t$	0.362***	1.431***	0.062**	0.335***	1.421***	1.061***
	(6.541)	(9.145)	(2.436)	(7.015)	(9.072)	(6.537)
$Tobin's\ Q_t$	−0.023***	−0.048**	0.004	−0.024***	−0.048**	−0.069***
	(−3.287)	(−2.535)	(1.095)	(−3.488)	(−2.564)	(−3.319)

(Continues)

TABLE 2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$LN\_INDGAP1_t$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$HEDGE_{t+1}$
$CAPX_t/Assets_t$	0.246	0.800	−0.017	0.156	0.768	0.691
	(1.385)	(1.622)	(−0.174)	(0.976)	(1.560)	(1.312)
ROA_t	0.056	−0.087	−0.052	0.073	−0.063	0.193
	(0.576)	(−0.355)	(−1.034)	(0.790)	(−0.255)	(0.673)
$Cash_t/Assets_t$	−0.203***	−0.609***	0.033	−0.216***	−0.608***	−0.599***
	(−3.535)	(−3.844)	(1.360)	(−3.850)	(−3.842)	(−3.525)
$PPE_t/Assets_t$	−0.176**	−0.541**	−0.050	−0.137**	−0.538**	−0.516**
	(−2.391)	(−2.515)	(−1.635)	(−2.061)	(−2.509)	(−2.369)
$Cashflow\ vol_t$	−0.286	−0.896*	0.176*	−0.324*	−0.901*	−0.856
	(−1.578)	(−1.843)	(1.950)	(−1.815)	(−1.858)	(−1.593)
$Z\text{-}score_t$	−0.004	0.014	0.006**	−0.004	0.012	−0.014
	(−0.551)	(0.696)	(1.979)	(−0.498)	(0.596)	(−0.650)
$ln(1+Firm\ age_t)$	−0.041***	−0.098**	−0.003	−0.035***	−0.097**	−0.120***
	(−2.669)	(−2.374)	(−0.520)	(−2.721)	(−2.360)	(−2.657)
$Nondebt\ tax\ shield_t$	−0.039	0.457	0.215	−0.053	0.432	−0.150
	(−0.104)	(0.445)	(1.181)	(−0.152)	(0.421)	(−0.135)
$Inventory_t$	0.118**	0.280*	0.011	0.116**	0.276*	0.345**
	(2.046)	(1.729)	(0.506)	(2.189)	(1.704)	(2.015)
$Trade\ credit_t$	0.063	0.636	0.020	0.061	0.642	0.195
	(0.424)	(1.496)	(0.316)	(0.469)	(1.514)	(0.443)
$ln(Ind\ \#\ CEOs_t)$	−0.145**	−0.402***	−1.309***	−0.129***	−0.413***	−0.445***
	(−2.548)	(−2.621)	(−25.893)	(−2.604)	(−2.690)	(−2.617)

(Continues)

TABLE 2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	$HEDGE_{t+1}$	$ln(1{+}HEDGE\ count_{t+1})$	$LN\_INDGAP1_t$	$HEDGE_{t+1}$	$ln(1{+}HEDGE\ count_{t+1})$	$HEDGE_{t+1}$
ln(Ind CEO comp$_t$) (IV)			1.580***			
			(65.136)			
ln(#Higher paid ind CEOs$_t$) (IV)			0.421***			
			(33.724)			
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,631	19,631	19,631	19,631	19,631	19,631
Adj. R-squared		0.272	0.801	0.169	0.271	
Pseudo R-squared	0.146					
Endogeneity, relevance, and overidentification tests						
Exogeneity test (Hausman/Wald p-value)				0.071*	0.031**	0.041**
First-stage F-statistics				6427.804***	6427.804***	
Hansen J-test (p-value)				0.315	0.836	

Note: This table presents the results of OLS and instrumental variables (IV) estimation of ITIs on corporate hedging with year and industry fixed effects. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The details on these hedging variables are discussed in Appendix B. *LN_INDGAP1* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 industry (FF30) and the CEO's total compensation. In the first stage, we regress *LN_INDGAP1* variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same FF30 industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. Models (1), (4), and (6) present marginal effects of Probit (IVProbit) models at the mean. T (Z)-statistics (in parentheses) are computed using robust standard errors corrected for clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3 Industry tournament incentives and corporate hedging (based on FF30 size-median industry)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	*HEDGE*$_{t+1}$	*ln(1+HEDGE count*$_{t+1}$*)*	*LN_INDGAP2*$_t$	*HEDGE*$_{t+1}$	*ln(1+HEDGE count*$_{t+1}$*)*	
Predicted ***LN_INDGAP2***$_t$				**0.022*****	**0.099*****	**0.072*****
				(2.833)	(3.988)	(2.664)
LN_INDGAP2$_t$	**0.008****	**0.028*****				
	(2.357)	(2.849)				
ln(Firm gap$_t$*)*	0.025***	0.076***	0.303***	0.030***	0.105***	0.094***
	(3.881)	(4.136)	(16.860)	(4.320)	(5.127)	(4.348)
ln(CEO delta$_t$*)*	0.006	0.006	0.015	0.005	0.007	0.017
	(0.749)	(0.288)	(1.178)	(0.747)	(0.370)	(0.797)
ln(CEO vega$_t$*)*	−0.006	−0.013	0.006	−0.004	−0.013	−0.019
	(−1.252)	(−0.887)	(0.706)	(−0.923)	(−0.934)	(−1.264)
ln(CEO tenure$_t$*)*	−0.011	−0.036*	0.009	−0.010	−0.037*	−0.033
	(−1.372)	(−1.647)	(0.578)	(−1.358)	(−1.662)	(−1.405)
ln(CEO age$_t$*)*	0.008	−0.116	−0.046	0.002	−0.121	0.020
	(0.125)	(−0.655)	(−0.454)	(0.041)	(−0.688)	(0.109)
ln(Total assets$_t$*)*	0.055***	0.262***	0.368***	0.043***	0.234***	0.145***
	(5.434)	(9.418)	(23.617)	(4.647)	(7.790)	(4.316)
R&D$_t$*/Assets*$_t$	0.334*	1.106**	0.872***	0.383**	1.100**	0.990*
	(1.768)	(2.069)	(3.266)	(2.088)	(2.074)	(1.769)
Leverage$_t$	0.363***	1.451***	−0.184**	0.338***	1.442***	1.071***
	(6.513)	(9.235)	(−2.133)	(7.016)	(9.202)	(6.576)
Tobin's Q$_t$	−0.023***	−0.049**	0.052***	−0.025***	−0.050***	−0.070***
	(−3.346)	(−2.577)	(4.059)	(−3.603)	(−2.676)	(−3.416)

(Continues)

TABLE 3 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$LN\_INDGAP2_t$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	
$CAPX_t/Assets_t$	0.286	0.970**	−0.387	0.206	0.972**	0.845
	(1.621)	(1.968)	(−1.090)	(1.287)	(1.980)	(1.614)
ROA_t	0.050	−0.102	−0.392**	0.069	−0.074	0.167
	(0.518)	(−0.412)	(−2.272)	(0.749)	(−0.298)	(0.586)
$Cash_t/Assets_t$	−0.202***	−0.601***	0.062	−0.210***	−0.570***	−0.577***
	(−3.508)	(−3.781)	(0.687)	(−3.731)	(−3.597)	(−3.381)
$PPE_t/Assets_t$	−0.180**	−0.560***	−0.531***	−0.134**	−0.524**	−0.504**
	(−2.463)	(−2.615)	(−4.171)	(−2.028)	(−2.455)	(−2.327)
$Cashflow\ vol_t$	−0.300	−0.943*	1.018***	−0.355*	−1.049**	−0.963*
	(−1.637)	(−1.921)	(3.200)	(−1.957)	(−2.127)	(−1.768)
$Z\text{-}score_t$	−0.004	0.014	0.042***	−0.004	0.007	−0.016
	(−0.535)	(0.697)	(4.326)	(−0.588)	(0.352)	(−0.724)
$ln(1+Firm\ age_t)$	−0.042***	−0.102**	0.049**	−0.038***	−0.108***	−0.129***
	(−2.742)	(−2.452)	(2.186)	(−2.903)	(−2.580)	(−2.831)
$Nondebt\ tax\ shield_t$	−0.030	0.397	2.180***	−0.084	0.188	−0.227
	(−0.079)	(0.384)	(3.368)	(−0.238)	(0.181)	(−0.202)
$Inventory_t$	0.130**	0.331**	−0.222***	0.136**	0.359**	0.404**
	(2.234)	(2.052)	(−2.845)	(2.553)	(2.251)	(2.363)
$Trade\ credit_t$	0.041	0.570	0.983***	0.014	0.445	0.038
	(0.276)	(1.332)	(4.887)	(0.102)	(1.027)	(0.085)
$ln(Ind\ \#\ CEOs_t)$	−0.145***	−0.436***	0.043	−0.154***	−0.534***	−0.493***
	(−2.753)	(−2.833)	(0.231)	(−3.281)	(−3.386)	(−3.066)

(Continues)

TABLE 3 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS			Second stage
	Probit	OLS	First stage	Second stage	Second stage	IVProbit
Dependent variable	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$LN\_INDGAP2_t$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	
$ln(Ind\ CEO\ comp_t)$ (IV)			1.263^{***}			
			(14.806)			
$ln(\#Higher\ paid\ ind\ CEOs_t)$ (IV)			1.631^{***}			
			(36.908)			
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,274	19,274	19,274	19,274	19,274	19,274
Adj. *R*-squared		0.271	0.502	0.166	0.266	
Pseudo *R*-squared	0.145					
Endogeneity, relevance, and overidentification tests						
Exogeneity test (Wald/Hausman *p*-value)				0.006^{***}	0.000^{***}	0.029^{**}
First-stage *F*-statistics				3554.301^{***}	3554.301^{***}	
Hansen *J*-test (*p*-value)				0.065^{*}	0.217	

Note: This table presents the results of OLS and instrumental variables (IV) estimation of ITIs on corporate hedging with year and industry fixed effects. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The details on these hedging variables are discussed in Appendix B. *LN_INDGAP2* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 size-median industry and the CEO's total compensation. In the first stage, we regress *LN_INDGAP2* variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. Models (1), (4), and (6) present marginal effects of Probit (IVProbit) models at the mean. *T* (*Z*)-statistics (in parentheses) are computed using robust standard errors corrected for clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

et al. (2013) find a 42%–67% correlation between the notional values of hedging derivatives and hedging proxies, based on the number of hedging-related words in the 10-Ks, we can deduct that a one standard deviation increase in *LN_INDGAP1* leads to a 5.88% (14% × 42%) to 9.38% (14% × 67%) increase in the notional value of hedging.[22] Additionally, the marginal effect reported in Column 6 suggests that a one standard deviation increase in *LN_INDGAP1* increases *HEDGE* by 23% (0.201/0.865).[23]

Further to this, following Coles et al. (2017) and Huang et al. (2019), we test the relation between ITIs and corporate hedging using year and CEO-firm fixed effects. We perform a 2SLS regression analysis using binary *HEDGE* or *HEDGE count* variables. We use the two instruments *Ind CEO comp* and *Geo CEO mean*, where *Geo CEO mean* is the average total compensation received by all other CEOs who is employed at firms in different industries that are headquartered within a 250-km radius of the firm. We report the results of this test in Table 4. Columns 1–3 show the results relating to ITIs based on the FF30 industry classification, whereas Columns 4–6 illustrate the results relating to ITIs based on the FF30 size-median industry classification. Similar to the previous results, Hausman exogeneity tests confirm the endogeneity of ITIs proxies, high first-stage *F*-statistics show the relevance of the instruments, and overidentification tests (Hansen's *J*-test) indicate that the instruments are valid. Consistent with our earlier analyses, we find a significantly positive association between ITIs and corporate hedging at conventional levels.

These results are consistent with our *risk management hypothesis*, which suggests that the likelihood of hedging and the level of corporate hedging that takes place increases in line with the size of industry tournament prizes.[24] These results also confirm that a CEO influenced by ITIs is more inclined to hedge and that they tend to hedge more due to the positive effect doing so has on their career, rather than refraining from hedging as a result of being motivated for risk-taking activities. This indicates the dominance of the *risk management hypothesis* over the *risk incentive hypothesis*. Similarly, we detect a positive association between internal tournament incentives, *Firm gap*, and corporate hedging.[25] This result shows that other senior executives, too, tend to hedge to get an upward leap to CEO position when they are induced by within-firm tournaments among vice presidents. This is consistent with the argument by Chava and Purnanandam (2010), who state that senior executives below the rank of CEO can also influence financial policies.[26] Kini and Williams (2012) find that internal tournament incentives induce next-level senior executives to pursue riskier firm activities. However, contrary to these findings, we show that the advantages of hedging prevail over any risk incentives offered by an internal tournament.

Consistent with Graham and Rogers (2002), Knopf et al. (2002), and Kumar and Rabinovitch (2013), we find a positive (albeit statistically insignificant) association between CEO delta and corporate hedging in all regression models. This result is consistent with the arguments put forward by Smith and Stulz (1985) and Guay (1999), which note that a lack of diversification in a CEO's wealth may lead them to be more conservative and risk averse. The coefficients on *ln(CEO vega)* are negative (albeit statistically insignificant) in all the regressions shown in Tables 2 and 3. Coles et al. (2006), Rajgopal and Shevlin (2002), and Mao and Zhang (2018) report that CEO vega, which is defined as the sensitivity of managerial wealth to firm risk, maintains convexity in managerial compensation; as such, it incentivizes risk-taking activities. Thus, a CEO influenced by CEO vega may be inclined to abstain from hedging, which can stabilize the volatility of cash flows.

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[22] Similarly, as seen in Table 3 (Column 5), we can suggest that a one standard deviation increase in *LN_INDGAP2* leads to a 7% (17% × 42%) to 11% (17% × 67%) rise in the notional value of hedging.

[23] Similarly, for the FF30 size-median industry classification in Table 3, the marginal effect reported in Column 6 suggests that a one standard deviation increase in *LN_INDGAP2* increases *HEDGE* by 4% (0.072/1.767).

[24] To separate the impact of ITIs from the CEO incentives through their compensation package, we control for CEO pay incentives (delta and vega). We also test the difference between compensation schemes offered by high-ITIs industry firms and low-ITIs industry firms. We cannot find a significant difference between their total compensations and their components (salary, bonus, option, and stock pays) within the high- versus low-ITIs groups.

[25] In the untabulated coefficients on the controls shown in Table 4, we also have a significantly positive coefficient on *Firm gap*.

[26] The significance of the coefficients on job market incentives for both CEOs and lower ranked senior executives suggests that both types of executives have a significant effect on risk management policies.

TABLE 4 Industry tournament incentives and corporate hedging (with CEO-firm and year fixed effects)

	(1)	(2)	(3)	(4)	(5)	(6)
	ITIs based on FF30 industry classification			ITIs based on FF30 size-median industry classification		
	First stage	Second stage 2SLS		First stage	Second stage 2SLS	
Dependent variable	*$LN\_INDGAP1_t$*	*$HEDGE_{t+1}$*	*$ln(1+HEDGE\ count_{t+1})$*	*$LN\_INDGAP2_t$*	*$HEDGE_{t+1}$*	*$ln(1+HEDGE\ count_{t+1})$*
Predicted ***$LN\_INDGAP1_t$***		**0.040*****	**0.105*****			
		(2.818)	(2.628)			
Predicted ***$LN\_INDGAP2_t$***					**0.037****	**0.098****
					(2.544)	(2.293)
$ln(Ind\ CEO\ comp_t)$ (IV)	1.741***			1.690***		
	(54.779)			(15.581)		
$ln(Geo\ CEO\ mean_t)$ (IV)	−0.049**			0.019		
	(−2.409)			(0.295)		
$Controls_t$	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
CEO-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,899	18,899	18,899	18,555	18,555	18,555
Adj. *R*-squared	0.795	0.064	0.126	0.487	0.035	0.098
Endogeneity, relevance, and overidentification tests						
Exogeneity test (Hausman *p*-value)		0.004***	0.007***		0.014***	0.020**
First-stage *F*-statistics		2680.121***	2680.121***		249.123***	249.123***
Hansen *J*-test (*p*-value)		0.917	0.276		0.986	0.166

Note: This table presents the results of instrumental variables (IV) estimation of ITIs on corporate hedging with CEO-firm and year fixed effects. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The details on these hedging variables are discussed in Appendix B. *LN_INDGAP1* (*LN_INDGAP2*) is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same FF30 industry (FF30 size-median) and the CEO's total compensation. The controls are the same as in Table 2. In the first stage of 2SLS, we regress *LN_INDGAP1* (*LN_INDGAP2*) variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the average total compensation received by all other CEOs working in the firms in different industries that are headquartered within a 250-km radius of the firm, *Geo CEO mean*. All the other variables are defined in Appendix A. We include year fixed effects and CEO-firm fixed effects in all specifications. *T*-statistics (in parentheses) are computed using robust standard errors corrected for clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

We discover a positive relation, similar to that found in previous studies, between firm size and corporate hedging.[27] Nance et al. (1993) and Mian (1996) explain this link through the presence of fixed costs, which obstruct the feasibility of hedging for small firms. We also find a positive relation between leverage and corporate hedging. Nance et al. (1993) hypothesize that firms with higher leverage are more inclined to hedge due to possessing greater underinvestment problems. Furthermore, we observe that corporate hedging is positively related to R&D activities and firm inventory levels. A firm might decide to hedge while dealing with intense R&D activities, stockpiling more inventory so that it can mitigate the firm risk related to such activities. Additionally, we find a negative association between cash levels and hedging, which is consistent with findings by Francis and Gao (2018), whereas Holmstrom and Tirole (2000) assert that firms tend to hold liquid assets as buffers against shocks. Accordingly, as cash holding reduces the need for risk management, it functions as a substitute for hedging. The signs of the coefficients on the other control variables are mostly consistent with previous literature.

Overall, the findings are consistent with the *risk management hypothesis* that, when the industry tournament prize is high, CEOs are more likely to hedge and have a greater incentive to undertake more corporate-hedging activities, as these can potentially increase the probability that they will win the tournament.

4.2 | ITIs and different types of hedging

In this section, we investigate how ITIs affect the hedging of different types of risk, including FX, IR, and CMD risk. We employ the IV Probit regression model to analyze the dichotomous variables for each hedging type (*FX hedge*, *IR hedge*, and *CMD hedge*), testing the likelihood that a CEO will engage in hedging, and use the 2SLS regression model to account for continuous hedging variables (*FX count*, *IR count*, and *CMD count*), testing hedging intensity under the FF30 (*LN_INDGAP1*) and FF30 size-median (*LN_INDGAP2*) industry classifications. The instrumental variables used for IV Probit and 2SLS regressions are *Ind CEO comp* and *#Higher paid ind CEOs*. We report our findings in Table 5.

We explore a significantly positive association between ITIs and the likelihood and intensity of FX hedging, IR hedging, and CMD hedging at various conventional significance levels. However, we could not find a significant impact on the likelihood that a CEO will engage in hedging CMD risk.[28] These results illustrate that, consistent with the *risk management hypothesis*, as the tournament prize increases, so does the intensity of different hedging types.

4.3 | Possible reasons for the link between ITIs and corporate hedging

In this section, we examine possible reasons for the positive relation between ITIs and corporate hedging. Although Coles et al. (2017) report that ITIs, which are risk incentives, have a positive effect on firm value, some papers find that they have harmful effects as well. Kubick and Lockhart (2021) detect a positive relation between ITIs and stock price crash risk. They argue that CEOs who are more strongly motivated to progress in the CEO labor market

[27] This result is also consistent with the argument by Bandiera et al. (2020), who find more leadership behaviors and more CEO dominance to be evident in financial policy choices in multinational firms, public firms, and high-R&D industries, where risk management is essential.

[28] Possible reasons for the weak association between ITIs and the likelihood of CMD hedging might be as follows. Commodities are at the core of a firm's business, whereas IR and FX risks are more likely to be related to financial instruments. Therefore, a CEO might not be willing to change corporate traditions regarding how the firm's business is run. Also, in comparison with other types of derivatives, CMD derivatives involve carrying costs, which include interest, insurance, and storage costs. The CEO has to manage both CMD price risks and the costs associated with holding those commodities. Therefore, CMD hedging can be seen as more complicated in terms of the actions needed to manage risk. Further to this, Brogaard et al. (2019) show that index commodities damage firm performance following the financialization of commodity markets. Lastly, it is not always possible to find the same underlying commodity in the financial markets as the firm's own products. Therefore, perfect hedging related to commodity prices through financial markets can become impracticable. Hence, a CEO may not be motivated by the outside CEO labor market to hedge CMD risk. The INVERTO Raw Materials Study (Häfele, 2018), conducted with input from 112 managing directors, board members, and purchasing managers from companies in various European countries, found that hedging methods are only rarely used by the sample companies. This is due to a lack of hedging knowledge and skills, as well as the awareness that there are insufficient hedging instruments for most raw materials.

TABLE 5 Industry tournament incentives and different types of hedging activities

	Foreign exchange hedging				Interest rate hedging				Commodity hedging			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var	*FX hedge*$_{t+1}$		*ln(1+FX count*$_{t+1}$*)*		*IR hedge*$_{t+1}$		*ln(1+IR count*$_{t+1}$*)*		*CMD hedge*$_{t+1}$		*ln(1+ CMD count*$_{t+1}$*)*	
LN_INDGAP1$_t$	**0.111****		**0.049**		**0.088***		**0.095****		**0.001**		**0.086*****	
	(2.237)		(1.181)		(1.829)		(2.349)		(0.020)		(3.561)	
LN_INDGAP2$_t$		**0.088*****		**0.077*****		**0.028**		**0.046****		**0.020**		**0.021***
		(3.361)		(3.448)		(1.177)		(2.237)		(0.574)		(1.907)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,631	19,274	19,631	19,274	19,631	19,274	19,631	19,274	19,631	19,274	19,631	19,274
Adj. *R*-squared			0.278	0.275			0.246	0.244			0.332	0.336
Exogeneity test	0.632	0.005***	0.584	0.011***	0.325	0.578	0.269	0.035**	0.122	0.910	0.000***	0.070*
First-stage *F*-stat			6393.710***	3554.301***			6393.710***	3554.301***			6393.710***	3554.301***
Hansen *J*-test (*p*)			0.714	0.324			0.182	0.075*			0.008***	0.000***

Note: This table presents the results of the second stage of instrumental variables (IV) estimation of ITIs on different types of hedging instruments. *FX hedge*, *IR hedge*, and *CMD hedge* are dummy variables that are set equal to 1 if a firm is defined to use the foreign exchange hedging, interest rate hedging, and commodity hedging, respectively; set to 0 otherwise. *FX count*, *IR count*, and *CMD count* are the number of times a firm mentions its foreign exchange hedging, interest rate hedging, and commodity hedging, respectively, in the 10-K statement. The details on these hedging variables are discussed in Appendix B. *LN_INDGAP1* (*LN_INDGAP2)* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same FF30 (FF30 size-median) industry and the CEO's total compensation. The controls are the same as in Table 2. In the first stage, we regress *LN_INDGAP1* (*LN_INDGAP2*) variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. For dummy dependent variables, we report the marginal effects of IVProbit models at the mean. *T* (*Z*)-statistics (in parentheses) are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

tournament have a higher propensity to withhold negative firm-specific information. This inclination can result in large negative stock price corrections when the accumulated information is disclosed. However, Kim et al. (2021) document that hedging has a mitigating effect on stock price crash risk by lowering information asymmetry and enhancing transparency.

In addition, Kubick et al. (2020) find a positive association between ITIs and the cost of borrowing. They argue that greater risk-taking incentives associated with ITIs may result in higher-cost bank loans; this is because the increase in firm risk is harmful to creditors, who then try to protect themselves by charging higher interest rates. However, Smith and Stulz (1985) assert that hedging reduces the probability of distress by alleviating the likelihood of violating a covenant. Thus, hedging might provide the borrower with an opportunity to negotiate contract terms with lenders. Additionally, Campello et al. (2011) explore the negative association between hedging and the cost of debt, whereas Bessembinder (1991) has indicated that hedging can reduce the agency cost of benefiting shareholders at the expense of lenders by weakening the probability of default. Lastly, Stulz (1996) argues that firms hedge in order to assure against the possibility of costly lower-tail outcomes.

Further to this, hedging provides a shield against unpredicted shocks, securing adequate and stable internal cash flows and preventing a firm from inefficient liquidation. Thus, it has a mitigating impact on firm risk levels. Therefore, we argue that a CEO who anticipates the amplifying impact of ITIs on the cost of debt and stock price crash risk can use hedging derivatives to alleviate these effects, making the application of riskier policies more possible (Levine, 2005). To test whether hedging mitigates the amplifying effects of ITIs on the cost of debt and stock price crash risk, we analyze the models for subsamples of hedgers and nonhedgers. We define hedgers and nonhedgers based on the binary variable *HEDGE* (i.e., whether a firm mentions the use of hedging instruments in its 10-K). We also add hedge count variables and the interaction between hedge count variables and the industry pay gap into the regression models.

Following the literature on the stock price crash risk (e.g., Chen et al., 2001; Kim et al., 2011; Kim et al., 2016), we form *CRASH* (a dummy variable set to 1 if the firm has a weekly return that is less than 3.2 standard deviations below the average weekly return for the entire fiscal year), *DUVOL* (the natural logarithm of the ratio of the standard deviation of weekly returns for below-average weeks to the standard deviation of weekly returns for above-average weeks, over the fiscal year), and *NCSKEW* (the negative conditional skewness of firm-specific weekly returns during the entire fiscal year).[29]

Table 6 shows the impact of hedging on the relation between ITIs and stock price crash risk. Columns 1–6 show the results relating to the subsample analyses of hedgers and nonhedgers, whereas Columns 7–9 show the interaction between *LN_INDGAP1* and *HEDGE count*. The results indicate that the effect of ITIs on stock price crash risk is less pronounced for hedgers (Columns 2, 4, and 6) than it is for nonhedgers (Columns 1, 3, and 5). Additionally, the coefficients on the interaction between *LN_INDGAP1* and *ln(1+HEDGE count)* are significantly negative in Columns 7 and 8 at the 5% and 10% levels, respectively.

Following Kubick et al. (2020), we measure the cost of debt as the amount the firm pays in basis points above the LIBOR, plus any additional fees for each dollar drawn down from the loan facility. For the impact of hedging on the relation between ITIs and the cost of debt, we employ the 2SLS regression model. The instruments used are *Ind CEO comp* and *#Higher paid ind CEOs*. Table 7 illustrates the results of the investigation into the effect of hedging on the association between ITIs and the cost of borrowing. Columns 1 and 2 illustrate the results relating to the subsample hedger analyses, whereas Columns 3 and 4 report on the nonhedger analyses. The results indicate that the effect of ITIs on the cost of borrowing is less pronounced, both in terms of significance and magnitude, for hedgers than it is for nonhedgers.

[29] The details about the proxies of stock price crash risk are in Appendix C.

TABLE 6 The effect of ITIs on stock price crash risk differing in hedging activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							Full sample with the interaction of ITIs on hedging		
	Nonhedgers	Hedgers	Nonhedgers	Hedgers	Nonhedgers	Hedgers			
	$CRASH_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$
Dependent variable	Tobit	Tobit	OLS	OLS	OLS	OLS	Tobit	OLS	OLS
$LN\_INDGAP1_t$	**0.101*****	**0.025**	**0.055*****	**0.025****	**0.159*****	**0.065****	0.085***	0.050***	0.126***
	(2.640)	(0.945)	(3.099)	(2.249)	(3.201)	(2.132)	(3.208)	(4.293)	(3.857)
$LN\_INDGAP1_t$ * ln(1+HEDGE count$_t$)							**−0.017****	**−0.007***	**−0.014**
							(−2.009)	(−1.912)	(−1.417)
ln(1+HEDGE count$_t$)							0.188**	0.075**	0.158
							(2.249)	(2.076)	(1.605)
ln(Firm gap$_t$)	0.047**	0.019	0.030***	0.009	0.080***	0.026	0.030**	0.018***	0.049***
	(2.193)	(1.118)	(2.849)	(1.136)	(2.738)	(1.211)	(2.289)	(2.817)	(2.801)
ln(CEO delta$_t$)	0.057***	0.000	0.031***	0.015**	0.116***	0.048**	0.024*	0.022***	0.076***
	(2.766)	(0.023)	(3.226)	(2.099)	(4.230)	(2.372)	(1.944)	(3.851)	(4.675)
ln(CEO vega$_t$)	−0.019	−0.026***	−0.010	−0.020***	−0.037*	−0.061***	−0.027***	−0.018***	−0.056***
	(−1.188)	(−2.594)	(−1.353)	(−4.297)	(−1.744)	(−4.867)	(−3.167)	(−4.453)	(−5.204)
ln(CEO tenure$_t$)	−0.050*	0.039**	−0.018	0.014*	−0.054*	0.036	0.008	0.003	0.004
	(−1.952)	(2.206)	(−1.573)	(1.671)	(−1.701)	(1.603)	(0.538)	(0.411)	(0.228)
ln(CEO age$_t$)	−0.271*	−0.028	−0.090	0.012	−0.236	0.102	−0.124	−0.025	−0.024
	(−1.705)	(−0.233)	(−1.271)	(0.226)	(−1.159)	(0.687)	(−1.268)	(−0.576)	(−0.198)
$DTURN_t$	4.030	2.351	0.015	1.724	1.598	5.367	3.132	1.115	3.959
	(0.949)	(0.676)	(0.008)	(1.230)	(0.283)	(1.356)	(1.153)	(0.965)	(1.214)
$NCSKEW_t$	0.015	0.001	0.003	−0.005	0.006	−0.010	0.007	−0.002	−0.003
	(0.863)	(0.084)	(0.367)	(−0.933)	(0.263)	(−0.623)	(0.688)	(−0.451)	(−0.206)

(Continues)

TABLE 6 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							Full sample with the interaction of ITIs on hedging		
	Nonhedgers	Hedgers	Nonhedgers	Hedgers	Nonhedgers	Hedgers			
	$CRASH_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$
Dependent variable	Tobit	Tobit	OLS	OLS	OLS	OLS	Tobit	OLS	OLS
$SIGMA_t$	1.220	0.617	0.576	0.978^{***}	1.718^{*}	2.637^{***}	0.969^{**}	0.884^{***}	2.412^{***}
	(1.542)	(1.041)	(1.641)	(3.841)	(1.717)	(3.725)	(2.043)	(4.296)	(4.208)
RET_t	17.090^{***}	10.176^{***}	10.384^{***}	8.329^{***}	28.502^{***}	22.877^{***}	12.966^{***}	9.137^{***}	25.199^{***}
	(5.859)	(4.361)	(8.198)	(8.612)	(7.982)	(8.243)	(6.945)	(11.883)	(11.450)
$OPAQUE_t$	-0.425^{***}	-0.415^{**}	-0.134^{**}	-0.153^{**}	-0.396^{**}	−0.303	-0.415^{***}	-0.142^{***}	-0.375^{***}
	(−2.621)	(−2.373)	(−2.216)	(−2.010)	(−2.337)	(−1.325)	(−3.483)	(−2.991)	(−2.928)
$ln(Total\ assets_t)$	-0.038^{*}	−0.013	0.004	0.013^{*}	−0.012	0.009	-0.022^{*}	0.009	0.001
	(−1.665)	(−0.834)	(0.404)	(1.868)	(−0.393)	(0.501)	(−1.657)	(1.579)	(0.036)
MTB_t	0.026^{*}	0.052^{***}	0.042^{***}	0.051^{***}	0.137^{***}	0.162^{***}	0.040^{***}	0.046^{***}	0.148^{***}
	(1.687)	(3.568)	(4.952)	(5.894)	(5.770)	(6.642)	(3.737)	(7.703)	(8.847)
$Leverage_t$	0.009	−0.015	−0.094	−0.057	−0.243	−0.118	−0.000	-0.058^{*}	−0.131
	(0.065)	(−0.162)	(−1.459)	(−1.431)	(−1.328)	(−1.077)	(−0.005)	(−1.726)	(−1.394)
ROA_t	0.332	0.749^{***}	0.163^{*}	0.386^{***}	0.096	0.762^{***}	0.562^{***}	0.292^{***}	0.491^{***}
	(1.590)	(4.086)	(1.744)	(4.588)	(0.357)	(3.155)	(4.118)	(4.751)	(2.814)

(Continues)

TABLE 6 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							Full sample with the interaction of ITIs on hedging		
	Nonhedgers	Hedgers	Nonhedgers	Hedgers	Nonhedgers	Hedgers			
	$CRASH_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	$CRASH_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$
Dependent variable	Tobit	Tobit	OLS	OLS	OLS	OLS	Tobit	OLS	OLS
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5127	10,283	5110	10,261	5110	10,261	15,410	15,372	15,372
Adj. *R*-squared			0.079	0.056	0.092	0.061		0.063	0.071
Pseudo *R*-squared	0.027	0.019					0.019		

Note: This table presents the results of OLS and Tobit estimation of the effect of ITIs on stock price crash risk in the firms differing in hedging activities. We use three measures of crash risk: *CRASH* is a dummy variable set to 1 if the firm has a weekly return that is less than 3.2 standard deviations below the average weekly return for the entire fiscal year; *DUVOL* is the natural logarithm of the ratio of the standard deviation of weekly returns for below-average weeks to the standard deviation of weekly returns for above-average weeks, over the fiscal year; *NCSKEW* is the negative conditional skewness of firm-specific weekly returns during the entire fiscal year. The details on these measures are discussed in Appendix C. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The details on these hedging variables are discussed in Appendix B. The subsample with *HEDGE* equals 1 is defined as *Hedgers*, and with *HEDGE* equals 0 is defined as *Nonhedgers*. *LN_INDGAP1* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 industry (FF30) industry and the CEO's total compensation. All the other variables are defined in Appendix A. Models (1), (2), and (7) present marginal effects of Tobit models at the mean. *T* (*Z*)-statistics (in parentheses) are computed using robust standard errors corrected for clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7 The effect of ITIs on loan spread differing in hedging activities

	Hedgers		Nonhedgers	
	(1)	(2)	(3)	(4)
Dependent variable	*ln(Loan spread$_t$)*			
Predicted *LN_INDGAP1$_{t-1}$*	**0.099***	**0.074****	**0.162*****	**0.187*****
	(1.896)	(1.977)	(2.671)	(2.748)
ln(CEO delta$_{t-1}$)	0.010	0.005	−0.020	−0.017
	(0.973)	(0.627)	(−1.513)	(−1.189)
ln(CEO vega$_{t-1}$)	−0.026***	−0.008	0.013	0.026**
	(−3.479)	(−1.340)	(1.084)	(1.996)
ln(Total assets$_{t-1}$)	−0.179***	−0.015	−0.232***	−0.024
	(−8.014)	(−0.831)	(−9.830)	(−0.667)
ln(MTB$_{t-1}$)	−0.171***	−0.131***	−0.171***	−0.120***
	(−7.298)	(−7.788)	(−9.103)	(−5.042)
Leverage$_{t-1}$	0.838***	0.486***	0.471***	0.246*
	(8.556)	(6.780)	(3.883)	(1.675)
ROA$_{t-1}$	−0.135	−0.116	−0.122	−0.077
	(−0.773)	(−0.886)	(−0.510)	(−0.236)
Asset maturity$_{t-1}$	−0.000	0.001	0.003	0.004
	(−0.026)	(0.225)	(0.599)	(0.702)
(PPE$_{t-1}$/Assets$_{t-1}$)	−0.480***	−0.253***	−0.616***	−0.483***
	(−4.213)	(−2.887)	(−4.162)	(−2.702)
Cashflow vol$_{t-1}$	2.650***	2.228***	1.931***	2.266***
	(6.828)	(7.272)	(3.732)	(3.541)
Z-score$_{t-1}$	−0.114***	−0.064***	−0.065***	−0.032
	(−6.212)	(−5.005)	(−3.447)	(−1.237)
Rated Dummy$_{t-1}$	0.102***	0.036	0.114***	0.075
	(3.231)	(1.563)	(2.724)	(1.508)
ln(Loan maturity$_t$)		0.171***		0.138***
		(10.419)		(5.777)
Loan Secured$_t$		0.445***		0.563***
		(22.127)		(14.824)
Covenant count$_t$		0.042***		0.031**
		(5.625)		(2.248)
Performance pricing$_t$		−0.148***		−0.049
		(−8.552)		(−1.438)
ln(No. of Lenders$_t$)		−0.016		0.039*
		(−1.351)		(1.722)
ln(Loan Amount$_t$)		−0.170***		−0.214***
		(−14.809)		(−8.490)

(Continues)

TABLE 7 (Continued)

	Hedgers		Nonhedgers	
	(1)	(2)	(3)	(4)
Dependent variable		*ln(Loan spread$_t$)*		
Term loan$_t$		−0.010		0.034
		(−0.148)		(0.340)
Revolver loan$_t$		−0.256***		−0.312***
		(−3.776)		(−2.934)
Bridge loan$_t$		0.440***		0.293*
		(4.835)		(1.727)
General purpose loan$_t$		0.009		0.028
		(0.376)		(0.665)
Takeover/Recap loan$_t$		0.100***		0.167***
		(3.595)		(3.247)
Working capital loan$_t$		0.053**		0.079*
		(2.206)		(1.679)
Credit spread$_t$	−14.463***	−9.873***	−4.386	−0.153
	(−6.056)	(−5.800)	(−1.184)	(−0.042)
Term spread$_t$	6.000***	7.554***	3.576***	3.620***
	(6.340)	(11.266)	(2.714)	(2.732)
Crisis dummy$_t$	0.150***	0.054	0.318***	0.197**
	(2.633)	(1.294)	(4.019)	(2.483)
Postcrisis dummy$_t$	0.622***	0.580***	0.818***	0.764***
	(17.718)	(19.457)	(19.201)	(13.687)
ln(Ind # CEOs$_{t-1}$)	0.239**	0.136*	−0.117	−0.215
	(2.341)	(1.723)	(−0.960)	(−1.597)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	8732	8732	2744	2744
Adj. *R*-squared	0.381	0.604	0.406	0.598
Endogeneity, relevance, and overidentification tests				
Hausman *p*-value	0.028**	0.033**	0.00***	0.00***
First-stage *F*-statistic	55.345***	55.183***	21.22***	21.22***
Hansen *J*-test (*p*-value)	0.000***	0.000***	0.000***	0.000***

Note: This table presents the results of the 2SLS estimation of the effect of ITIs on loan spread in the firms differing in hedging activities. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. The subsample with *HEDGE* equals 1 is defined as *Hedgers*, and with *HEDGE* equals 0 is defined as *Nonhedgers*. *LN_INDGAP1* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 industry (FF30) industry and the CEO's total compensation. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry (*Ind CEO comp*) and the total number of CEOs with higher total compensation within the same industry (*#Higher paid ind CEOs*). All the other variables are defined in Appendix A. The sample period is from 1997 to 2015. *T*-statistics (in parentheses) are computed using robust standard errors corrected for clustering at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Accordingly, these results provide supporting evidence that corporate hedging has a mitigating effect on the magnifying impact of ITIs on stock price crash risk and the cost of debt. These could be possible reasons why a CEO might use hedging tools, besides the reasons that fall under the *risk management hypothesis* discussed earlier.

5 | HETEROGENEITIES IN THE ASSOCIATION BETWEEN ITIs AND CORPORATE HEDGING

5.1 | Financial distress and the effect of ITIs on corporate hedging

In this section, we test how financial distress affects the relation between ITIs and hedging practices. As we find in Section 4.3, one of the possible reasons for a positive relation between ITIs and corporate hedging is that hedging decreases the adverse impact of ITIs on the cost of debt. In this context, hedging mitigates cash flow volatility, thus curtailing the probability of financial distress (Smith & Stulz, 1985). Therefore, hedging cuts down the likelihood of violating a covenant. Also, hedging can reduce the probability of default (Bessembinder, 1991) and mitigate the possibility of costly lower-tail outcomes (Stulz, 1996). Campello et al. (2011) establish that the mitigating impact of hedging on the cost of debt is stronger in firms that are near to being in distress. Lastly, Gilje (2016) finds that when firms approach financial distress, they tend to cut down on their investment risks.

Purdanandam (2008) empirically models the impact of financial distress on hedging. His model forecasts a nonlinear association between financial distress and hedging, and a U-shaped association between costs relating to financial distress and hedging. Consequently, it discovers a negative relation between leverage and hedging for highly leveraged firms, despite finding a positive relation between leverage and hedging for gently leveraged firms.[30] Therefore, we expect that a CEO working at a firm that is in financial distress is likely to influence hedging, but we do not predict the sign of this effect.

In our analysis, we use the modified Altman's (1968) *Z*-score, the Merton model expected default frequency (EDF), and the Naïve model expected default frequency (EDF) as proxies for firm-specific financial distress. The Merton EDF is computed following the Merton (1974) bond-pricing model, whereas Naïve EDF is computed based on the "simplified" Merton model used to measure the probability of default, following Bharath and Shumway (2008). (A detailed explanation of both the Merton and Naïve EDF models is given in Appendix D.) A lower Altman *Z*-score and higher EDF values indicate that a firm is experiencing financial distress.

Table 8 shows how financial distress impacts the relation between ITIs and corporate hedging. We report the results of the second stage of the IV Probit estimation of ITIs on *ln(1+HEDGE count)* across firms experiencing different levels of financial distress. The sample is grouped into two subsamples based on the sample-year median of the financial distress variables. The instruments used are *Ind CEO comp* and *#Higher paid ind CEOs*. The coefficients on *LN_INDGAP1* in Models 1, 3, and 5 are larger and significant at the 1% level, whereas those in Models 2, 4, and 6 are insignificant. Consistent with Purdanandam's (2008) argument, these findings suggest that the effect of ITIs on hedging is significantly less pronounced for financially distressed firms.

5.2 | CEO characteristics that affect CEO mobility

This section examines the effect of CEO characteristics (that would determine the likelihood that a CEO will move up in the tournament) on the relation between ITIs and corporate hedging. A retiring or a founding CEO (to whom the external job market might be less attractive) might have a lower motivation to transfer to a leading firm compared to other CEOs. Similarly, Coles et al. (2017) find that if a CEO is close to retirement or is the founder of their company,

[30] Purdanandam (2008) uses the leverage as a proxy for financial distress.

TABLE 8 Industry tournament incentives and corporate hedging (financial distress analysis)

	Altman's *Z*-score		Merton EDF		Naïve EDF	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low distress	High distress	Low distress	High distress	Low distress	High distress
Dependent variable			*ln(1+HEDGE count$_{t+1}$)*			
Predicted *LN_INDGAP1$_t$*	**0.216*****	**0.086**	**0.237*****	**0.034**	**0.237*****	**0.037**
	(3.727)	(1.370)	(3.596)	(0.549)	(3.589)	(0.585)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9817	9814	8270	8264	8271	8263
Adj. *R*-squared	0.182	0.127	0.123	0.122	0.122	0.122
Endogeneity, relevance, and overidentification tests						
Exogeneity test (*p*-value)	0.207	0.203	0.040**	0.560	0.039**	0.555
First-stage *F*-statistics	3567.209***	2883.911***	2559.888***	2583.875***	2562.866***	2582.746***
Hansen *J*-test (*p*-value)	0.375	0.958	0.808	0.942	0.819	0.933

Note: This table presents the results of second stage of instrumental variables (IV) estimation of ITIs on hedging varying across firms with different levels of financial distress. The dependent variable is the natural logarithm of one plus *HEDGE count* variable, which is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The sample is grouped in two subsamples based on whether a firm has below or above sample-year median Altman *Z*-score, Merton model expected default frequency (EDF), and Naïve model expected default frequency (EDF). The Altman's *Z*-score is the modified Altman's (1968) *Z*-score, where a below-median value indicates a higher likelihood of default (High distress). The Merton EDF is computed following the Merton (1974) bond pricing model, and the Naïve EDF is computed based on the "simplified" Merton model probability of default following Bharath and Shumway (2008). The above-median values of Merton and Naïve EDF indicate a higher likelihood of default (High distress). The details are in Appendix D. *LN_INDGAP1* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same FF30 industry and the CEO's total compensation. The controls are the same as in Table 2. In the first stage, we regress *LN_INDGAP1* variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the incentives to exert greater effort and engage in riskier corporate activities offered by the external CEO labor market vanish. Thus, we test how being at retirement age or being the founder of the firm influences whether a CEO's motivation to hedge can be affected by ITIs.

A CEO is defined as the founder CEO based on ExecuComp's title and as the retiring CEO if they are aged over 65 years. The full sample is partitioned into two subsamples, based on whether a CEO is a founder (or not) or whether they are of retirement age (or not). As shown in Table 9, the likelihood of hedging and the intensity of hedging activities significantly increase when a CEO is not a founder (Columns 2 and 4) or not of retirement age (Columns 6 and 8). Similar to Coles et al. (2017), we find that those effects disappear when a CEO is a founder (Columns 1 and 3) or of retirement age (Columns 5 and 7).

5.3 | The enforceability of noncompetition agreements

Noncompetition agreements in employment contracts are designed to mitigate the possibility that employees or executives will accept employment offers from their firm's competitors (Garmaise, 2011; Jeffers, 2019). Therefore, the enforceability of noncompetition agreements can reduce CEOs' ability to accept offers from the leading firms in their industry, thus decreasing the impact of ITIs. Because the effectiveness of these agreements relies on their ability to block executives' transfers, any modification in their enforceability builds a shock into ITIs (Garmaise, 2011); for example, an increase in the enforceability of a noncompetition agreement mitigates any motivation created by ITIs to engage in hedging under the *risk management hypothesis*. Such a consequence is primarily the result of a lesser need to hedge for career-enhancing purposes due to a decline in the probability that the CEO will benefit from incentives offered by the CEO external job market should they hedge in states where noncompetition agreements are strictly enforced.[31] Thus, the staggered changes in the enforceability of noncompetition agreements across states provide an identification strategy that can be used to examine a causal relation between ITIs and corporate hedging.

Following Garmaise (2011), Jeffers (2019), and Huang et al. (2019), we construct a variable *NON_COMPETE* that takes on the value of +1 for firms headquartered in Florida from 1997 to 2016, in Kentucky from 2007 to 2016, in Idaho and Oregon from 2009 to 2016, in Texas and Wisconsin from 2010 to 2016, in Colorado and Georgia from 2012 to 2016, in Illinois from 2012 to 2013, and in Virginia from 2014 to 2016. It takes the value of −1 for firms in Texas from 1995 to 2006, in Louisiana from 2002 to 2003, in South Carolina from 2011 to 2016, and in Montana from 2012 to 2016. It is set to 0 otherwise. We then interact the *NON_COMPETE* variable with the industry pay gap variable *LN_INDGAP1* (*LN_INDGAP2*). CEOs in those firms that enforce the noncompetition agreements have a lesser ability to move to the leading firms in their industry; therefore, we predict a negative coefficient on the interaction of *NON_COMPETE* and *LN_INDGAP1* (*LN_INDGAP2*).

Garmaise (2011) claims that the importance of within-state competition is enhanced for those firms exposed to a higher number of within-state competitors due to the limited geographic scope of noncompete covenants and the ease of imposing them within a state. Therefore, the impact of the exogenous shock on the relation between ITIs and corporate hedging caused by the enforceability of noncompetition agreements is likely to be more pronounced due to the high number of within-state competitors. Accordingly, we expect that the negative coefficient on the interaction of *NON_COMPETE* and *LN_INDGAP1* (*LN_INDGAP2*) will become significantly stronger when the number of in-state competitors rises.

[31] Noncompetition agreements are enforceable in the United States within a restricted geographical area (usually within a state); their effectiveness diminishes when crossing state boundaries (Germaise, 2011). The use of those agreements is common (Jeffers, 2019), providing us with a useful setting in which to implement our analysis. State rulings regarding the enforceability of noncompetition agreements vary in terms of the business type or area, executives' compensation levels, and/or the time span covered by the employment contract. State rulings on this matter are generally stable, but changes can still occur. A change in the enforceability of noncompetition agreements usually stems from changes in state laws or state-level court rulings, the latter of which annul any previous rules and practices, immediately altering an agreement's enforceability (Jeffers, 2019).

TABLE 9 Untangling the effect of ITIs on corporate hedging based on the likelihood of a CEO to move

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Founder CEO	Nonfounder CEO	Founder CEO	Nonfounder CEO	Retiring CEO	Nonretiring CEO	Retiring CEO	Nonretiring CEO
Dependent variable	*ln(1+HEDGE count$_{t+1}$)*		*HEDGE$_{t+1}$*		*ln(1+HEDGE count$_{t+1}$)*		*HEDGE$_{t+1}$*	
Predicted ***LN_INDGAP1$_t$***	**0.054**	**0.162*****	**0.069**	**0.196*****	**0.214**	**0.155*****	**0.218**	**0.195*****
	(0.411)	(3.431)	(0.336)	(3.766)	(1.437)	(3.288)	(1.202)	(3.753)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1446	18,185	1384	18,185	1400	18,231	1370	18,231
Adj. *R*-squared	0.361	0.269			0.349	0.270		
Endogeneity, relevance, and overidentification tests								
Exogeneity test (Hausman/Wald *p*-value)	0.448	0.047**	0.742	0.057**	0.133	0.086	0.233	0.067*
First-stage *F*-statistics	455.802***	5854.720***			299.324***	5954.125***		
Hansen *J*-test (*p*-value)	0.271	0.996			0.690	0.784		

We employ the DID approach to investigate the effect of the exogenous shock on the association between ITIs and corporate hedging. Firms based in states that have not experienced any judicial or regulatory variation act as a control group in the DID setting. Panel A of Table 10 reports the OLS estimates of the DID approach. We estimate our specification for three subsamples based on the number of in-state competitors each year, noting whether they are above the 25th, 50th, or 75th percentiles (5, 14, and 43 in-state competitors, respectively). As seen in Panel A of Table 10, the coefficient on *NON_COMPETE* × *LN_INDGAP1* is significantly negative only when the number of in-state competitors is above the 75th percentile. This is consistent with Garmaise (2011) and Huang et al. (2019), who confirm that any enhancement of noncompete enforceability is stronger when the number of rivals in a state rises.

We then perform a subsample analysis using IV Probit estimation. We partition our sample into two subsamples, based on whether or not a firm is headquartered in a state that has enforced a noncompetition agreement in a given year,[32] and report the results in Panel B of Table 10. The positive effect of ITIs on corporate hedging is shown to be significant only for the group that has not experienced the enforcement of a noncompetition law in its state in that year (i.e., where *ENFORCE* is equal to 0).

Overall, the results of the quasi-natural experiment examining changes in the enforceability of noncompete agreements identify a causal relation between ITIs and corporate hedging.

5.4 | Cross-industry variation in the effects of ITIs on corporate hedging

The CEO talent pool can be defined as the proportion of insider CEO hires, diversified across industries (Cremers & Grinstein, 2014). Parrino (1997) reports varying characteristics, across industries, that influence the CEO labor market; further to this, each industry may have a different approach to its risk management policies. Thus, we examine cross-industry variations in the incentivizing effects of CEO external job markets on corporate hedging.

In order to measure the relation between ITIs and corporate hedging in each industry, we re-estimate the second stage of the 2SLS regression model in Table 2 for each FF30 industry classification. Table 11 illustrates the coefficients on *LN_INDGAP1* for each industry. The industries that evidence the strongest ITI impacts on corporate hedging are Precious Metals, Non-Metallic and Industrial Metal Mining, and Business Equipment. We also observe significant positive relations between ITIs and corporate hedging in Aircraft, Ships, and Railroad Equipment, Petroleum and Natural Gas, Transportation, Retail, and Other Industries. However, we cannot determine any significant associations between ITIs and corporate hedging for the remainder of the industries. Generally speaking, there seems to be considerable variation in the effect of ITIs on corporate hedging across industries.

5.5 | Additional robustness tests

In this section, we employ additional measures to assess the industry tournament prize (industry pay gap), using different industry classifications. First, we scale the industry pay gap variable by the CEO's total compensation under the FF30 (FF30 size-median) industry classification: *Scaled_INDGAP1* (*Scaled_INDGAP2*). Further to this, we test the relation between ITIs and corporate hedging under the Fama–French 48 (FF48) and FF48 size-median industry classifications.

We report these robustness results in Table 12. As seen in Columns 1–4, our previous findings regarding the positive effects of ITIs in terms of the likelihood and intensity of corporate hedging persist even if we scale the industry pay gap variable using the CEO's total compensation. Moreover, we obtain similar results under the FF48 and FF48 size-median industry classifications; these are reported in Columns 5–8. Hence, our results are robust to using different measures of the industry pay gap and different industry classifications.

[32] We construct a variable, *ENFORCE*, which is set equal to 1 if a noncompetition agreement is enacted in the state for a given year; otherwise, it is set to 0.

TABLE 10 Effect of enforceability of noncompetition agreements on the relation between ITIs and corporate hedging

Panel A: OLS estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging						
	ITIs based on FF30 industry classification			ITIs based on FF30 size-median industry classification		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var = *ln(1+HEDGE count$_t$)*	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43
LN_INDGAP1$_t$* NON_COMPETE$_t$	**−0.077**	**−0.019**	**−0.248****			
	(−1.094)	(−0.254)	(−2.386)			
LN_INDGAP1$_t$	0.110***	0.085**	0.158**			
	(3.308)	(2.032)	(2.411)			
LN_INDGAP2$_t$* NON_COMPETE$_t$				**−0.027**	**0.010**	**−0.127****
				(−0.865)	(0.284)	(−2.418)
LN_INDGAP2$_t$				0.049***	0.057***	0.090***
				(3.442)	(3.111)	(3.162)
NON_COMPETE$_t$	0.755	0.221	2.606**	0.245	−0.049	1.260***
	(1.104)	(0.308)	(2.510)	(0.859)	(−0.153)	(2.593)
ln(Firm gap$_t$)	0.060***	0.066***	0.086***	0.071***	0.082***	0.102***
	(2.665)	(2.673)	(2.607)	(3.056)	(3.249)	(3.032)
ln(CEO delta$_t$)	−0.017	−0.018	0.017	−0.015	−0.016	0.016
	(−0.743)	(−0.634)	(0.432)	(−0.659)	(−0.575)	(0.419)
ln(CEO vega$_t$)	−0.017	−0.018	−0.027	−0.021	−0.022	−0.035
	(−0.942)	(−0.810)	(−0.816)	(−1.140)	(−0.967)	(−1.052)
ln(CEO tenure$_t$)	−0.007	−0.003	−0.085*	−0.003	0.001	−0.081*
	(−0.233)	(−0.097)	(−1.785)	(−0.111)	(0.016)	(−1.692)

(Continues)

TABLE 10 (Continued)

Panel A: OLS estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging						
	ITIs based on FF30 industry classification			ITIs based on FF30 size-median industry classification		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var = *ln(1+HEDGE count$_t$)*	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43
ln(CEO age$_t$)	−0.075	−0.190	0.040	−0.086	−0.206	−0.012
	(−0.342)	(−0.751)	(0.113)	(−0.392)	(−0.815)	(−0.034)
ln(Total assets$_{t-1}$)	0.314***	0.339***	0.338***	0.287***	0.310***	0.301***
	(9.733)	(9.222)	(7.278)	(8.494)	(8.026)	(6.007)
R&D$_{t-1}$/Assets$_{t-1}$	0.752	0.732	1.054	0.711	0.690	1.041
	(1.268)	(1.165)	(1.418)	(1.187)	(1.091)	(1.394)
Leverage$_{t-1}$	1.364***	1.167***	0.959***	1.378***	1.170***	0.938***
	(6.960)	(4.930)	(3.320)	(6.987)	(4.915)	(3.232)
Tobin's Q$_{t-1}$	−0.024	−0.032	−0.046*	−0.025	−0.033	−0.046*
	(−1.182)	(−1.428)	(−1.726)	(−1.233)	(−1.461)	(−1.682)
CAPX$_{t-1}$/Assets$_{t-1}$	−0.100	−0.226	−0.750	0.050	−0.144	−0.716
	(−0.166)	(−0.346)	(−0.835)	(0.081)	(−0.223)	(−0.832)
ROA$_{t-1}$	−0.161	−0.126	−0.022	−0.196	−0.160	−0.077
	(−0.539)	(−0.398)	(−0.056)	(−0.657)	(−0.504)	(−0.201)
Cash$_{t-1}$/Assets$_{t-1}$	−0.915***	−0.820***	−0.953***	−0.895***	−0.791***	−0.913***
	(−4.886)	(−3.781)	(−3.968)	(−4.761)	(−3.640)	(−3.800)
PPE$_{t-1}$/Assets$_{t-1}$	0.042	−0.079	0.393	0.019	−0.101	0.350
	(0.151)	(−0.245)	(0.906)	(0.069)	(−0.316)	(0.820)

(Continues)

TABLE 10 (Continued)

Panel A: OLS estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging						
	ITIs based on FF30 industry classification			ITIs based on FF30 size-median industry classification		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var = *ln(1+HEDGE count$_t$)*	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43	#In-state competitors > 5	#In-state competitors > 14	#In-state competitors > 43
Cashflow vol$_{t-1}$	−0.421	−0.823	−1.152	−0.464	−0.985	−1.462*
	(−0.732)	(−1.279)	(−1.358)	(−0.804)	(−1.532)	(−1.733)
Z-score$_{t-1}$	0.020	0.018	0.022	0.020	0.016	0.020
	(0.851)	(0.750)	(0.734)	(0.861)	(0.664)	(0.670)
ln(1+Firm age$_{t-1}$)	−0.178***	−0.183***	−0.338***	−0.181***	−0.182***	−0.337***
	(−3.393)	(−2.836)	(−3.446)	(−3.429)	(−2.827)	(−3.464)
Nondebt tax shield$_{t-1}$	−0.209	−0.084	0.611	−0.199	0.058	0.911
	(−0.169)	(−0.060)	(0.348)	(−0.160)	(0.042)	(0.531)
Inventory$_{t-1}$	0.037	0.015	0.006	0.057	0.039	0.032
	(0.195)	(0.067)	(0.021)	(0.301)	(0.177)	(0.119)
Trade credit$_{t-1}$	0.331	0.743	1.170	0.229	0.645	1.123
	(0.595)	(1.185)	(1.408)	(0.405)	(1.019)	(1.355)
ln(Ind # CEOs$_t$)	−0.391*	−0.255	−0.223	−0.338	−0.175	0.118
	(−−1.725)	(−0.795)	(−0.388)	(−1.559)	(−0.567)	(0.218)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,455	7700	3924	11,455	7700	3924
Adj. *R*-squared	0.293	0.314	0.353	0.293	0.316	0.356

(Continues)

TABLE 10 (Continued)

Panel B: IV estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging								
	ITIs based on FF30 industry classification				ITIs based on FF30 size-median industry classification			
	$HEDGE_{t+1}$		$ln(1{+}HEDGE\ count_{t+1})$		$HEDGE_{t+1}$		$ln(1{+}HEDGE\ count_{t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0
Predicted ***LN_INDGAP1***$_t$	**−0.184**	**0.221*******	**−0.046**	**0.176*******				
	(−1.178)	(4.236)	(−0.349)	(3.799)				
Predicted ***LN_INDGAP2***$_t$					**0.060**	**0.076*******	**0.075**	**0.101*******
					(0.797)	(2.734)	(1.265)	(4.001)
ln(Firm gap$_t$*)*	0.021	0.076***	0.039	0.072***	0.085	0.086***	0.098	0.096***
	(0.337)	(3.662)	(0.680)	(3.884)	(1.154)	(3.767)	(1.465)	(4.582)
ln(CEO delta$_t$*)*	−0.042	0.031	0.004	0.006	−0.041	0.035	0.011	0.012
	(−0.806)	(1.340)	(0.077)	(0.290)	(−0.784)	(1.495)	(0.223)	(0.564)
ln(CEO vega$_t$*)*	−0.019	−0.019	−0.015	−0.012	−0.025	−0.023	−0.024	−0.017
	(−0.518)	(−1.222)	(−0.482)	(−0.805)	(−0.679)	(−1.476)	(−0.759)	(−1.152)
ln(CEO tenure$_t$*)*	−0.052	−0.037	−0.041	−0.034	−0.039	−0.035	−0.045	−0.034
	(−0.777)	(−1.510)	(−0.727)	(−1.507)	(−0.570)	(−1.425)	(−0.785)	(−1.518)
ln(CEO age$_t$*)*	−0.031	0.005	−0.336	−0.120	−0.062	−0.007	−0.287	−0.125
	(−0.059)	(0.025)	(−0.777)	(−0.679)	(−0.116)	(−0.036)	(−0.666)	(−0.703)

(Continues)

TABLE 10 (Continued)

Panel B: IV estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging								
	ITIs based on FF30 industry classification				ITIs based on FF30 size-median industry classification			
	$HEDGE_{t+1}$		$ln(1+HEDGE\ count_{t+1})$		$HEDGE_{t+1}$		$ln(1+HEDGE\ count_{t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0
$ln(Total\ assets_t)$	0.351***	0.176***	0.365***	0.273***	0.349***	0.129***	0.342***	0.220***
	(4.659)	(5.823)	(5.784)	(9.997)	(4.353)	(3.699)	(5.063)	(7.089)
$R\&D_t/Assets_t$	−1.526	0.561	0.941	0.696	−1.488	0.461	1.179	0.645
	(−0.629)	(0.964)	(0.503)	(1.335)	(−0.621)	(0.786)	(0.638)	(1.230)
$Leverage_t$	1.451***	1.098***	1.647***	1.440***	1.394***	1.112***	1.625***	1.461***
	(3.238)	(6.593)	(4.203)	(9.160)	(3.102)	(6.643)	(4.132)	(9.232)
$Tobin's\ Q_t$	−0.088	−0.067***	−0.090*	−0.045**	−0.066	−0.069***	−0.080	−0.048**
	(−1.337)	(−3.130)	(−1.801)	(−2.359)	(−1.029)	(−3.279)	(−1.643)	(−2.519)
$CAPX_t/Assets_t$	1.454	0.538	0.103	0.785	1.369	0.772	0.308	0.997**
	(0.998)	(0.979)	(0.095)	(1.553)	(0.938)	(1.414)	(0.294)	(1.964)
ROA_t	−0.037	0.318	−0.473	0.053	−0.218	0.293	−0.592	0.061
	(−0.043)	(1.042)	(−0.740)	(0.209)	(−0.256)	(0.964)	(−0.920)	(0.239)
$Cash_t/Assets_t$	0.253	−0.836***	1.084**	−0.855***	0.365	−0.808***	1.172**	−0.818***
	(0.394)	(−4.770)	(2.042)	(−5.485)	(0.548)	(−4.585)	(2.138)	(−5.234)
$PPE_t/Assets_t$	−0.083	−0.488**	0.538	−0.565**	−0.116	−0.485**	0.483	−0.548**
	(−0.181)	(−2.055)	(1.292)	(−2.494)	(−0.249)	(−2.074)	(1.150)	(−2.433)
$Cashflow\ vol_t$	−1.293	−0.692	−1.656	−0.558	−1.939	−0.785	−2.045	−0.701
	(−0.853)	(−1.225)	(−1.323)	(−1.115)	(−1.285)	(−1.375)	(−1.567)	(−1.385)

(Continues)

TABLE 10 (Continued)

Panel B: IV estimation for enforceability of noncompetition agreements on the relation between ITIs and corporate hedging								
	ITIs based on FF30 industry classification				ITIs based on FF30 size-median industry classification			
	$HEDGE_{t+1}$		$ln(1{+}HEDGE\ count_{t+1})$		$HEDGE_{t+1}$		$ln(1{+}HEDGE\ count_{t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0	ENFORCE = 1	ENFORCE = 0
$Z\text{-}score_t$	0.028	−0.022	0.037	0.007	0.013	−0.024	0.026	0.002
	(0.441)	(−0.935)	(0.690)	(0.358)	(0.205)	(−0.985)	(0.489)	(0.101)
$ln(1{+}Firm\ age_t)$	−0.311***	−0.080*	−0.155*	−0.070	−0.323***	−0.089*	−0.165*	−0.078*
	(−2.665)	(−1.670)	(−1.786)	(−1.572)	(−2.724)	(−1.832)	(−1.892)	(−1.734)
$Nondebt\ tax\ shield_t$	−2.176	−0.299	−1.455	−0.021	−1.735	−0.412	−1.249	−0.317
	(−0.699)	(−0.263)	(−0.565)	(−0.020)	(−0.557)	(−0.357)	(−0.491)	(−0.303)
$Inventory_t$	−0.269	0.285	−0.316	0.247	−0.235	0.342*	−0.125	0.301*
	(−0.506)	(1.595)	(−0.792)	(1.513)	(−0.422)	(1.921)	(−0.294)	(1.851)
$Trade\ credit_t$	1.034	−0.148	2.122**	0.190	0.917	−0.308	1.939**	−0.009
	(0.897)	(−0.313)	(2.277)	(0.419)	(0.772)	(−0.637)	(2.021)	(−0.019)
$ln(Ind\ \#\ CEOs_t)$	0.752	−0.534***	0.178	−0.544***	0.628	−0.573***	0.119	−0.662***
	(1.208)	(−2.939)	(0.336)	(−3.389)	(1.044)	(−3.433)	(0.233)	(−4.099)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2296	17,335	2296	17,335	2242	17,032	2197	17,074
Adj. *R*-squared			0.224	0.190			0.229	0.185
Endogeneity, relevance, and overidentification tests								
Exogeneity test (Hausman/Wald *p*-value)	0.054*	0.027**	0.299	0.059*	0.814	0.017**	0.803	0.000***
First-stage *F*-statistics			671.124***	5911.474***			309.952***	3242.490***
Hansen *J*-test (*p*-value)			0.644	0.953			0.349	0.132

(Continues)

TABLE 10 (Continued)

Note: This table presents the results of OLS and instrumental variables (IV) estimation of ITIs on corporate hedging differing in the enforceability of noncompetition agreements. *NON_COMPETE* takes on the value of +1 for firms headquartered in Florida from 1997 to 2016, in Kentucky from 2007 to 2016, in Idaho and Oregon from 2009 to 2016, in Texas and Wisconsin from 2010 to 2016, in Colorado and Georgia from 2012 to 2016, in Illinois from 2012 to 2013, and in Virginia from 2014 to 2016; takes the value of −1 for firms in Texas from 1995 to 2006, in Louisiana from 2002 to 2003, in South Carolina from 2011 to 2016, and in Montana from 2012 to 2016; and is set to equal 0 otherwise. Panel A reports OLS estimation for three groups partitioned on the number of in-state competitors in the given year, greater than 5, 14, and 43 (25th, 50th, and 75th percentiles, respectively). Panel B reports the second stage of IV estimation where *ENFORCE* is set equal to 1 if the noncompetition agreement is enacted in the state for the given year, otherwise set to 0. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. *LN_INDGAP1* (*LN_INDGAP2*) is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 (FF30 size-median) industry and the CEO's total compensation. For Panel B, in the first stage, we regress industry pay gap variables on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. We use 2SLS model for *HEDGE count* variable and IVProbit model for indicator *HEDGE* variable. Models (1), (2), (5), and (6) in Panel B present marginal effects of IVProbit models at the mean. *T* (*Z*)-statistics (in parentheses) are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 11 Industry tournament incentives and corporate hedging in various industries

Fama–French 30 industry	Coefficient on predicted *LN_INDGAP1*$_t$	*T*-statistics	*N*
Food Products, Beer and Liquor, and Tobacco	0.158	(0.617)	667
Games & Recreation	0.173	(0.578)	299
Books, Printing, and Publishing	0.091	(0.294)	285
Household Consumer Goods	−0.271	(−0.587)	406
Clothing and Accessories	−0.885	(−1.509)	382
Healthcare, Medical Equip., & Pharmaceuticals	0.155	(0.558)	2093
Chemicals	−0.063	(−0.197)	674
Textiles	1.776	(1.552)	104
Construction and Construction Materials	−0.265	(−0.699)	723
Steel Works	0.103	(0.390)	411
Fabricated Products and Machinery	0.335	(1.190)	968
Electrical Equipment	0.189	(0.326)	288
Automobiles and Trucks	−0.190	(−0.475)	409
Aircraft, Ships, and Railroad Equipment	0.627**	(2.330)	161
Mines & Coal	1.278***	(2.667)	180
Oil, Petroleum, and Natural Gas	0.556**	(2.108)	960
Telecommunications	−0.526	(−1.363)	469
Personal and Business Services	0.301	(0.750)	2585
Business Equipment	0.580***	(2.590)	3126
Paper and Business Supplies	−0.377	(−1.360)	548
Transportation	0.646*	(1.825)	714
Wholesale	0.131	(0.240)	869
Retail	0.478*	(1.949)	1561
Restaurants, Hotels, and Motels	0.012	(0.040)	441
Others	0.783*	(1.951)	308

Note: This table presents the results of 2SLS estimation of ITIs on corporate hedging for different Fama–French 30 (FF30) industries. Due to a small number of firms, we combine firms in Food Products, Beer and Liquor, and Tobacco Products together. We also merge firms in Mines and Coal industry due to the same reason. We separately run our main model in Table 2 for each FF30 industry. We report the coefficients on the predicted *LN_INDGAP1* variable in the second-stage regression where the dependent variable is *ln(1+HEDGE count)*. *HEDGE* count is a count of the number of times a firm mentions the use of any hedging instruments in its 10-K statement. *LN_INDGAP1* is the natural logarithm of one plus pay gap between the second-highest-paid CEO's total compensation within the same FF30 industry and the CEO's total compensation. In the first stage, we regress *LN_INDGAP1* variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the control variables are defined in Appendix A. *T*-statistics are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 12 Robustness check: Scaled measure of ITIs and FF48 industry classification

	Scaled measure of ITIs based on FF30 industry		Scaled measure of ITIs based on FF30 size-median industry		ITIs based on FF48 industry		ITIs based on FF48 size-median industry	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$	$HEDGE_{t+1}$	$ln(1+HEDGE\ count_{t+1})$
Scaled_INDGAP1$_t$	**0.011*****	**0.009*****						
	(3.724)	(3.233)						
Scaled_INDGAP2$_t$			**0.014*****	**0.019*****				
			(2.633)	(3.632)				
LN_INDGAP1$_t$					**0.182*****	**0.149*****		
					(3.428)	(3.143)		
LN_INDGAP2$_t$							**0.067****	**0.067****
							(2.313)	(2.550)
Controls$_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,631	19,631	19,274	19,274	19,628	19,628	19,293	19,293
Adj. R-squared		0.260		0.263		0.283		0.281

(Continues)

TABLE 12 (Continued)

	Scaled measure of ITIs based on FF30 industry		Scaled measure of ITIs based on FF30 size-median industry		ITIs based on FF48 industry		ITIs based on FF48 size-median industry	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	***HEDGE$_{t+1}$***	***ln(1+HEDGE count$_{t+1}$)***	***HEDGE$_{t+1}$***	***ln(1+HEDGE count$_{t+1}$)***	***HEDGE$_{t+1}$***	***ln(1+HEDGE count$_{t+1}$)***	***HEDGE$_{t+1}$***	***ln(1+HEDGE count$_{t+1}$)***
Endogeneity, relevance, and overidentification tests								
Exogeneity test (Wald/Hausman *p*-value)	0.000***	0.000***	0.000***	0.000***	0.054*	0.016**	0.076*	0.019**
First-stage *F*-statistics		1178.701***		2545.666***		4497.968***		2003.630***
Hansen *J*-test (*p*-value)		0.608		0.574		0.657		0.097*

Note: This table presents the second-stage results of instrumental variables (IV) estimation of ITIs on corporate hedging. *HEDGE* is a dummy variable assigned to 1 if a firm is defined to use any hedging activity (foreign exchange, interest rate, or commodity derivatives) in a given fiscal year and set to 0 otherwise. *HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement. The details on these hedging variables are discussed in Appendix B. *INDGAP1* (*INDGAP2*) is the pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 or 48 (size-median) industry and the CEO's total compensation. *Scaled_INDGAP1* (*Scaled_INDGAP2*) is the *INDGAP1* (*INDGAP2*) divided by CEO's total compensation. *LN_INDGAP1* (*LN_INDGAP2*) is the natural logarithm of one plus the industry pay gap variable. The controls are the same as in Table 2. In the first stage, we regress the respective industry pay gap variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. For the models using scaled variables on the industry pay gap, we also use scaled variable on *Firm gap* by dividing it by the CEO's total compensation. All the other variables are defined in Appendix A. Models (1), (3), (5), and (7) present marginal effects of IVProbit models at the mean. *T* (*Z*)-statistics (in parentheses) are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 13 Robustness check: Additional measures of hedging

Dependent variable	(1) *FRWD HEDGE* $_{t+1}$	(2) *BCWD HEDGE* $_{t+1}$	(3) *Scaled HEDGE count* $_{t+1}$
LN_INDGAP1$_t$	**0.002**	**0.089*****	**0.007*****
	(0.818)	(3.588)	(3.497)
Controls$_t$	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	19,631	19,631	19,631
Adj. *R*-squared	0.054	0.168	0.172
Endogeneity, relevance, and overidentification tests			
Exogeneity test	0.680	0.043**	0.024**
First-stage *F*-statistics	3709.286***	3709.286***	3709.286***
Hansen *J*-test (*p*-value)	0.069*	0.528	0.806

Note: This table presents the second-stage results of instrumental variables (IV) estimation of ITIs on various measures of corporate hedging. *FRWD HEDGE* is the number of forward-looking hedging sentences used in 10-K scaled by the total number of sentences in 10-K. *BCWD HEDGE* is the number of backward-looking hedging sentences used in 10-K scaled by the total number of sentences in 10-K. *Scaled HEDGE count* is a count of the number of times a firm mentions the use of any hedging instrument in its 10-K statement scaled by the total number of words in 10-K statement. We multiplied these variables by 100 to get them in the percentage form. *LN_INDGAP1* is the natural logarithm of one plus the industry pay gap variable. The controls are the same as in Table 2. In the first stage, we regress the respective industry pay gap variable on contemporaneous control variables and instruments. The instruments are the natural logarithms of the sum of total compensation of all other CEOs in the same industry, *Ind CEO comp*, and the total number of CEOs with higher total compensation within the same industry, *#Higher paid ind CEOs*. All the other variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors corrected for clustering of observations at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Firms can choose to strategically provide stakeholders with more forward-looking hedging information in their 10-Ks, instead of picturing their current position; this is especially true when CEOs need to impact outsiders' perceptions. Therefore, we cannot rule out the possibility that CEOs motivated by external job-market tournaments are induced to make forward-looking hedging disclosures. Accordingly, forward-looking 10-K disclosures related to hedging can distort our hedging variable. Thus, using the approach taken by Muslu et al. (2015) to define forward-looking sentences, we generate our textual hedging variables by taking into account both forward-looking and backward-looking hedge disclosures. We define the first variable, *FRWD HEDGE*, as the number of forward-looking hedging sentences scaled by the total number of sentences in the 10-K.[33] The other variable is *BCWD HEDGE*, which is the number of backward-looking hedging sentences scaled by the total number of sentences in the 10-K.[34] We then multiply these variables by 100 to put them in percentage form.

The results are illustrated in Columns 1 and 2 of Table 13. We do not find a significant relation between *FRWD HEDGE* and *LN_INDGAP1* (Column 1), whereas we find a significantly positive relation between *BCWD_HEDGE* and *LN_INDGAP1* (Column 2). Based on our results, we can rule out the possibility that ITIs motivate CEOs to make speculative disclosures related to hedging. However, our results also suggest that ITIs incentivize CEOs to provide stakeholders with disclosures regarding both their current and previous hedging activities.

[33] We identify a forward-looking hedging sentence if a sentence contains any of the hedging-related keywords from Appendix B and is recognized as forward-looking based on the approach from Muslu et al. (2015).

[34] We identify a hedging-related sentence as backward-looking if it is not recognized as a forward-looking sentence based on the approach from Muslu et al. (2015).

Lastly, we scale *HEDGE count* variable by the total number of words in the 10-K, thereby avoiding any correlation to the size or complexity of the firm and the word counts. Based on the results shown in Column 3 of Table 13, the positive relation between ITIs and hedging is robust to the scaling of the hedging count variable.

6 | CONCLUSION

Corporate hedging is mostly carried out by firms that wish to protect themselves against unexpected shocks. The primary benefit of hedging is that it can prevent a firm from inefficient liquidation by allowing it to secure adequate and stable internal cash flows. This paper investigates how ITIs act as a factor affecting corporate hedging policies. Promotion-based tournament theory suggests that competition among employees can induce them to work harder and change their risk appetite (Goel & Thakor, 2008; Hvide, 2002; Lazear & Rosen, 1981). Accordingly, Coles et al. (2017) claim that CEOs compete with one another to obtain CEO positions in the leading firms in their industries because these aspirational positions incorporate higher compensation levels, status, and visibility, and an enlarged span of control. They find that CEOs motivated by the pay gap between their original compensation and that of the highest-paid CEO within their industry tend to increase their effort and engage in riskier activities; this can, in turn, impact their attitude toward corporate hedging.

Following Almeida et al. (2017), Hoberg and Moon (2017), Manconi et al. (2017), and Qiu (2019), we undertake a textual analysis of 10-Ks, using them to form corporate hedging measures. In line with our *risk management hypothesis*, we find that ITIs positively influence both the likelihood that a CEO will hedge and the hedging intensity. This finding indicates that ITIs motivate CEOs to engage in corporate hedging.

We then explore possible reasons for the positive relation between ITIs and corporate hedging, finding that corporate hedging alleviates the amplifying impact of ITIs on the cost of debt and stock price crash risk. This effect can encourage CEOs to hedge. Additionally, we show that the association between ITIs and corporate hedging is less pronounced for firms that are in greater financial distress, and that this association causes the likelihood of a CEO moving up in the tournament to soar.

Using an exogenous shock provided by changes in the enforceability of noncompetition agreements, we identify a causal relation between ITIs and corporate hedging. Overall, our analysis illustrates that the compensation gaps among CEOs are important incentive mechanisms that can be used to motivate them to influence their corporate hedging policies.

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APPENDIX A: DATA SOURCES AND DEFINITIONS

Variable	Definition
A. Hedging variables (Source: 10-K statements from SEC)	
HEDGE	Dummy variable set to 1 if a firm mentions the use of any hedging instruments (foreign exchange, interest rate, or commodity derivatives) in its 10-K for a given year and set to 0 otherwise; details in Appendix B.
HEDGE count	The number of times a firm mentions the use of any hedging instruments in its 10-K statement for a given year; details in Appendix B.
FX hedge	Dummy variable set to 1 if a firm uses foreign exchange hedging contracts in a given year and 0 otherwise; details in Appendix B.
FX count	The number of times a firm mentions foreign exchange hedging in a given year based on the combination of the keywords documented in Appendix B.
IR hedge	Dummy variable set to 1 if a firm uses interest rate hedging contract in a given year and 0 otherwise; details in Appendix B.
IR count	The number of times a firm mentions interest rate hedging in a given year, details in Appendix B.
CMD hedge	Dummy variable set to 1 if a firm uses commodity hedging contract in a given year and 0 otherwise; details in Appendix B.
CMD count	The number of times a firm mentions commodity hedging contract in a given year; details in Appendix B.
Scaled HEDGE count	The number of times a firm mentions the use of any hedging instrument in its 10-K statement scaled by the total number of words in the 10-K times 100.
FRWD HEDGE	The number of forward-looking hedging sentences used in 10-K scaled by the total number of sentences in the 10-K times 100.
BCWD HEDGE	The number of backward-looking hedging sentences used in 10-K scaled by the total number of sentences in the 10-K times 100.
B. Incentives variables (Source: ExecuComp)	
INDGAP1	The pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 industry and the CEO's total compensation (CPI-adjusted).
INDGAP2	The pay gap between the second-highest-paid CEO's total compensation within the same Fama–French 30 size-median industry and the CEO's total compensation (CPI-adjusted).
LN_INDGAP1	The natural logarithm of one plus *INDGAP1*.
LN_INDGAP2	The natural logarithm of one plus *INDGAP2*.
Firm gap	The pay gap between the CEO's total compensation and the median vice president total compensation (CPI-adjusted).
CEO delta	Dollar change in CEO wealth associated with a 1% change in the firm's stock price.
CEO vega	Dollar change in CEO wealth associated with a 0.01 change in the standard deviation of the firm's returns.
C. Firm characteristics (Source: Compustat and CRSP)	
Total assets	Book value of total assets (CPI-adjusted).
R&D/Assets	R&D expenditures divided by total assets, set to 0 if missing.

(Continues)

Variable	Definition
Leverage	The ratio of long-term debt plus debt in current liabilities to total assets.
Tobin's Q	The market value of equity plus book value of assets minus book value of equity minus balance sheet deferred taxes, divided by book value of assets.
CAPX/Assets	Capital expenditures divided by total assets.
ROA	Operating income before interest divided by total assets.
MTB	The ratio of the market value of equity to book value of equity.
Cash/Assets	Cash divided by total assets.
PPE/Assets	Investment in property, plant, and equipment divided by total assets.
Cashflow vol	The standard deviation of annual operating cash flows over the past five fiscal years, divided by the total assets.
Z-score	Modified Altman's (1968) *Z*-score is computed as (1.2 working capital + 1.4 retained earnings + 3.3 EBIT + 0.999 sales) divided by total assets. We exclude (0.6 market value/liabilities) because a similar term, market-to-book, is used as a control variable in the regressions.
Firm age	One plus the difference between the year under investigation and the first year the firm appears on the CRSP tapes.
Nondebt tax shield	Depreciation divided by total assets.
Inventory	Inventory divided by costs of goods sold.
Trade credit	Account payables divided by total assets.
Asset maturity	Asset maturity is the book value-weighted average maturity of long-term assets and current assets, where the maturity of long-term assets is computed as gross property, plant, and equipment divided by depreciation expense, and the maturity of current assets is computed as current assets divided by the cost of goods sold (see Billett, King, and Mauer, 2007; Graham, Li, and Qiu, 2008).
D. CEO characteristics (Source: ExecuComp)	
CEO founder	Dummy variable set to 1 if a CEO is also the founder of the firm and set to 0 otherwise.
CEO retire	Dummy variable set to 1 if the CEO's age is more than 65 years and set to 0 otherwise.
CEO tenure	The CEO's tenure at the firm, in years.
CEO age	The CEO's age, in years.
E. Industry and instrument variables (Source: ExecuComp)	
Ind # CEOs	The number of CEOs (or firms) within the same industry in the sample year.
Ind CEO comp	The sum of total compensation of all other CEOs in each Fama–French 30 industry, except the highest-paid CEO, CPI-adjusted.
Geo CEO mean	The average total compensation received by all other CEOs who work at firms in different industries that are headquartered within a 250-km radius of the firm (CPI-adjusted).
#Higher paid ind CEOs	The total number of CEOs with higher total compensation within the same Fama–French 30 (or FF30 size-median) industry.
F. Crash risk measures and related controls (Source: Compustat and CRSP)	
CRASH	Dummy variable equal to 1 if the firm has a weekly return that is less than 3.2 standard deviations below the average weekly return for the entire fiscal year.
NCSKEW	Negative conditional skewness of firm-specific weekly returns during the entire fiscal year.

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Variable	Definition
DUVOL	The natural logarithm of the ratio of the standard deviation of weekly returns for below-average weeks to the standard deviation of weekly returns for above-average weeks, for weekly returns over the fiscal year.
DTURN	The difference between average daily share turnover during the current fiscal year and the previous fiscal year. Daily stock turnover is calculated as the ratio of daily trading volume over the number of shares outstanding.
SIGMA	The standard deviation of firm-specific weekly stock returns over the fiscal year.
RET	Average firm-specific weekly return during the entire fiscal year.
OPAQUE	The absolute value of discretionary accruals, which are measured using the modified Jones model following Dechow et al. (1995).
G. Bank loan characteristics and related controls (Source: DealScan)	
Loan spread	Loan spread is measured as all-in spread drawn.
Loan maturity	Loan maturity measured in months.
Covenant count	A count of the number of covenants in the loan facility.
Loan Secured	A dummy variable equal to 1 if the loan facility is secured by collateral and 0 otherwise.
Performance pricing	A dummy variable equal to 1 if the loan facility has a performance pricing feature and 0 otherwise.
No. of Lenders	The number of lenders funding the loan facility (i.e., the size of the loan syndicate).
Loan amount	The loan amount measured in dollars, CPI-adjusted.
Term loan	A dummy variable equal to 1 if the loan facility is a term loan and 0 otherwise.
Revolver loan	A dummy variable equal to 1 if the loan facility is a revolver or 364-day facility and 0 otherwise.
Bridge loan	A dummy variable equal to 1 if the loan facility is a bridge loan and 0 otherwise.
General purpose loan	A dummy variable equal to 1 if the loan purpose is for general corporate purposes, project finance, or other purpose and 0 otherwise.
Takeover/recap loan	A dummy variable equal to 1 if the loan purpose is for a takeover or recapitalization and 0 otherwise.
Working capital loan	A dummy variable equal to 1 if the loan purpose is to finance working capital and 0 otherwise.
Rated dummy	Dummy variable equal to 1 if the firm has an S&P long-term debt rating (Compustat).
H. Macroeconomic controls (Source: The Federal Reserve)	
Credit spread	The difference between BBB corporate bond yield and AAA corporate bond yield.
Term spread	The difference between the 10-year U.S. constant maturity Treasury yield and the 3-month constant maturity U.S. Treasury yield (see Kubick, Lockhart, and Mauer, 2020).
Crisis dummy	A dummy variable equal to 1 if the loan activation date falls in the calendar year 2007 or 2008 and 0 otherwise.
Postcrisis dummy	A dummy variable equal to 1 if the loan activation date is after the calendar year 2008 and 0 otherwise.

APPENDIX B: HEDGING VARIABLES

We develop hedging variables using textual analysis of 10-K statements. We search for 10-Ks to find if a firm utilizes hedging activities. First, we create measures for three different types of hedging: foreign exchange (FX), interest rate (IR), and commodity (CMD) hedging. Then we combine them to form an overall hedging variable. The details of these variables are as follows.

Foreign exchange hedging

We closely follow Chen and King (2014) and Huang et al. (2013) to generate FX hedging variable. A firm is concluded to follow FX hedging in a year if it mentions any of the following combinations of the words in its 10-K statement:

(currency/currency rate/exchange/exchange rate/cross-currency) AND (cap/collar/contract/derivative/floor/forward/future/option/swap)

(e.g., the combination of two words from each list, such as currency cap, currency collar, currency contract).

We also exclude false-positive hits by searching following different words surrounded by the above FX combination that would make a firm not to use in FX hedging activities such as "in the future," "forward-looking," "not material," "do not engage in foreign exchange," and "does not have any currency forward." We develop the following two FX hedging variables:

- *FX hedge* is set to 1 if a firm uses FX hedging contract in a year and 0 otherwise;
- *FX count* is the number of times a firm mentions FX hedging in a given year based on the combination of the words specified above.

Interest rate hedging

For IR hedging, we use the following list of words documented in Huang et al. (2013): "interest rate swap," "interest rate cap," "interest rate collar," "interest rate floor," "interest rate forward," "interest rate option," and "interest rate future." We develop the following two IR hedging variables:

- *IR hedge* is set to 1 if a firm mentions any of the words from the above interest rate hedging-related word list in a year and 0 otherwise;
- *IR count* is the total number of IR hedging words documented in the 10-K statement.

Commodity hedging

For commodity hedging, we use the following word list documented in Almeida et al. (2017):

hedge fuel	uses derivative financial instruments to manage the price risk
fuel hedge	uses financial instruments to manage the price risk
fuel call option	uses derivative financial instruments to manage price risk
commodity derivative	uses derivatives to manage the price risk
commodity contract	uses derivatives to manage price risk
commodity forward	forward contracts for certain commodities
commodity future	forward contracts for commodities derivatives to mitigate commodity price risk
commodity hedge	futures to mitigate commodity price risk

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commodity hedging	options to mitigate commodity price risk
commodity option	swaps to mitigate commodity price risk
commodity swap	corn future
hedges of commodity price	cattle future commodity price swap

We develop the following two commodity hedging variables:

- *CMD hedge* is set to 1 if a firm mentions any of the words from the above commodity hedging-related word list in a year and 0 otherwise;
- *CMD count* is the total number of commodity hedging words documented in the 10-K statement.

Finally, our two main overall hedging variables are formed as follow:

- *HEDGE* takes a value of 1 if any one of the hedging dummies (*FX hedge*, *IR* hedge, or *CMD* hedge) is 1, 0 otherwise.
- *HEDGE count* is the sum of *FX count*, *IR count*, and *CMD count*.

APPENDIX C: MEASURES OF STOCK PRICE CRASH RISK

For firm *i* during its fiscal year *t*, we first estimate firm-specific weekly residual returns from the expanded market model as follows:

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t-2} + \beta_{2,i} r_{m,t-1} + \beta_{3,i} r_{m,t} + \beta_{4,i} r_{m,t+1} + \beta_{5,i} r_{m,t+2} + \varepsilon_{i,t}, \tag{C1}$$

where $r_{i,\tau}$ is the return on stock *i* in week τ and $r_{m,\tau}$ is the return on the CRSP value-weighted market index in week τ. The firm-specific weekly returns are then defined as

$$W_{i,t} = \ln\left(1 + \varepsilon_{i,t}\right). \tag{C2}$$

Following stock price crash risk literature (e.g., Chen et al., 2001; Kim et al., 2011; Kim et al., 2016), we form three measures of crash risk. First, *CRASH* is a dummy variable that takes the value of 1 if the firm has experienced at least one weekly return ($W_{i,t}$)3.2 standard deviations below the average firm-specific weekly return during the entire fiscal year, and 0 otherwise.

The second measure of crash risk is the firm-specific negative conditional skewness (*NCSKEW*). *NCSKEW* is defined as the standardized negative value of the third central moment of firm-specific weekly return scaled by its sample variance raised to the power of 3/2. More specifically, *NCSKEW* of stock *i* in its fiscal year *t* is calculated as

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{3/2}}, \tag{C3}$$

where *n* is the number of weekly observations in year *t*. A larger value of *NCSKEW* indicates more negatively skewed returns and thus greater crash risk.

Our third measure of crash risk is the firm-specific down-to-up volatility ratio measured over the entire fiscal year (*DUVOL*). *DUVOL* is computed as a natural logarithm of the ratio of the standard deviation of weekly returns for "down" weeks to the standard deviation of weekly returns for "up" weeks. The "down" weeks are the weeks during which the weekly return is less than the annual firm-specific mean, and the "up" weeks are the weeks during which the weekly return is greater than the yearly firm-specific mean. Larger values of *DUVOL* indicate greater crash risk.

APPENDIX D: COMPUTATION OF EXPECTED DEFAULT FREQUENCY (EDF)

Merton's expected default frequency: The Merton's expected default frequency (EDF) measure is computed using the Merton (1974) bond pricing model. Merton's model assumes that the total value of a firm follows a geometric Brownian motion,

$$dV = \mu V dt + \sigma_V V dW, \tag{D1}$$

where V is the value of the firm, μ is the expected continuously compounded return on V, σ_V is the volatility of firm value, and dW is a standard Weiner process. Additionally, it assumes the firm has issued only one discount bond with maturity of T periods. Merton's expected default frequency is computed by the following three-step procedure.

Step 1: The following two equations are solved numerically for V and σ_V:

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{D2}$$

and

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1)\, \sigma_V, \tag{D3}$$

where E is the market value of equity, F is the face value debt, r is assumed to be constant risk-free rate,$N(.)$ is the cumulative standard normal distribution function, d_1 is given by

$$d_1 = \frac{ln\left(\frac{V}{F}\right) + \left(r + 0.5\,\sigma_V^2\right) T}{\sigma_V \sqrt{T}}, \tag{D4}$$

and

$$d_2 = d_1 - \sigma_V \sqrt{T}.$$

Step 2: After obtaining a numerical solution for V andσ_V, the distance to default is computed as

$$\mathrm{DD} = \frac{\ln\left(\frac{V}{F}\right) + \left(\mu - 0.5\,\sigma_V^2\right) T}{\sigma_V \sqrt{T}}, \tag{D5}$$

where μ is the expected annual returns.

Step 3: The implied probability of default or the Merton expected default frequency (EDF) is computed as

$$\text{Merton EDF} = N(-\mathrm{DD}). \tag{D6}$$

We set the inputs to the above procedure following the literature (Bharath and Shumway, 2008; Kubick et al., 2020; Sundaram and Yermack, 2007; Vassalou and Xing, 2004).$\mu$is set as EBITDA scaled by book value of total assets, σ_E is the annualized standard deviation of returns over the previous year, F is measured as (debt in current liabilities + 1.5 × long-term debt), E is measured as the end of the year common share price multiplied by common shares outstanding,

r is the 1-year Treasury Constant Maturity Rate (obtained from the Federal Reserve Board's website: http://www.federalreserve.gov), and T is assumed as 1 year.

Naïve expected default frequency: The Naïve expected default frequency (EDF) measure is computed based on the "simplified" Merton model probability of default documented in Bharath and Shumway (2008). This procedure assumes the firm's market value of debt equal to its face value of debt (i.e., $D = F$) and the volatility of debt as $\sigma_D = 0.05 + 0.25 \times \sigma_E$. The total volatility of the firm's value is then estimated as

$$\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}\sigma_D. \tag{D7}$$

The naïve distance to default is then computed as

$$\text{Naïve DD} = \frac{ln\left(\frac{E+F}{F}\right) + \left(\mu - 0.5\,\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{D8}$$

and the naïve expected default frequency is computed as

$$\text{Naïve EDF} = N\left(-\text{Naïve DD}\right). \tag{D9}$$

Higher values of Merton and Naïve EDF indicate a higher likelihood of default.