Recessions, Bank Distress, and Managerial Incentives to Innovate

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Abstract

During recessions, managers prioritize innovative projects. This study explores how crises and bank distress influence managerial incentives to innovate. We find that exogenous shocks to CEO option pay during tough economic periods lead to increased patent production in subsequent years. This suggests managers may favor innovation when conventional projects become riskier due to heightened systematic risk. However, not all firms can effectively leverage these incentives. The effect is stronger in financially unconstrained firms with more market power or higher Z scores. Additionally, higher option pay can diminish future firm innovation if managers are more risk-averse or have greater personal stakes in their firm.

JEL classification: G01, G34, O31

Keywords: Innovation, incentives, business cycle, executive compensation, option plans, bank distress.

I. Introduction

Understanding how incentives to innovate are formed is particularly important during times of economic distress. We have witnessed and continue to observe that extraordinary circumstances, such as the World Wars or the COVID-19 pandemic, spur significant advancements in innovation globally. Despite observing these spikes in demand for innovation and innovative output during severe downturn events, there is little consensus among researchers regarding the impact of economic shocks on innovative output.

Our paper contributes to the existing literature by identifying a direct channel through which crises affect future firm innovation. We investigate how CEO incentives to innovate, measured using CEO compensation data, are affected by business cycle shocks. Specifically, we analyze whether and to what extent long-term incentive compensation, such as stock option awards, motivates CEOs to generate more (or less) innovation.

While salary and bonuses of S&P 500 CEOs remained relatively constant over time, option pay has increased significantly from only 19% of total pay in 1992 to 49% by 2000 (Edmans, Gabaix, and Jenter, 2017). Despite CEO options playing a dominant role in compensation packages, we still know very little about what kind of incentives they provide to managers. In this paper, we provide empirical evidence suggesting that managers prioritize innovation particularly during periods of heightened bank distress.

Examining the causal relationship between CEO compensation and firm innovation has presented challenges in prior research. Biggerstaff, Blank, and Goldie (2019) address this issue by exploiting a one-time exogenous reduction in option compensation following the implementation of FAS 123R. They conclude that granting options to managers does not have a significant effect on firm innovative output. However, it is important to recognize that Biggerstaff, Blank, and Goldie (2019) concentrated solely on this specific shock that transpired during regulatory change, leaving questions about the applicability of their findings in diverse contexts and situations.

To analyze the impact of CEO option compensation under various conditions over time, we adopt the identification strategy proposed by Shue and Townsend (2017). This strategy is based on identified multi-year option plans, staggered across firms and over time, which allows us to study the impact of CEO option compensation on firm innovation under different conditions. Overall, we confirm an overall average zero to mildly negative impact of CEO option pay on firm innovation. However, notably, during periods characterized by significant bank distress, this relationship becomes positive. Our findings suggest that managerial incentives to innovate strengthen during elevated bank distress.

To provide economic intuition on when will managers prioritize innovation, we build a model where managers weigh the costs and benefits of exploring an innovative project and decide to innovate only when the benefits exceed the costs. For a risk-averse manager, an innovative project is always more costly. When the risk differential between a conventional and innovative project is high, managers are likely to choose the riskier innovative project due to the managerial aversion to losing (potentially) undiversifiable labor income.

During downturns, overall systematic risk tends to be higher. In our proposed model, we consider that as systematic risk rises, conventional projects become riskier. Market conditions, however, do not affect the volatility of the innovative project due to their idiosyncratic nature. Regardless of economic conditions, innovative projects are unconditionally the riskiest to invest in. During bad times, systematic risk increases, intensifying the risk associated with conventional projects and narrowing the risk gap between conventional and innovative projects. This situation provides risk-averse managers with stronger incentives to pursue innovative activities because conventional projects become relatively more costly in downturns. Consequently, we expect that increasing managerial incentive pay awarded in bad times will likely be more effective in stimulating innovation compared to such incentives being awarded in good times.

Figure 1 outlines the key implications of the model. It illustrates the expected utility levels for three potential managerial actions: (*i*) investing in an innovative project (in red), (*ii*) investing in a conventional project (in blue) or (*iii*) shirking (in black). A risk-averse

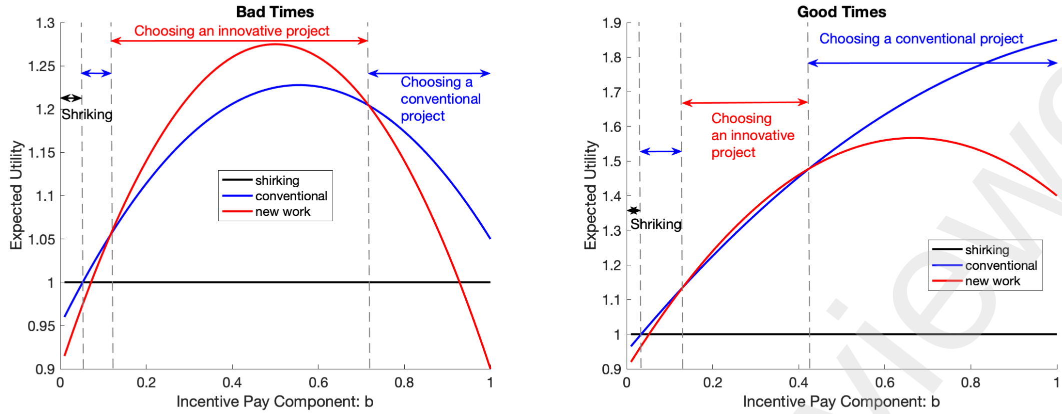


Figure 1: **Managerial expected utility from accepting a project.** Three projects are compared: an innovative project (in red), a conventional project (in blue) and shirking (in black). Section III depicts the model setup and Figure 4 describes parameters used.

manager will opt for the project offering the highest expected utility, which is calculated as the expected project payoff minus the costs associated with risk aversion and effort.

When the incentive component (b) approaches zero, the manager tends to choose shirking. As b surpasses a certain threshold, the decision shifts primarily between the conventional and innovative projects. With sufficiently high b, indicative of having 'skin in the game', the manager is more inclined to choose a conventional project over an innovative one. Choosing the riskier innovative project is optimal for moderately low levels of the incentive component b, as the higher expected firm profits from the innovative project are less likely to be outweighed by the increased cost of risk sharing at lower b levels.

During challenging economic times, when the volatility of conventional projects rises due to heightened systematic risk, providing managers with more options and increasing b creates stronger incentives for innovation compared to normal economic conditions when conventional projects are relatively less risky, as shown in Figure 1.

Our empirical findings corroborate the stylized predictions of our model. First, we show that awarding managers who have higher portfolio delta (and more 'skin in the game') with more option pay leads to significant reductions in future firm innovative output. Similar results are found among managers with high wealth-performance sensitivity, high current option pay, and relatively older CEOs with longer tenure. In contrast, managerial incentives to innovate seem to be unaffected by exogenous positive shocks to option pay among managers with low delta, low wealth-to-performance sensitivity, or younger CEOs. This first set of results indicates that increasing CEO option pay discourages firm innovation when managers have more 'skin in the game' and, thus, have more to lose.

Second, we document that when firms increase their CEO's option pay in bad times, their future total innovative output rises. Furthermore, this innovative output demonstrates higher quality, as evidenced by the increased number of citations received by the patents produced on average. We conclude that an exogenous rise in CEO compensation during periods of heightened financial distress has a positive impact on firm innovation.

We conclude that executive option compensation fosters firm innovation during challenging economic periods. This finding appears to contrast with the argument presented by Nanda and Rhodes-Kropf (2017), who suggest that investors respond to financing risk–represented by limited future funding–by reducing their interest in financing innovative firms. We propose that both negative external pressures discouraging innovation and positive internal factors linked to managerial incentives may coexist during bad times. Our analysis suggests that managerial incentives to innovate are likely to be countercyclical.

CEOs carefully weigh the costs and benefits associated with implementing innovative projects. We interpret these findings within the framework of our proposed model. In bad times, when systematic risk increases, the gap in risk between innovative and conventional projects narrows. We argue that in such circumstances, the relative benefits of pursuing innovative projects may outweigh their relative costs, explaining why more managers may opt to invest in riskier innovative endeavors.

This is the first paper to focus on examining how economic conditions may affect the role of CEO compensation in driving innovation. Given the importance of new technologies in driving productivity and economic growth, understanding how business cycles affect innovation via the executive rewards mechanism is an important issue for both firms and policymakers. Our paper contributes to the literature on executive compensation and innovation. Previous research has demonstrated that CEOs play an important role in motivating firm innovation, see, for example, Manso (2011); Ederer and Manso (2013); Islam and Zein (2020), or Sunder, Sunder, and Zhang (2017)). Our paper adds to this literature by showing that motivating executives to innovate and enhance firm innovative output works better during crises.

The rest of the paper is structured as follows. Section II reviews related literature. Section III presents the proposed model designed to study managerial incentives to innovate. Section IV discusses our data sample. The method used to identify exogenous shocks to CEO option compensation is described in Section V. Section VI presents our results and Section VII concludes.

II. Related Literature

Despite the importance of CEO option compensation, many questions remain about whether and how it affects firm's innovative output. In this paper, we examine the role of the internal managerial incentive system in fostering innovation. Specifically, we investigate the effectiveness of CEO option compensation in promoting innovation under various conditions and economic states.

Prior research has examined how CEO compensation impacts firm innovation. For instance, Ederer and Manso (2013) find that combining tolerance for early failure with long-term success rewards motivates innovation. Manso (2011) suggest that a combination of stock options with extended vesting periods, option repricing, golden parachutes, and managerial entrenchment can motivate managers to innovate.

We extend this literature by identifying factors that influence the relationship between CEO option pay and firm innovation. We emphasize the role of managerial 'skin in the game,' consistent with findings by Ma and Tang (2019), who show that managers with more 'skin in the game' build less risky investment portfolios.

Managerial characteristics also play a significant role in a firm's innovation productivity. For example, Islam and Zein (2020) find that CEOs with hands-on experience as inventors produce higher-quality innovation. Additionally, Sunder, Sunder, and Zhang (2017) discover that CEOs who are pilots tend to be involved in projects with significantly better innovation outcomes, attributing this to their risk-taking personality trait.

The existing literature presents conflicting views on impact of crises on innovation. The Schumpeterian view (Schumpeter, 1942; Caballero and Hammour, 1991) suggests that crises promote creative destruction, fostering innovation during economic downturns. On the contrary, several studies argue that financial distress during crises hampers firms' innovation activities. For instance, Nanda and Rhodes-Kropf (2017) propose an investment model predicting that investors shy away from financing innovative firms due to financing risks. Along the same vein, Nanda and Rhodes-Kropf (2013) find that that projects funded during boom times are more likely to fail but, conditional on success, create more value, result in more patents, and receive more patent cites. Using evidence from the Great Depression, Nanda and Nicholas (2014) document that bank distress negatively affects the level, quality and trajectory of firm-level innovation. More recently, Babina, Bernstein, and Mezzanotti (2023) study the impact of the Great Depression on firm and entrepreneur innovative activities. The authors document a sudden decline in patenting by independent inventors that follows shortly after the Great Depression. However, the drop of quantity in patents is accompanied by a significant rise in the average quality of surviving patents, which provides yet another sign of a positive impact of crises on innovation.

Our study contributes to this debate by focusing on the role of option compensation in incentivizing managers to innovate. We consider the influence of managerial 'skin in the game' and economic conditions, shedding light on the mechanisms driving firm innovation.

III. Motivating Innovation

Consider a one-period model with two agents; a firm, represented by a mass of equity holders, and a manager that is hired by the firm. At the beginning of the period, at time t, the manager is offered a package (w, b) that constitutes a flat wage w and a contingent claim on future firm profits, paid as a fraction b of firm profits, realized at the end of the period, denoted as T. The manager accepts the job offer when the expected utility from accepting the offer exceeds the current market spot wage s_t, which represents the manager's reservation utility.

A. *Project types and firm profits*

Firm gross profits θ are revealed at the end of the period and the manager is paid a fraction of these profits: $b\theta$, with $b \in \langle 0, 1\rangle$. θ is drawn from a normal distribution and the parameters of the normal distribution (i.e., both the mean and the standard deviation) depend on the project type chosen by the manager i, $i \in (0, 1, 2)$, and the expected state of the economy during the entire period, denoted as ω_t. For the sake of simplicity, we consider only two different economic states: good and bad, i.e., $\omega_t \in$ (good,bad).

	$i = 0$: shirking	$i = 1$: conventional project	$i = 2$: innovative project
$\omega_t =$ bad	$\theta_0 = 0$	$\theta_1 \sim N(\bar{\theta}_1^{bad}, \sigma^2_{1,bad})$	$\theta_2 \sim N(\bar{\theta}_2^{bad}, \sigma^2_2)$
$\omega_t =$ good	$\theta_0 = 0$	$\theta_1 \sim N(\bar{\theta}_1^{good}, \sigma^2_{1,good})$	$\theta_2 \sim N(\bar{\theta}_2^{good}, \sigma^2_2)$
Cost of effort	$c_0 = 0$	c_1	c_2

The manager can choose to shirk ($i = 0$), invest in a conventional project ($i = 1$), or an innovative project ($i = 2$). Shirking leads to zero output produced by the firm at the end of the period but does not cost any effort, $c_0 = 0$. The payoff of both the conventional and the innovative project is random and determined at the end of the period. Both projects are associated with a positive cost of effort with the innovative project being relatively more costly (harder to work on): $c_2 > c_1 > 0$.

B. Choosing a project

The manager has a constant absolute risk aversion r. Her expected utility EU_t from accepting the job offer depends on the flat wage net of the cost of effort, which are revealed immediately at time t, plus the expected benefits and costs from the risky payoffs revealed at the of the period (at time $t+1$).

$$EU_t = w - \underbrace{c_i}_{\text{cost of effort}} + b\mathbb{E}_t(\theta_i|\omega_t) - \underbrace{rb^2 \ \mathrm{var}_t(\theta_i|\omega_t)}_{\text{risk aversion disutility}}, \tag{1}$$

with index i representing the project chosen by the manager, $i = 0, 1, 2$. The cost of effort c_i is project-specific.

The manager will choose such a project that maximizes her expected utility,

$$\max_i EU_t(i) \tag{2}$$

subject to the manager's current expectations about the economic state prevailing during the period ($\omega_t = \{good, bad\}$) and the participation constraint being met, which ensures that the manager has accepted the job offer: $EU_t(i) \geq s_t$.

	$i = 0$: shirking	$i = 1$: conventional project	$i = 2$: innovative project
ω_t = bad	w	$w + b\bar{\theta}_1^{bad} - rb^2\sigma^2_{1,bad} - c_1$	$w + b\bar{\theta}_2^{bad} - rb^2\sigma^2_2 - c_2$
ω_t = good	w	$w + b\bar{\theta}_1^{good} - rb^2\sigma^2_{1,good} - c_1$	$w + b\bar{\theta}_2^{good} - rb^2\sigma^2_2 - c_2$

In this paper, we study the managerial incentives to innovate, which corresponds to the conditions under which the manager chooses the innovative project $i = 2$. The manager chooses to innovate over the conventional project when the additional expected payoff from the riskier innovative project exceeds the risk-aversion disutility and the cost of effort differential.

$$\underbrace{\theta_2^\omega - \theta_1^\omega}_{\text{payoff benefits}} > rb\left(\sigma^2_{2,\omega} - \sigma^2_{1,\omega}\right) + \frac{c_2 - c_1}{b} \tag{3}$$

Proposition 1 specifies the boundaries of the incentive pay b, as a function of the managerial degree of risk aversion, the project-level payoffs, or the costs of effort.

PROPOSITION 1 (**Manager choosing the innovative project**): *The manager chooses to invest in the innovative project ($i = 2$) when the following conditions are met.*

$$b > \frac{\bar{\theta}_2^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t})^2 - 4r\sigma_2^2 c_2}}{2r\sigma_2^2}, \tag{4}$$

$$b \geq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} - \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}, \tag{5}$$

or when

$$b \leq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}. \tag{6}$$

Figure 2 highlights the impact of the project's expected payoff differential ($\theta_2 - \theta_1$) and the risk differential ($\sigma_2^2 - \sigma_1^2$) on the expected utility differential form accepting the innovative over the conventional project: $EU_2 - EU_1$. These figures visualize under which levels of the incentive pay components b, the manager is likely to accept the innovative project over the conventional one. This analysis shows that a higher incentive pay doesn't always lead to stronger managerial incentives to innovate, especially when the risk differential is high.

C. Economic conditions and managerial incentives to innovate

Inspired by findings from the asset-pricing literature suggesting that systematic risk rises during market downturns, we make the following assumption about firm payoffs. We consider that during bad times, the payoff volatility of the conventional project rises due to the higher systematic risk (you can think of the conventional project as investing in the market, i.e. the average project). In contrast, the payoff volatility of the innovative project remains unaffected by market conditions since the outcome of this project is idiosyncratic.

ASSUMPTION 1: *The standard deviation of the payoff distribution for the conventional*

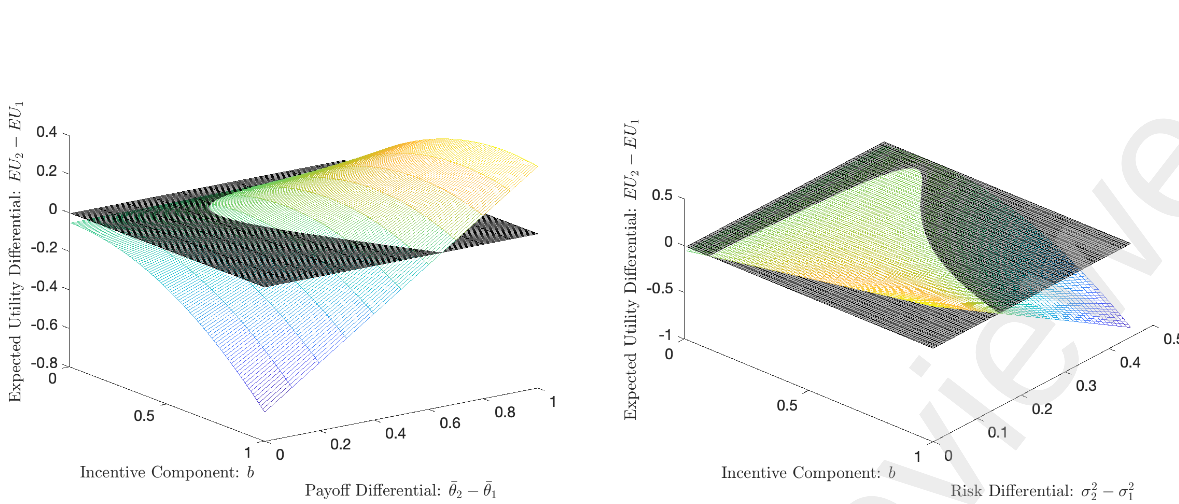


Figure 2: **Incentives to Innovate & Project-level Characteristics.** The gray surface represents zero expected utility differential, indicating the manager's indifference between choosing the innovative and conventional projects. Values above the gray surface (greater than 0) signify the manager's preference for the innovative project. The left figure illustrates the expected utility differential levels based on the payoff differential ($\bar{\theta}2^{\omega_t} - \bar{\theta}1^{\omega_t}$) and the incentive pay component b. Parameters used include $\sigma 1^2 = 0.3$, $\sigma 2^2 = 0.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$, and $w = 1$. The right figure depicts the expected utility differential levels as a function of the risk differential ($\sigma_2^2 - \sigma_2^1$) and the incentive pay component b. Parameters used are $\bar{\theta}_1 = 1$, $\bar{\theta}_2 = 1.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$, and $w = 1$.

project increases during bad times. The standard deviation of the payoff distribution for the innovative project σ_I^2 is unaffected by the economic state.

$$\sigma_{1,good}^2 < \sigma_{1,bad}^2 < \sigma_2^2 \tag{7}$$

Figure 3 graphically illustrates assumptions made about the payoff distribution of the two projects that the managers can choose from (other than shirking) in good (solid lines) and bad (dashed lines) times. Both projects have a lower expected payoff during bad times. For the sake of simplicity, we assume that the impact of economic conditions on the expected value of firm payoffs is similar across the two types of projects. As illustrated by the wider distribution with fatter tails, the conventional project becomes riskier in bad times, as highlighted by the red dashed line from Figure 3.

The intuition behind our assumption that the conventional project becomes more risky is based on the observation that systematic risk increases during bad times. The conven-

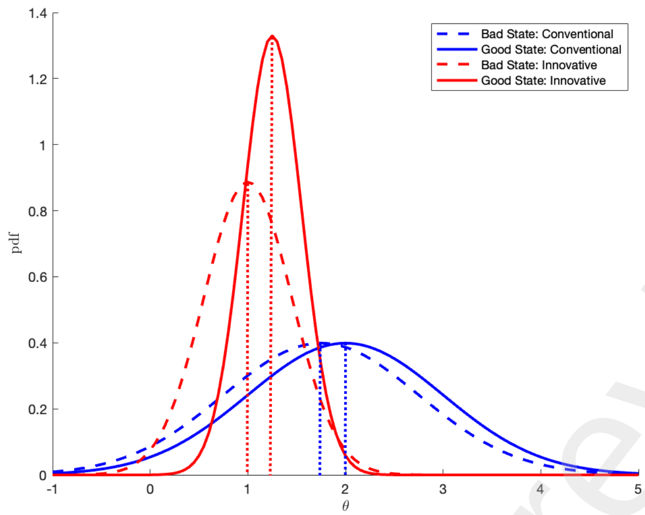


Figure 3: **Payoff distributions.** The blue (red) lines depict the payoff distributions for the innovative (conventional) project. Dashed lines represent the payoff distribution when the expected state of the economy is bad, while solid lines illustrate conditions when the expected economy is good.

tional project is largely exposed to systematic risk, as it represents an investment in an existing technology used by the market or firms within the same industry. Consequently, this conventional project also becomes riskier when economic conditions deteriorate.

The innovative project, on the other hand, is unconditionally risky and more exposed to idiosyncratic risk, which is uncorrelated with market conditions. This assumption does not imply that the conventional project would become riskier than the innovative project during bad times. The innovative project is always the riskiest project to choose, but the risk differential between the conventional and the innovative project narrows down during bad times.

Figure 4 shows that when incentive pay b is high, any further increase in b only expands the difference between the expected utility the manager draws from the conventional project over the innovative one. This is due to the higher risk sharing and the risk aversion of losing the wealth invested within the firm.

TESTABLE IMPLICATION 1: *Increasing option pay for risk-averse managers with already*

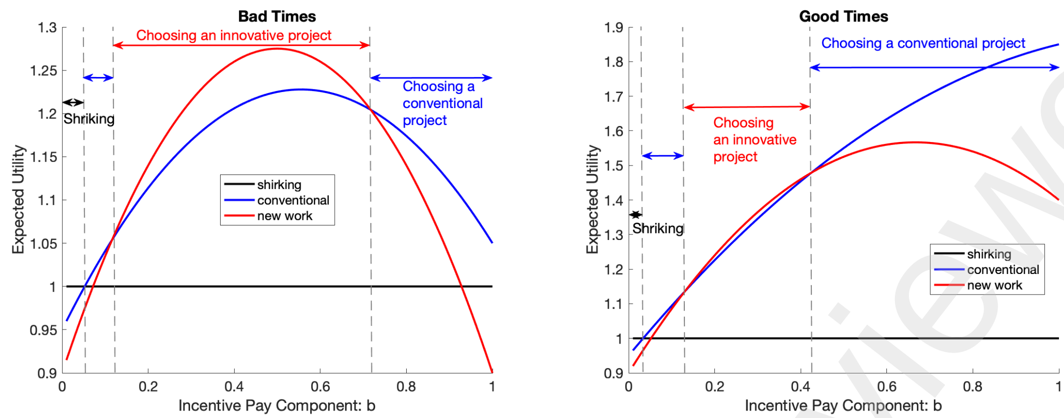


Figure 4: **Expected utility.** Parameters used to create this figure are: $\bar{\theta}_1^{bad} = 1$, $\bar{\theta}_1^{good} = 1.5$, $\bar{\theta}_2^{bad} = 1.5$, $\bar{\theta}_2^{good} = 2$, $\sigma_{1,bad}^2 = 0.3$, $\sigma_{1,good}^2 = 0.2$, $\sigma_2^2 = 0.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$ and $w = 1$.

high incentive pay (b) can discourage innovation due to higher disutility from risk aversion.

TESTABLE IMPLICATION 2: *When incentive pay b is relatively low, increasing b may incentivize more firm innovation.*

It may become optimal for the manager to choose the innovative project over other options of the benefits from innovating exceed the costs. When b is relatively low, the managerial costs of risk aversion are lower, which may lead to the manager choosing the innovative project over the conventional one. This effect becomes stronger in bad times, defined as times when the risk differential of the two projects decreases. This finding is described in the following testable implication.

TESTABLE IMPLICATION 3: *Managers are relatively more likely to choose an innovative project in bad times when the risk differential between the conventional and the innovative project decreases.*

In bad times, when market risk is high, conventional projects become more risky. Market risk is assumed to have a minimal zero role in driving the riskiness of the innovative project, because this project is by definition very different from what current market practices are and is, thus, assumed to be purely driven by the idiosyncratic risk associated with the particular innovative activity. Since the conventional project now becomes more risky and the volatility of its expected returns gets closer to the innovative project risks, the manager now becomes more likely to prefer to invest in the innovative project over the conventional one. This simple model mechanism demonstrates that poor economic conditions may encourage managers to invest in more innovative practices.

Incentives to innovate:	Economic state	
Components of the expected utility	Bad: $\omega = B$	Good: $\omega = G$
payoff benefits: $\theta_2^\omega - \theta_1^\omega$	constant	constant
risk-aversion costs: $\sigma_{2,\omega}^2 - \sigma_{1,\omega}^2$	**low**	high
cost of effort: $\frac{c_2 - c_1}{b}$	constant	constant

D. *Firm survival probability*

The manager may not want to invest in a riskier project if she believes that the firm may not survive until the end of the period, which is when the payoffs are realized. The survival probability p_t, thus, has a direct impact on the perceived value of the benefits and costs of accepting one of the projects that are available to the manager.

$$EU_t = w - \underbrace{c_i}_{\text{cost of effort}} + \left[b\mathbb{E}_t(\theta_i|\omega_t) - \underbrace{rb^2 \operatorname{var}_t(\theta_i|\omega_t)}_{\text{risk aversion disutility}} \right] \times \overbrace{p_t}^{\text{survival probability}} \tag{8}$$

Managers employed by a creditworthy firm with a higher survival probability will assign a higher weight to the expected benefits and costs that stem from accepting one of the two risky projects. We choose to model the survival probability to be exogenous to the manager's actions (such as which project she accepts) or the state of the economy because these effects are already captured by other variables in the model.

The disutility from risk aversion controls for the impact of the project choice on expected firm payoffs – that is, the riskier project which also may make the firm less likely to survive draws a higher disutility through the impact of the risk aversion parameter r. Moreover, the impact of the state of the economy on firm payoffs further takes into account the state dependence associated with individual projects. This is a modeling choice, which leaves the survival probability to be a sole function of any other firm-specific characteristics that the manager may view as important in assessing the likelihood of receiving future payoffs. These characteristics will include the firm level of debt, creditworthiness, interest payments, debt maturity, etc.

IV. Data

We describe the sample construction and main variables in this section. We first discuss how we construct the firms' patent and citation database and provide the definition of our key variables. We summarize the patent and citation characteristics of the firms in our sample. In this section, we also define how we identify exogenous shocks to CEO option compensation, measure business cycle variations, and provide summary statistics of our sample data.

A. Innovation Data

Our sample includes information on public firms that have successfully filed for and had at least one patent granted during the sample period. We exclude financial firms with a four-digit standard industrial classification (SIC) code between 6000 and 6799 (finance, insurance, and real estate sectors) and utility firms with an SIC code between 4900 and 4949.

For a firm observation to be included in our sample, we require all public firms to have (i) at least some patent applications during the sample period, (ii) be included in the ExecuComp database, (iii) be identified to have fixed-cycle plans, and (vi) be covered by the Compustat database. In total, our sample comprises 786 firms and 2,915 firm-year observations with complete information on compensation, patent, and citation data observed between

1992 and 2013. Our data does not cover the patenting activity of individual entrepreneurs. Babina, Bernstein, and Mezzanotti (2023) show, however, firm-affiliated patenting represents the vast majority of total patents granted over the period that we cover in our sample.

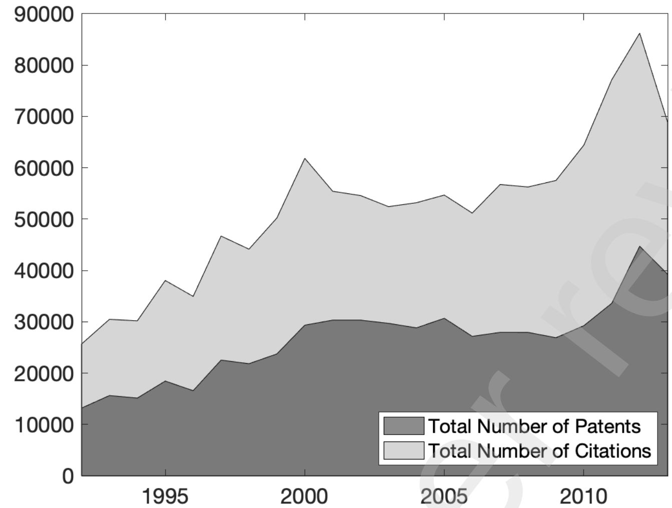


Figure 5: **Aggregate Patenting Trends.** This graph illustrates the time series trend in the annual total number of patents filed by all US firms and the total number of citations received by these patents.

Data on patents matched with US public firms are obtained from Bena, Ferreira, Matos, and Pires (2017) (referred to as the BFMP hereafter) and WRDS US Patents. Figure 5 reports the aggregate trends in total firm patenting activity between 1992 and 2013. The BFMP data set contains information on about 3 million (United States Patent and Trademark Office (USPTO) patents granted to publicly listed companies between 1980 and 2017. We use the BFMP database because all patents are already matched with firm identifiers. Moreover, we retrieve citation data from USPTO directly to augment our data sample by all citation records issued until our data collection day of May 20, 2020. We match these recent citation records with the existing patents using the USPTO patent ID.[1]

We end our sample with patents with application dates from 2013, even though WRDS US patent data is available until 2019. It typically takes three years for a patent to be

[1]Since the BFMP data includes all patents issued by public firms that are granted by 2017, we supplement the patent data using WRDS US Patent database, which covers patents granted by USPTO up to 2019.

granted after it was filed, i.e. after its application date. For example, a patent filed in 2019 is likely to have not been granted yet. Moreover, we measure future patenting activity over a horizon of the next one to four years. Therefore, we end the sample in 2013 to ensure that we capture most patents successfully filed in the year. While the sample of patent filings ends in 2013, the citations are counted up to the collection day of May 20, 2020. Figure 5 displays the total number of patents successfully filed between 1992 to 2013 and their received citations.

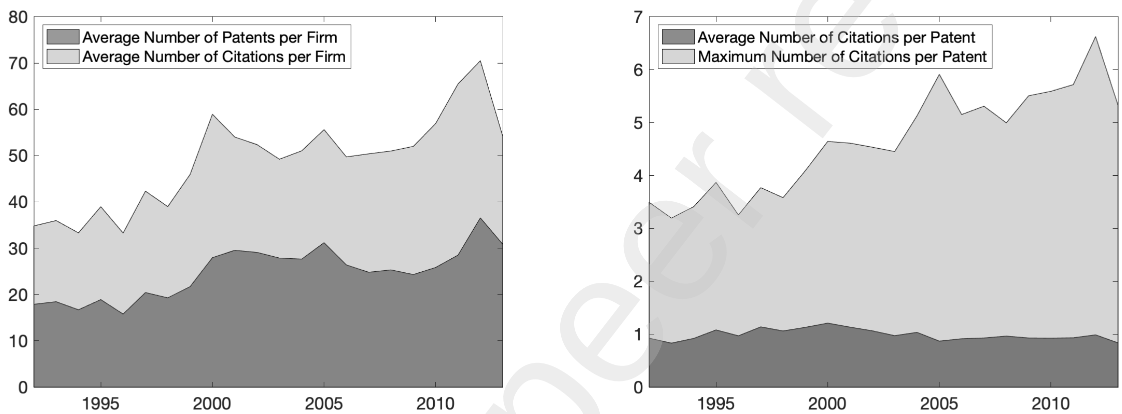


Figure 6: **Per-firm Patenting Trends.** This graph illustrates the time series trend in the annual average number of patents filed per firm and an average number of firm citations received by these patents, see Panel (a). Panel (b) shows the average total number of citations received per patent and the average maximum number of citations received by patents in firms. Patent-level citations are scaled by the average number of citations received by all patents applied at the same year and of the same technology class. Data used to create this Figure covers all public firms that have successfully filed for and had at least one patent granted during the sample period. Financial and utility firms are excluded.

Figure 6 presents the firm-level trends of innovation quantity (i.e. patent numbers) and quality (i.e. patent citations) produced by US-listed firms between 1992 to 2013. The total number of patents and citations produced by an average US firm is displayed on the left figure. The figure on the right shows the average number of citations received per patent and the maximum number of citations received by an average firm. We observe that the total firm-level patenting activity increased steadily over time and dropped in 2013. The average number of citations per patent, however, has decreased since 2000.

The USPTO patent database contains two time placers for each patent: the application and grant dates. We use the patent application year because it is closer to the date when the manager exerts effort to induce output and innovation.

In this paper, we focus on two dimensions of the total firm-level innovation output: 1) innovation quantity measured by the number of patents and 2) innovation quality measured using the number of citations that these patents receive.

Innovation Quality. Innovation quality is analyzed using the number of citations received by firm patents. The citation counts accumulate over the years. Therefore, a measure of the total number of citations suffers from the well-known truncation problem. That is, it would be unfair to compare a patent granted in 1970 with a patent granted in 2010 because the former has had about 50 years to generate citations while the latter only 10 years to do so. Therefore, to make the quality of patents of different ages comparable to each other, we scale each patent's citation count by the average number of citations received by all patents applied in the same year and of the same technology class. If citation information is missing in a given year, we set it to zero.

We measure firm innovation quality using three different ways; (i) the total number of citations received by patents filed in year t by firm i, (ii) the average number of citations received by patents filed in year t by firm i, and (iii) the maximum number of citations a patent has received so far among all the patents filed in year t by firm i.

B. Measuring Local Bank Distress

In this paper, we outline how severe economic conditions, experienced during crises, affect managerial incentives to innovate. We use bank distress data to proxy for severe market downturn conditions associated with heightened distress in the banking sector. The bank distress data are from the Federal Financial Institutions Examination Council (FFIEC). We calculate bank distress for each state, and scale the number of banks closed in year t by the total number of banks operating in the beginning of the year. A higher value indicates a more severe level of bank distress. Specifically, we measure the level of bank distress in state s and year t as

$$\text{Bank Distress}_{st} = \frac{\text{\# of Banks Closed}_{s,t}}{\text{Total \# of banks}_{s,t-1}}. \tag{9}$$

C. Summary Statistics

In Table I, we present the summary statistics for the sample of all firms and firm-year observations of identified multi-year option plans separately. Our main regressions are run on the sample of firms with identified fixed-cycle plans. This sample consists of observations where firms are either on an identified option plan or are predicted first years. Firms in our sample with identified fixed-cycle plans are very similar to an average firm in terms of its size, profitability, or Tobin's, see Table I. Firms we have identified to give multiyear option plans innovate slightly more on average, by producing about ten more patents every year. On average, firms in our sample file 35 patents annually. The total (scaled) number of citations received by all patents filed in a year is 71.3, and the median of the total number of citations received by firm i in year t is 0.61, which suggests that the total number of citations is substantially right-skewed.

Typically, firms in our sample spend 4% of total assets on R&D. Their average market capitalization of firms in our sample is 7.48 million, which is quite close to the sample median, of 7.36 million. The average Tobin's Q of our sample is quite high, 2.0, while the 25th and the 75th percentile are 1.23 and 2.29, respectively. This is not surprising as firms included in our sample are mostly research-active firms producing patents. All variables are winsorized at the 1% and 99% levels.

Table I: **Summary Statistics**

This table presents summary statistics for the main variables analyzed. It includes the mean, median, standard deviation, 25th and 75th percentiles, and the number of observations for each variable. The sample consists of all nonfinancial, nonutility firms with at least one successfully filed patent between 1992 and 2015. Panel A reports on the sample of firms with fixed-cycle plans is limited to firm-year observations where the firm CEO is identified to be on a plan and years with predicted first year of plans. Panel B reports descriptive statistics for all firms in our sample. Detailed descriptions of all variables are provided in Table A1.

	N	Mean	STD	25%	Median	75%
Panel A						
Firms with fixed-cycle plans						
Number of patents	2,915	35.49	144.69	0	1	16
Total number of citations	2,915	71.30	279.19	0	0.61	27.32
Max number of citations	2,915	6.16	15.89	0	0.57	6.47
Number of cit. per patent	2,915	1.15	2.82	0	0.33	1.65
R&D	2,915	0.04	0.07	0	0	0.05
Tobin's Q	2,915	2.00	1.26	1.23	1.62	2.29
Market Capital	2,915	7.48	1.63	6.33	7.36	8.50
Profitability	2,915	0.14	0.11	0.10	0.14	0.19
Fin. Constraints (SA index)	2,888	2.00	22.32	-2.97	-1.68	-0.86
ΔBS Value$_t$	2,994	0.05	0.64	-0.20	0.04	0.32
ΔBS Value$_t^{Max}$	2,997	0.04	0.65	-0.24	0.02	0.34
ΔFace Value$_t$	2,994	0.06	0.58	-0.15	0.04	0.29
ΔFace Value$_t^{Max}$	2,997	0.04	0.60	-0.19	0.02	0.30
First Year$_t$	2,915	0.15	0.36	0	0	0
Bank Distress (BD_{st})	2,915	0.11	0.06	0.07	0.09	0.12
Panel B						
All firms						
Number of patents	25,841	24.28	132.67	0	0	6
Total number of citations	25,841	47.22	269.38	0	0	9.32
Max number of citations	25,841	4.62	14.47	0	0	3.97
Number of cit. per patent	25,841	0.96	2.55	0	0	1.26
R&D	25,841	0.04	0.07	0	0.00	0.05
Tobin's Q	25,372	2.05	1.41	1.20	1.59	2.33
Market Capital	25,376	7.11	1.68	6.00	6.99	8.16
Profitability	25,776	0.13	0.12	0.08	0.13	0.19
Fin. Constraints (SA index)	25,416	1.00	18.05	-2.63	-1.47	-0.76
ΔBS Value$_t$	10,629	0.04	0.85	-0.32	0.07	0.41
ΔBS Value$_t^{Max}$	10,571	0.03	0.85	-0.35	0.05	0.41
ΔFace Value$_t$	10,629	0.05	0.79	-0.28	0.07	0.39
ΔFace Value$_t^{Max}$	10,571	0.03	0.80	-0.31	0.05	0.39
Bank Distress (BD_{st})	25,268	0.10	0.06	0.07	0.09	0.12

V. Identifying Exogenous Shocks to Incentives

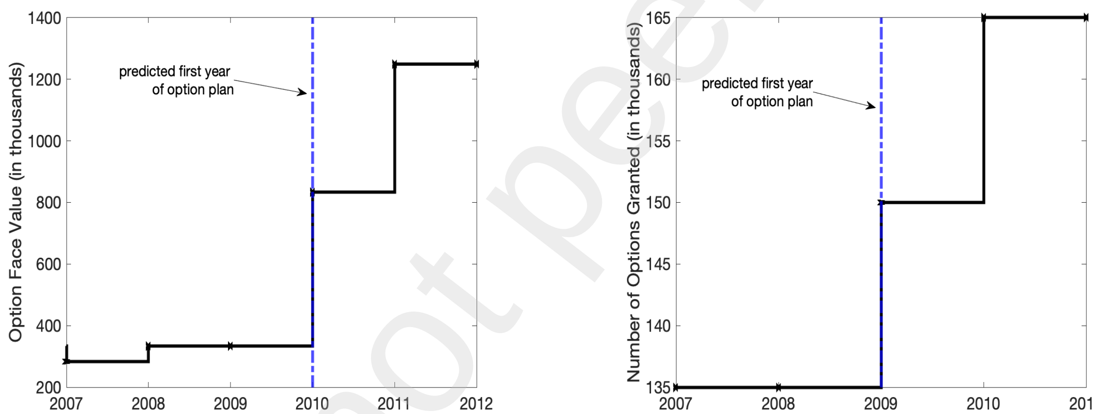
Executive multiyear option plans provide us with a tool to identify variations in managerial incentives to exert effort, that is arguably exogenous to current firm economic conditions (e.g. current firm profitability). The end of each multiyear option plan is determined years ahead, and should not be affected by current firm conditions.

Unfortunately, firms are not required to disclose whether and when CEOs are on multiyear compensation cycles. Therefore, we use empirical methods that estimate the cycles of multiyear option plans using compensation data from ExecuComp. We follow the methodology proposed by Hall (1999) and Shue and Townsend (2017). We employ the plan identification strategy used by Shue and Townsend (2017), which compares the values of option grants in subsequent years and assigns a CEO to be on an option plan if the option value paid is fixed (a fixed-value plan) or the number of options paid is fixed (a fixed-number plan).

Fixed-Value Plans. We identify an executive to be on a fixed-value cycle for two consecutive years if the executive receives the value of the options within 3% of the preceding year. Although in most cases, executives receive a single option grant, we are aware of the possibility that executives receive multiple grants per year. If this is the case, we only take the largest grant that is part of the multiyear option plan, which follows Shue and Townsend (2017). To make sure that the largest grants are significant relative to other option grants, we require that the value of the grants exceed more than 50% of the total value of all options granted to the executive in the given year.

We compute option values as either the Black-Scholes value or face value; that is the number of option grants multiplied by the price of the underlying stock on the grant date. We acknowledge that face value has little theoretical relation to the value of an option grant, nevertheless, it is a common practice that firms offering fixed-value option plans to their executives target face value in our sample. We require that a fixed-value cycle be defined using the same valuation method: either the Black-Scholes or face value in all years. As mentioned above, we allow for a 3% tolerance because firms often grant options in round lots. In fact, in many cases, the value of option grants is not exactly fixed, even by their internal valuation methodology (Shue and Townsend, 2017).

Fixed-Number Plans. We determine an executive to be on a fixed-number plan if the executive receives the same number of option grants in two consecutive years. The number of option grants is adjusted for stock splits. To identify fixed-value plans, we only consider the largest option grants in situations where there are multiple grants paid to an executive in a given year. We again require the number of grants to account for more than 50% of the total number of all grants to the executive in the given year, to ensure that the number of grants is significant relative to other grants.



(a) Netflix: Fixed-value plan

(b) Nike: Fixed-number plan

Figure 7: **Two Examples of Identified Fixed Cycle Plans.** This figure displays two examples of fixed-plan option cycles identified in the ExecuComp data. Panel (a) shows the Black-Scholes value of executive option grants awarded in Netflix, which represents an example of a fixed-value plan. An example from Panel (b), Nike.Inc, represents an identified fixed-number plan. The predicted first years of a fixed cycle are marked by dash-dotted vertical lines.

In Figure 7, we present two real examples of fixed-value and fixed-number cycles identified in our data sample. In Panel A, we report the Netflix CEO option grant values in the years between 2007 and 2012. The predicted first year is represented by the dash-dotted line. We identify that Netflix's CEO was on a two-year fixed-value plan in 2008 and 2009. Therefore, 2010 is predicted to be the first year of a new plan. We also show an example of an identified fixed-number plan (from our data sample) in Panel B. We detect that Nike's CEO was granted the same number of options in 2007 and 2008. Therefore, we identify Nike's CEO to be on a two-year fixed-cycle plan in 2007 and 2008 and 2009 to be the first year of a new plan or a new option compensation scheme. These predicted first years help us identify shocks to CEO compensation that are unrelated to other firm-level characteristics.

Our identification of exogenous shocks to CEO option compensation closely follows Shue and Townsend (2017). We set the predicted first-year dummy variable to one in the first year following the identified fixed value of the fixed-number option plan. The predicted first years are staggered across CEOs and firms in the sample period, therefore, which allows us to control for year-fixed effects.

We can detect 1,080 predicted first years. Among the firms that offer fixed-cycle plans, 640 firms increase the Black-Scholes value of the option grant in the year following the end of a fixed plan; while 440 firms decrease the option face value. Additionally, in companies that increase the option pay the year after a fixed plan is identified, the percentage of the Black-Scholes value increase is on average 72.2% with a median increase of 38.4%.

We identify exogenous shocks to CEO option compensation using the predicted first-year dummy variable introduced by Shue and Townsend (2017). To avoid introducing a bias from the potential endogenous renegotiation of executive option plans, we use predicted first years rather than the actual first years to identify exogenous variation in option pay. To illustrate that the predicted first years truly depict a change in CEO option pay, we plot the average change in the Black-Scholes option grant value three years before, three years after the predicted first years, as well as in the predicted first year in Figure 8. The substantial jump in the change in option grant value that coincides with the predicted first years suggests that the identified predicted first years are closely tied to the changes in option pay, validating the relevance of our instrumental variable. When regressing the actual change in CEO option pay on the predicted first-year dummy variable, we confirm that the relation between the change in CEO option pay and predicted first-year dummy variable is indeed significant with a t-statistics exceeding the level of 4, see Table II.

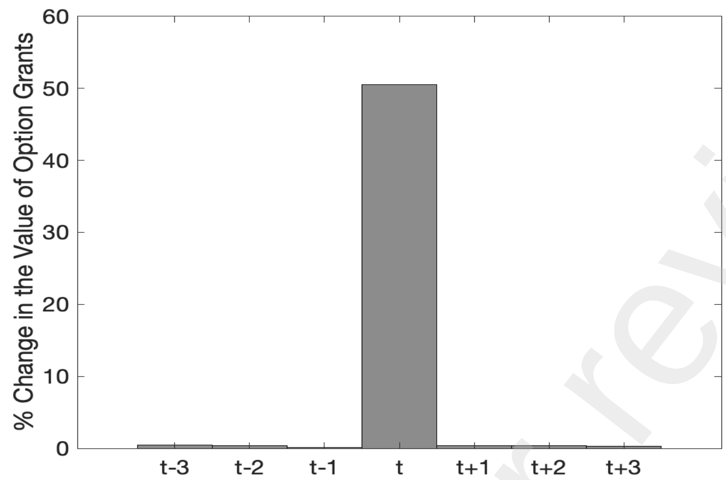


Figure 8: **Change in CEO Option Grant Value in and around Predicted First Years.** This figure displays the average percentage change in the Black-Scholes value of option grants received in the predicted first years (t), one to three years before the predicted first year ($t-1$ to $t-3$), and one to three years after the predicted first year ($t+1$ to $t+3$).

Table II: **CEO Option Pay in Predicted First Years of Option Plans**

The table displays the outcomes of OLS regression analysis, with the dependent variables listed at the top of each column. The key independent variable is the dummy variable denoting the predicted first years, labeled as First Year_t. All regressions account for year-fixed effects and incorporate time-varying CEO and firm characteristics, including CEO tenure, the logarithm of cash compensation (salary + bonus), logarithm of sales, logarithm of assets, sales growth, and Tobin's Q. These control variables are assessed in the year preceding the grant. T-statistics are presented in parentheses, and standard errors are clustered at the firm level. Coefficients that reach statistical significance at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

	Predicted First Year Dummy Variable (First Year_t)			
	(1)	(2)	(3)	(4)
	ΔFace Value_t	ΔBS Value_t	ΔFace Value_t^{Max}	ΔBS Value_t^{Max}
First Year_t	0.126***	0.129***	0.121***	0.120***
	(4.24)	(4.54)	(4.51)	(4.79)
Observations	2,712	2,720	2,712	2,720
Number of firms	763	767	763	767
Adjusted R-squared	0.068	0.054	0.069	0.056
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes

We confirm that during the predicted first years of option plans, managerial option compensation increases on average. In our sample, the predicted first-year dummy variable is associated with an average 12.6% increase in the face value of total option grants or a 12.9% increase in the Black-Scholes value of total option grants. We use both the face value and the Black-Scholes values of options because some firms target face value when offering fixed-value plans to executives, even though face value has little theoretical relation to the value of option grants.

Some CEOs may receive more than one option grant in a given year, which may complicate the identification of multi-year plans. We, therefore use both the total option grants and the largest option grants value to measure CEO option compensation for plan identification as well as the annual change in CEO option pay. In our sample, the largest option grant represents, on average, more than 93.3% of the total annual option grant value. This is because most firms issue only one option grant per year to their executive managers. Consequently, our results remain largely unchanged when we use either the total value of option grants (a sum across all grants in a given year) or the largest option grant.

In our regressions, we control for firm and year fixed effects and time-varying CEO and firm characteristics, such as CEO tenure, log of cash compensation (salary + bonus), firm log sales, firm log assets, firm sales growth, are firm's Tobin's Q, which are all measured in the year before the year when an option grant is received.

We use the Shue and Townsend (2017)'s predicted first-year variable, which is the first year after the identified completion of an option plan, as our primary identification variable that arguably captures exogenous shocks to option compensation. This binary variable, denoted as 'First Year$_t$' is set to be 1 if the year is identified to be the predicted first year and 0, otherwise. We use this variable as an instrument for shocks in CEO option pay.

VI. Results

How does increasing CEO option pay impact future firm innovation? We employ an instrumental variable (IV) approach that exploits predicted first years of identifying option plans to instrument for shocks in CEO option compensation. These shocks are considered to be plausibly exogenous to other drivers of current firm performance that would confound our results. Using this instrumental approach, we find that increasing the value of CEO option awards has a zero to mildly negative impact on future firm innovation. When explaining the total number of patents produced by firms over the next four-year period, we find that the coefficient attached to the change in option value has a t-statistic of -1.62, see Table III, a value that is just below the typically considered significance margin. We conclude that, for an average firm in our sample, increasing CEO option compensation does not significantly improve the quantity or the quality of patents produced over the next one to four years.

Since our instrument–the predicted first-year variable–is staggered, we can control for year-fixed effects. Our main results are always controlling for fixed effects and cluster standard errors by firms. Additionally, in both the first and second stages of our IV regressions, we control for the following firm characteristics: market capitalization, Tobin's Q, R&D expenditures scaled by total assets, and firm profitability. We report the results of the second-stage regressions in Table 3 and disclose the first-stage *F-statistics* at the bottom of each column. The *F-statistics* are above 50, which indicates that the chosen instrument is sufficiently strong to identify (positive) shocks in CEO option compensation.

In the next sections of this paper, we explore under which conditions CEO option pay affects future firm innovation. We focus on three main factors impacting this relationship: (*i*) the impact of economic conditions, namely bank distress, (*ii*) managerial risk aversion, and (*iii*) the 'skin in the game' of managers.

Table III: **The Causal Impact of Option Pay on Firm Innovation**

The table presents the IV 2SLS regression results. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year_t to instrument $\overline{\Delta\text{BS Value}}_t$. First Year_t is equal to 1 if the year is the predicted first year of a fixed-cycle plan and 0, otherwise. All regressions control for year-fixed effects, bank distress, and firm characteristics, i.e. R&D scaled by total assets, market capital, and profitability. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	(1) # $\text{Patents}_{t+1,t+4}$	(2) # $\text{Citations}_{t+1,t+4}$	(3) # Cit. per $\text{Patent}_{t+1,t+4}$	(4) Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}}_t$	-0.882	-0.864	0.078	-0.485
	(-1.62)	(-1.37)	(0.27)	(-1.12)
Observations	2915	2915	2915	2915
Adj. R^2	0.650	0.628	0.619	0.638
F-stat of $\overline{\Delta\text{BS Value}}$	57.09	57.09	57.09	57.09
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

A. *The Impact of CEO pay on Innovation in Bad Times*

We examine under which conditions awarding CEOs with option pay impacts the innovative output produced by firms in future. We are particularly interested in studying how bank distress impacts managerial incentives to innovate. We analyze the impact of an exogenous increase in option pay awarded during times of high bank distress using an interaction term that is incorporated into the IV regression model. Appendix B details our empirical strategy used to assess the impact of CEO pay awarded in times of high bank distress.

The impact of an increase in CEO pay awarded during times of high bank distress on firm innovation is positive. We find that a firm innovative output, produced over the next one to four years, is positively related to long-term managerial compensation awarded in bad times, see Table 3. Our results suggest that increasing the option value paid to CEOs in times of high bank distress motivates managers to exert more effort and accept more risky projects that result in more patents produced that are of a higher quality.

We document that when bank distress is high (i.e. the bank distress dummy variable equals 1), an increase in the Black-Scholes value of the CEO option pay by one standard deviation leads to firms producing about 2.02 more patents, that receive about 2.55 more citations, over the next four years. The maximum number of citations also increases by 1.64. The results from the IV regressions largely support the view that motivating managers through option awards in times of high bank distress helps increase firm innovative output. These effects on patent quantity and quality are significant both statistically and economically. These findings are suggestive of CEO executives having stronger incentives to innovate during times of economic distress.

We graphically illustrate the impact of an exogenous increase in CEO option pay as a function of the bank distress variable. The impact of CEO option pay on firm innovation increases in bank distress variable. This positive relation is described by the blue line from Figure 9. Our results confirm that the impact that CEO long-term compensation has on the quantity and quality of innovation strengthens in bad times. We document that the effects of CEO option pay on the number of patents produced by firms in the future one to four years are positive only when the bank distress variable exceeds 15.3%, which corresponds to about 17.8% of the worst realizations of the bank distress used. This means that bank distress levels must be sufficiently high, else, the impact of increasing CEO option pay on firm patenting activity is either non-existent or negative.

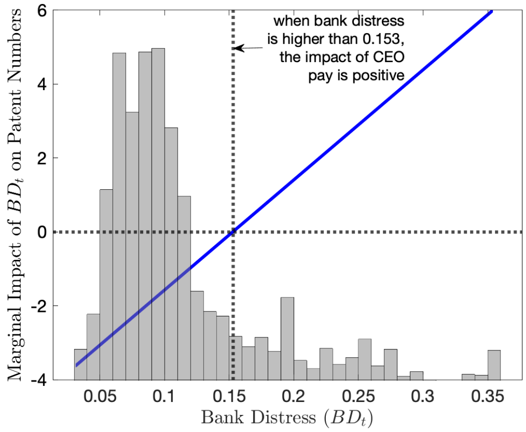
When focusing on patent quality, measured either by the total number of citations or the maximum number of citations received by firm patents, we arrive at similar conclusions. The bank distress variable must exceed the value of 14.3% (14.7%) for the estimated coefficient attached to the exogenous increase in CEO option pay to become positive when explaining the total (the maximum) number of patent citations. This corresponds to about 18.8% (19.3%) of the worst realizations of bank distress. Our main results reveal that the positive relation between CEO option pay and firm innovation exists only when bank distress is sufficiently high.

Table 3: **Option Pay and Innovation in Bad Times**

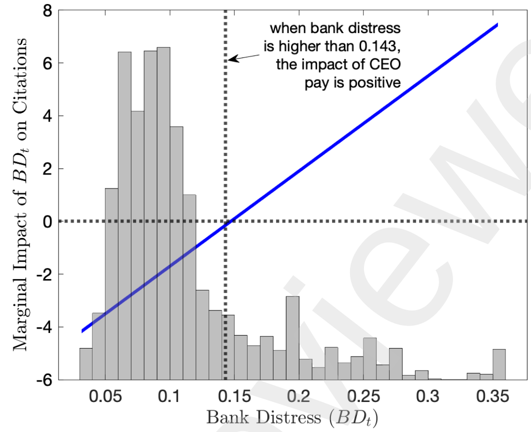
The table presents the IV 2SLS regression second-stage results. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year$_t$ to instrument $\overline{\Delta \text{BS Value}}_t$. First Year$_t$ is equal to 1 if the year is the predicted first year of a fixed-cycle plan and 0, otherwise. The independent variable of interest is the instrumented interaction term between the predicted first year (First Year$_t$) and the bank distress. We use two proxies of bank distress, the level of bank distress (Bank Distress$_t$), reported in Panel A, and the bank distress dummy variable reported in Panel B. The level of bank distress is measured by the number of banks closed scaled by the total number of banks in the beginning period at the state-year level. The bank distress dummy variable is set to be 1 if the level of bank distress is above the sample median and 0, otherwise. All regressions control for year-fixed effects and firm characteristics, i.e. contemporaneous R&D scaled by total assets, market capital, and profitability (which includes the contemporaneous level as well as levels with up to two-year lags). The first-stage F-statistics are reported at the end of the table. T-statistics are in parentheses. Standard errors are clustered at the firm level. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: Bank Distress				
	(1)	(2)	(3)	(4)
	# Patents$_{t+1,t+4}$	# Citations$_{t+1,t+4}$	# Cit. per Patent$_{t+1,t+4}$	Max # of Citations$_{t+1,t+4}$
$\overline{\Delta \text{BS Value}}_t$	-4.551**	-5.306**	-0.631	-3.450**
	(-2.40)	(-2.43)	(-0.81)	(-2.30)
Bank Distress$_t$ (BD)	-1.646	-1.638	0.617	-0.643
	(-1.38)	(-1.20)	(1.18)	(-0.70)
$\overline{\text{BD} \times \Delta \text{BS Value}}_t$	29.798**	36.066**	5.760	24.077**
	(2.22)	(2.35)	(1.09)	(2.28)
Observations	2915	2915	2915	2915
Adj. R^2	0.615	0.588	0.616	0.602
F-stat of $\overline{\Delta \text{BS Value}}$	32.23	32.23	32.23	32.23
F-stat of $\overline{\text{BD} \times \Delta \text{BS Value}}$	32.94	32.94	32.94	32.94
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

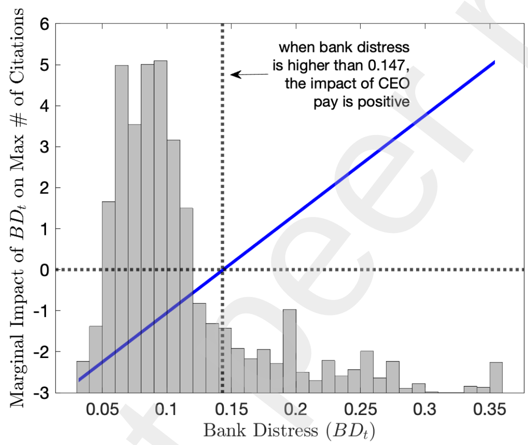
Panel B: Bank Distress Dummy				
	(1)	(2)	(3)	(4)
Variables	# Patents$_{t+1,t+4}$	# Citations$_{t+1,t+4}$	# Cit. per Patent$_{t+1,t+4}$	Max # of Citations$_{t+1,t+4}$
$\Delta ln(BSval)(t)$	-2.937**	-3.456**	-0.424	-2.157**
	(-2.19)	(-2.24)	(-0.78)	(-2.07)
Bank Distress Dummy$_t$ (BD)	-0.187	-0.191	0.059	-0.067
	(-1.52)	(-1.39)	(1.05)	(-0.70)
$\overline{\text{BD} \times \Delta \text{BS Value}}_t$	3.162**	3.985**	0.767	2.566**
	(2.09)	(2.32)	(1.23)	(2.20)
Observations	2915	2915	2915	2915
Adj. R^2	0.616	0.586	0.612	0.602
F-stat of $\overline{\Delta \text{BS Value}}$	31.17	31.17	31.17	31.17
F-stat of $\overline{\text{BD} \times \Delta \text{BS Value}}$	22.65	22.65	22.65	22.65
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes



(a) Number of Patents



(b) Total Number of Citations



(c) Maximum Number of Citations of Patents

Figure 9: **The Marginal Impact of CEO Option Pay on Innovation.** This figure describes the marginal effects of increasing CEO option pay on the number of patents produced by firms (Panel (a)), the total number of citations received by all patents filed by a firm in a given year (Panel (b)) and the maximum number of citations received by all patents filed by a firm in a year (Panel (c)), for different levels of bank distress. The shaded area represents the observed density of the bank distress variable. The marginal impact values in this Figure are based on regression results from Table 3.

B. Managerial 'skin in the game'

More risk-averse managers or managers with more 'skin in the game,' who are afraid of losing their potentially undiversified labor income, are generally less likely to invest in innovative projects.[2] We test whether the CEOs from our sample are less likely to choose riskier innovative strategies if they have more to lose or are more risk averse. We proxy for managerial 'skin in the game' using several proxies: managerial wealth-performance sensitivity, managerial current option pay, delta of total CEO holdings, CEO tenure, and CEO age. CEOs with shorter tenure or younger CEOs are likely to have generated less wealth that is invested in the company they work for and are, thus, expected to have less 'skin in the game.'

We find that managers with more 'skin in the game' choose to innovate less when they are awarded a higher option pay. Our main results are consistent across all measures of the managerial 'skin in the game' we use. When explaining the total number of patents produced by firms over the next four-year period, we find strongly significant and negative coefficients attached to increases in CEO option compensation among CEOs with high wealth-performance sensitivity and high delta of their total stock and option holdings.

The impact on the citations per patent is rather modest and appears to be significant and negative only among relatively older CEOs. Overall, our results indicate that option pay diminishes the total innovative output produced by firms with CEOs that are more invested in it but it does not substantially affect the quality of an average patent produced. Managers seem to produce patents of similar quality, they just choose to innovate less in total, which leads to a lower production of patents.

[2] Ma and Tang (2019) find that managers with more 'skin in the game' build less risky investment portfolios.

Table V: **Managerial 'Skin in the Game'**

The table presents the IV 2SLS regression results in sample splits. Methodology follows description from Table III. We create two sub-samples (below median and above media) using the following measures of managerial 'skin in the game': Edmans, Gabaix, and Landier (2009)'s wealth-performance sensitivity (Panel A), the delta of CEO total holdings (Panel B), CEO age (Panel C), CEO tenure (Panel D), and CEO current option pay (Panel E). The impact of CEO pay on the number of patents and citations per patent produced over the next four-year period is analyzed.

	High WPS		Low WPS	
	(1)	(2)	(3)	(4)
Panel A	# $Pat_{t+1,t+4}$	# Cit. per $Pat._{t+1,t+4}$	# $Pat_{t+1,t+4}$	# Cit. per $Pat_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-3.429**	-0.355	-0.202	0.080
	(-1.98)	(-0.46)	(-0.36)	(0.30)
Observations	1635	1635	1360	1360
Adj. R^2	0.574	0.607	0.658	0.633
F-stat	52.31	52.31	10.21	10.21
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

	High delta		Low delta	
	(1)	(2)	(3)	(4)
Panel B	# $Pat_{t+1,t+4}$	# Cit. per $Pat._{t+1,t+4}$	# $Pat_{t+1,t+4}$	# Cit. per $Pat_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-1.249**	-0.030	-0.068	0.258
	(-2.00)	(-0.09)	(-0.06)	(0.47)
Observations	1786	1786	1206	1206
Adj. R^2	0.675	0.643	0.603	0.580
F-stat	44.92	44.92	16.22	16.22
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

	Older CEOs		Younger CEOs	
	(1)	(2)	(3)	(4)
Panel C	# $Pat_{t+1,t+4}$	# Cit. per $Pat._{t+1,t+4}$	# $Pat_{t+1,t+4}$	# Cit. per $Pat_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-1.889**	-0.624*	-0.162	0.668
	(-2.56)	(-1.76)	(-0.17)	(1.21)
Observations	1498	1498	1407	1407
Adj. R^2	0.630	0.606	0.652	0.601
F-stat	40.4	40.4	19.95	19.95
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel D	High CEO tenure (1) # $\text{Pat}_{t+1,t+4}$	(2) # Cit. per $\text{Pat.}_{t+1,t+4}$	Low CEO tenure (3) # $\text{Pat}_{t+1,t+4}$	(4) # Cit. per $\text{Pat}_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-1.109	0.132	0.121	0.308
	(-1.56)	(0.34)	(0.13)	(0.68)
Observations	1674	1674	1330	1330
Adj. R^2	0.610	0.582	0.699	0.668
F-stat	41.41	41.41	16.72	16.72
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel E	High current option pay (1) # $\text{Pat}_{t+1,t+4}$	(2) # Cit. per $\text{Pat.}_{t+1,t+4}$	Low current option pay (3) # $\text{Pat}_{t+1,t+4}$	(4) # Cit. per $\text{Pat}_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-0.727	0.024	-0.239	0.213
	(-1.52)	(0.10)	(-0.06)	(0.09)
Observations	1501	1501	1494	1494
Adj. R^2	0.703	0.669	0.579	0.557
F-stat	97.33	97.33	0.98	0.98
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

C. *The impact of risk aversion on managerial incentives to innovate in bad times*

We identify a subset of CEOs from our sample who are likely to be more sensitive to the effects of the economic conditions on their incentives to innovate. We cannot directly measure the degree of risk aversion of CEOs in our sample but existing literature has offered some clues on which types of managers may have higher or lower degrees of risk aversion. For instance, Dittmann and Maug (2007) show that liquidity constraints are stronger for CEOs who have joined the company more recently, which may make them more risk averse.

We find that our main results linking CEO option pay awarded in bad times are substantially stronger among firms with CEOs with longer tenure. In fact, among firms with CEOs with shorter tenure, CEO option pay does not induce innovation, which suggests that the impact of risk aversion on managerial incentives to innovate dominates the costs of not innovating during bad times, see Table 6.

Graham, Harvey, and Puri (2013) construct a survey-based measure of risk aversion and show that male CEOs are generally less risk averse. We split our sample into firms with male and female CEOs and report our sub-sample results in Table 7. The positive and significant impact of CEO option pay awarded in bad times on future firm innovation exists only among firms with male CEOs. This finding confirms our hypothesis that in firms with highly risk-averse CEOs, the incentives to innovate in bad times are weaker and, indeed, non-existent.

We summarize that the found effect stating that managerial incentives to innovate strengthen during bad times is stronger among firms with male CEOs and firms with CEOs with longer tenure, see Tables 7 and 6. These results are consistent with our model that suggests that when managerial risk aversion is high, accepting the innovative project may never become optimal. The lower wedge between the project payoff volatilities, observed during bad times, may therefore not have any impact on CEO actions.

Table 7: **Risk Aversion: CEO Gender**

The table presents IV 2SLS regression results for the sub-samples analysis of financial constrained and less constrained firms. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year_t to instrument $\overline{\Delta\text{BS Value}_t}$. We show the results for firms with male CEOs in Panel A and firms with female CEOs in Panel B. All regressions control for year fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capital and profitability. T-statistics are in parentheses. Coefficients statistically significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	Panel A: Firms with male CEOs			
	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-4.052**	-4.689**	-2.948**	-0.534
	(-2.37)	(-2.38)	(-2.20)	(-0.71)
Bank Distress_t (BD)	-1.662	-1.618	-0.591	0.634
	(-1.39)	(-1.17)	(-0.65)	(1.19)
$\overline{\text{BD} \times \Delta\text{BS Value}_t}$	25.231**	30.401**	19.566**	4.617
	(2.22)	(2.33)	(2.22)	(0.96)
Observations	2861	2861	2861	2861
Adj. R^2	0.624	0.599	0.615	0.619
F-stat of $\overline{\Delta\text{BS Value}}$	35.59	35.59	35.59	35.59
F-stat of $\overline{\text{BD} \times \Delta\text{BS Value}}$	35.76	35.76	35.76	35.76
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
	Panel B: Firms with female CEOs			
	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-20.019	-23.273	-21.662	-4.977
	(-0.20)	(-0.20)	(-0.20)	(-0.19)
Bank Distress_t (BD)	-5.034	-7.325	-6.233	0.158
	(-0.29)	(-0.36)	(-0.33)	(0.03)
$\overline{\text{BD} \times \Delta\text{BS Value}_t}$	58.158	67.842	64.371	14.456
	(0.17)	(0.17)	(0.18)	(0.17)
Observations	51	51	51	51
Adj. R^2	-2.026	-2.875	-4.671	-1.390
F-stat of $\overline{\Delta\text{BS Value}}$	13.86	13.86	13.86	13.86
F-statistics of $Bdist(t) \times \Delta ln(BSval)(t)$	14.18	14.18	14.18	14.18
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 6: **Risk Aversion: CEO Tenure**

The table presents IV 2SLS regression results for the sub-sample analysis of firms with CEOs with longer and shorter tenure. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year_t to instrument $\overline{\Delta\text{BS Value}_t}$. We measure CEO tenure as the number of years of a CEO being in a given company. We show results for firms with CEOs with longer tenure (i.e. higher than the sample median) in Panel A and results for firms with CEOs with shorter tenure (i.e. lower than the sample median) in Panel B. All regressions control for year fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capital and profitability. T-statistics are in parentheses. Coefficients statistically significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	Panel A: Firms with CEOs with longer tenure			
	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-4.120**	-4.241**	-2.679*	-0.330
	(-2.29)	(-2.08)	(-1.90)	(-0.40)
Bank Distress_t (BD)	-3.205**	-3.260*	-1.545	0.510
	(-2.08)	(-1.88)	(-1.32)	(0.75)
$\overline{\text{BD} \times \Delta\text{BS Value}_t}$	25.706**	28.096**	18.092*	3.943
	(2.08)	(2.00)	(1.86)	(0.72)
Observations	1632	1632	1632	1632
Adj. R^2	0.585	0.568	0.579	0.582
F-stat of $\overline{\Delta\text{BS Value}}$	22.51	22.51	22.51	22.51
F-stat of $\overline{\text{BD} \times \Delta\text{BS Value}}$	21.57	21.57	21.57	21.57
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

	Panel B: Firms with CEOs with shorter tenure			
	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-5.104	-7.587	-5.130	-0.820
	(-1.02)	(-1.21)	(-1.19)	(-0.44)
Bank Distress_t (BD)	0.343	0.805	0.792	0.849
	(0.22)	(0.43)	(0.62)	(1.19)
$\overline{\text{BD} \times \Delta\text{BS Value}_t}$	38.958	55.611	38.915	8.780
	(1.12)	(1.28)	(1.29)	(0.70)
Observations	1283	1283	1283	1283
Adj. R^2	0.669	0.618	0.633	0.664
F-stat of $\overline{\Delta\text{BS Value}}$	9.88	9.88	9.88	9.88
F-stat of $\overline{\text{BD} \times \Delta\text{BS Value}}$	11.12	11.12	11.12	11.12
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

D. *Firm characteristics and managerial incentives to innovate*

We have documented that increasing the value of CEO option grants in times when the bank distress level is high improves patent quality and innovation efficiency of citations. Not all firms have enough available resources that can be allocated to produce innovation during periods of heightened bank distress levels. We hypothesize that financially-constrained firms would be the first ones to cut on R&D during crises, which would negatively affect their future innovation.

To test our hypothesis, we examine the effects of managerial compensation on innovation across two groups of firms: A) firms that are relatively more financially constrained and B) firms that are relatively less financially constrained. We use the SA index (Hadlock and Pierce, 2010) to measure financial constraints: a measure that depends on firm asset size and age and, is calculated as $(-0.737 \times Assets + 0.043 \times Assets^2 - 0.040 \times Age)$. We determine that a firm belongs to group A (and is financially more constrained) if its SA index is greater than the sample median.

We find that, in firms that are financially more constrained (see Panel A from Table 8), increasing managerial compensation during bad times is less successful in inducing innovation. This is consistent with our proposed model that implies that when managers view survival probability are high (due to, e.g., high financial constraints), they may not be willing to engage in innovative projects during economic downturns. In contrast, firms that are relatively less constrained financially can benefit from the stronger incentives to innovate observed during bad times, see Panel B from Table 8.

Additionally, we split the sample using the firm-level Z score and firm age and find results consistent with the argument that managerial incentives to innovate strengthen only when the perceived survival probability is low, see Tables 9 and 9.

Table 8: **Firm Financial Constrains**

The table presents IV 2SLS regression results for the sub-samples analysis of financial constrained and less constrained firms. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year$_t$ to instrument $\overline{\Delta \text{BS Value}}_t$. We measure firm financial constraints using the SA index, computed as $(-0.737 \times Assets + 0.043 \times Assets^2 - 0.040 \times Age)$. We show the results for relatively higher financially-constrained firms (i.e. firms with SA index greater than the sample median) in Panel A and for relatively less financially constrained firms (i.e. firms with SA index less than or equal to the sample median) in Panel B. All regressions control for year fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capital and profitability. T-statistics are in parentheses. Coefficients statistically significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Panel A: Financially More Distressed Firm

	(1) # Patents$_{t+1,t+4}$	(2) # Citations$_{t+1,t+4}$	(3) # Cit. per Patent$_{t+1,t+4}$	(4) Max # of Citations$_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-1.824	-3.215	-0.449	-2.366
	(-0.73)	(-1.07)	(-0.43)	(-1.11)
Bank Distress Dummy$_t$ (BD)	1.891	3.367	0.399	2.421
	(0.67)	(1.03)	(0.36)	(1.05)
$\overline{\text{BD} \times \Delta \text{BS Value}_t}$	0.035	0.009	0.114	0.054
	(0.17)	(0.04)	(1.44)	(0.35)
Observations	1440	1440	1440	1440
Adj. R^2	0.702	0.672	0.674	0.669
F-stat of $\overline{\Delta \text{BS Value}}$	13.69	13.69	13.69	13.69
F-stat of $\overline{\text{BD} \times \Delta \text{BS Value}}$	12.36	12.36	12.36	12.36
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Financially Less Distressed Firm

	(1) # Patents$_{t+1,t+4}$	(2) # Citations$_{t+1,t+4}$	(3) # Cit. per Patent$_{t+1,t+4}$	(4) Max # of Citations$_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-2.135	-2.283	-0.521	-1.339
	(-1.58)	(-1.42)	(-0.70)	(-1.17)
Bank Distress Dummy$_t$ (BD)	-0.219*	-0.232	-0.013	-0.114
	(-1.72)	(-1.50)	(-0.16)	(-1.00)
$\overline{\text{BD} \times \Delta \text{BS Value}_t}$	2.835*	3.456*	1.219	2.202
	(1.83)	(1.87)	(1.36)	(1.64)
Observations	1448	1448	1448	1448
Adj. R^2	0.572	0.527	0.540	0.550
F-stat of $\overline{\Delta \text{BS Value}}$	16.17	16.17	16.17	16.17
F-stat of $\overline{\text{BD} \times \Delta \text{BS Value}}$	11.22	11.22	11.22	11.22
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 9: **Z-score**

The table presents IV 2SLS regression results for the sub-sample analysis of firm age. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year$_t$ to instrument $\overline{\Delta \text{BS Value}_t}$. We show the results for firms that have high bankruptcy probability (i.e. Z-score below the annual median) in Panel A and for firms that have low bankruptcy probability (i.e. Z-score above or equal to the annual median) in Panel B. All regressions control for year-fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capitalization, and profitability. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Zscore low (high bankruptcy probability)

Variables	(1) ln(pat+1)	(2) ln(cit_tot+1)	(3) ln(cit_per_pat+1)	(4) ln(cit_max+1)
$\Delta ln(BSval)(t)$	-2.192	-3.832	-0.429	-2.547
	(-0.92)	(-1.34)	(-0.41)	(-1.27)
Bdist(t)	1.109	1.015	1.306*	0.787
	(0.62)	(0.47)	(1.66)	(0.54)
$Bdist(t) \times \Delta ln(BSval)(t)$	10.232	23.672	5.022	16.288
	(0.60)	(1.14)	(0.62)	(1.11)
N	1188	1188	1188	1188
adj. R-sq	0.650	0.607	0.630	0.618
F-statistics of $\Delta ln(BSval)(t)$	9.8	9.8	9.8	9.8
F-statistics of $Bdist(t) \times \Delta ln(BSval)(t)$	9.27	9.27	9.27	9.27
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Zscore high (low bankruptcy probability)

Variables	(1) ln(pat+1)	(2) ln(cit_tot+1)	(3) ln(cit_per_pat+1)	(4) ln(cit_max+1)
$\Delta ln(BSval)(t)$	-5.297**	-5.168*	-0.434	-3.350*
	(-2.00)	(-1.78)	(-0.38)	(-1.69)
Bdist(t)	-1.918	-1.828	0.537	-0.591
	(-1.40)	(-1.19)	(0.83)	(-0.58)
$Bdist(t) \times \Delta ln(BSval)(t)$	38.036**	38.352*	4.911	25.588*
	(2.04)	(1.90)	(0.69)	(1.88)
N	1727	1727	1727	1727
adj. R-sq	0.643	0.636	0.625	0.642
F-statistics of $\Delta ln(BSval)(t)$	21.16	21.16	21.16	21.16
F-statistics of $Bdist(t) \times \Delta ln(BSval)(t)$	22.33	22.33	22.33	22.33
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 9: **Firm Age**

The table presents IV 2SLS regression results for the sub-sample analysis of firm age. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year$_t$ to instrument $\overline{\Delta \text{BS Value}_t}$. We show the results for young firms (i.e. firm age below the annual median) in Panel A and for old firms (i.e. firm age above or equal to the annual median) in Panel B. All regressions control for year-fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capitalization, and profitability. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Firm age young (t+1, t+4)

	(1) # Patents$_{t+1,t+4}$	(2) # Citations$_{t+1,t+4}$	(3) # Cit. per Patent$_{t+1,t+4}$	(4) Max # of Citations$_{t+1,t+4}$
$\Delta ln(BSval)(t)$	-1.811	-2.143	0.381	-1.055
	(-1.18)	(-1.16)	(0.44)	(-0.80)
Bdist(t)	-2.027	-2.313	0.260	-1.084
	(-1.06)	(-1.05)	(0.29)	(-0.75)
$Bdist(t) \times \Delta ln(BSval)(t)$	7.409	13.469	-1.382	7.153
	(0.67)	(1.01)	(-0.21)	(0.72)
N	1224	1224	1224	1224
adj. R-sq	0.606	0.580	0.567	0.592
F-statistics of $\Delta ln(BSval)(t)$	12.55	12.55	12.55	12.55
F-statistics of $Bdist(t) \times \Delta ln(BSval)(t)$	10.71	10.71	10.71	10.71
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Firm age old (t+1, t+4)

	(1) # Patents$_{t+1,t+4}$	(2) # Citations$_{t+1,t+4}$	(3) # Cit. per Patent$_{t+1,t+4}$	(4) Max # of Citations$_{t+1,t+4}$
$\Delta ln(BSval)(t)$	-8.992*	-10.643*	-2.331	-7.566*
	(-1.73)	(-1.79)	(-1.28)	(-1.80)
Bdist(t)	0.172	0.706	1.465**	1.012
	(0.09)	(0.33)	(2.05)	(0.69)
$Bdist(t) \times \Delta ln(BSval)(t)$	57.677*	67.406*	15.576	48.461*
	(1.69)	(1.73)	(1.33)	(1.77)
N	1691	1691	1691	1691
adj. R-sq	0.559	0.517	0.618	0.516
F-statistics of $\Delta ln(BSval)(t)$	18.41	18.41	18.41	18.41
F-statistics of $Bdist(t) \times \Delta ln(BSval)(t)$	20.79	20.79	20.79	20.79
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

In the Aghion and Howitt (1992) endogenous growth model, old technology is being replaced by new industrial innovations through the process of creative destruction. The speed of economic growth depends on market competition, or the degree of market power available to incumbents, i.e. past innovators. Incumbents are naturally interested in blocking new innovators from entering the market as they wish to keep their current positions for as long as possible.

We argue that in bad times, when firms' prospects are more uncertain and new entry becomes more difficult due to, e.g. a lower availability of funding capital, only firms with more market power will be able to benefit from the stronger incentives to innovate.

To test our hypothesis, we split firms into two groups, firms with relatively high and low market power. We measure market power using the portion of firm sales in the industry in a given year. The industry is defined by a 3-digit SIC code. Our results from Table 5 confirm our hypothesis. We find that in firms with high market power, CEOs' incentives to innovate increase significantly during bad times. In firms with relatively low market power, this effect of CEO option pay on firm innovation does not exist. These results are consistent with our claims that only incumbents can benefit from stronger incentives to engage in innovative projects.

Table 5: **Firm Market Power**

The table presents IV 2SLS regression results for the sub-sample analysis of firm market power. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year_t to instrument $\overline{\Delta\text{BS Value}}_t$. We measure market power using the ratio of sales in the firm's industry in a given year. We show the results for firms with relatively high market power (i.e. greater than the year median in its industry) in Panel A and firms with relatively low market power (i.e. lower than the year median in its industry). All regressions control for year fixed effects and firm characteristics, i.e. R&D scaled by total assets, market capital and profitability. T-statistics are in parentheses. Coefficients statistically significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Panel A: Low Market Power	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}}_t$	-4.301	-4.164	1.022	-2.235
	(-1.44)	(-1.27)	(0.96)	(-1.04)
Bank Distress_t (BD)	-1.990	-1.873	0.777	-0.902
	(-1.19)	(-1.00)	(1.08)	(-0.73)
$\overline{\text{BD} \times \Delta\text{BS Value}}_t$	34.735	34.179	-5.227	19.233
	(1.36)	(1.25)	(-0.69)	(1.10)
Observations	1372	1372	1372	1372
Adj. R^2	0.676	0.654	0.654	0.671
F-stat of $\overline{\Delta\text{BS Value}}$	15.29	15.29	15.29	15.29
F-stat of $\overline{\text{BD} \times \Delta\text{BS Value}}$	15.83	15.83	15.83	15.83
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: High Market Power	(1)	(2)	(3)	(4)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}}_t$	-5.786**	-7.461**	-2.512*	-5.329**
	(-2.15)	(-2.31)	(-1.96)	(-2.30)
Bank Distress_t (BD)	-1.145	-1.174	0.617	-0.200
	(-0.81)	(-0.72)	(0.94)	(-0.18)
$\overline{\text{BD} \times \Delta\text{BS Value}}_t$	33.055**	45.296**	16.547**	32.853**
	(2.04)	(2.28)	(2.02)	(2.28)
Observations	1543	1543	1543	1543
Adj. R^2	0.529	0.482	0.518	0.485
F-stat of $\overline{\Delta\text{BS Value}}$	14.78	14.78	14.78	14.78
F-stat of $\overline{\text{BD} \times \Delta\text{BS Value}}$	15.52	15.52	15.52	15.52
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

VII. Conclusion

We identify exogenous changes in CEO option pay using the Shue and Townsend (2017)'s fixed-cycle methodology. First, we confirm that the predicted first years are associated with changes in option grant values, confirming this instrument to be a useful tool to measure changes in CEO option compensation. Using this instrument, we examine how managerial characteristics as well as broad economic conditions, namely bank distress, affect CEO motivation to innovate.

Our findings reveal that managerial incentives to innovate intensify during economic downturns. Specifically, we observe that when managers receive increased option pay during challenging times, their firm's innovative output escalates in both quantity and quality. When options are granted to managers during normal times, this impact is non-existent. This validates previous findings reported in the literature (Biggerstaff, Blank, and Goldie, 2019; Mao and Zhang, 2018) and aligns with the notion that the costs of risk sharing offset the benefits of exploiting innovative projects.

Moreover, we highlight that rewarding managers with greater 'skin in the game' with more options can in discourage firm innovation. This effect remains consistent across various measures of managerial 'skin in the game,' ranging from the Edmans, Gabaix, and Landier (2009)'s wealth-performance sensitivity, delta of CEO holdings, current CEO option pay, CEO tenure, to CEO age.

Considering the pivotal role new technologies play in fostering creative destruction and productivity growth in the economy, motivating innovation emerges as a central concern for firms, academics, and policymakers alike. Our study offers fresh insights into the factors driving the nexus between incentives and innovation by scrutinizing the internal executive rewards mechanism. As a policy recommendation, we advocate for firms to closely monitor the degree of managerial 'skin in the game' to gauge whether the costs of risk sharing outweigh the perceived benefits of innovation among managers, thus promoting future growth through innovation.

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Appendix A. Incentives to Shirk or to Choose the Conventional Project

Managerial incentives to shirk

PROPOSITION A.1 (**Manager choosing to shirk**): *The manager will choose to shirk ($i = 0$) when the outcome of sharing the risky profits with the firm, net of the cost of effort, is negative for both projects.*

$$0 \leq b < \frac{\bar{\theta}_i^{\omega_t} + \sqrt{(\bar{\theta}_i^{\omega_t})^2 - 4r\sigma_{i,\omega_t}^2 c_i}}{2r\sigma_{i,\omega_t}^2}, \tag{A1}$$

for $\forall i \in (1, 2)$.

Proof. Determining the negativity conditions for the incentive pay component that describes the situation when the expected utility from shirking exceeds the expected utility from accepting any of the two projects.

$$\underbrace{w}_{\text{exp. utility from shirking}} > \underbrace{w + b\bar{\theta}_i^{\omega_t} - rb^2\sigma_{i,\omega_t}^2 - c_i}_{\text{exp. utility from accepting project } i}, \tag{A2}$$

for $\forall i \in (1, 2)$. □

The conclusion that managers shirk when their incentive pay component is very low is consistent with Yermack (2014), who use the travel records of 66 public company CEOs to show that CEOs spend more time away from firm headquarters when they have lower ownership in their firms. Bitler, Moskowitz, and Vissing-Jørgensen (2005) use a dataset containing privately owned firms and confirm a similar relation between an entrepreneur's contractual incentives and effort levels.

Intuitively, shirking is more prevalent when managerial risk aversion r, the cost of effort c_i, or the payoff volatility of the two projects σ_i^2 is high. Managers are less likely to shirk when expected project payoffs $\bar{\theta}_i^{\omega_t}$ are high.

Is shirking more common during bad economic times? In bad times, expected payoffs are lower, which makes managers more likely to shirk. Moreover, the volatility of the conventional project increases in bad times, which disincentivizes managers from exerting any effort even further. Managers are also less likely to choose innovative projects over shirking since expected payoffs of all projects are generally lower during bad times. Our model implies that managers are likely to shirk more during market downturns.

Managerial incentives to choose the conventional project

PROPOSITION A.2 (**Manager choosing the conventional project**): *The manager will choose to invest in the conventional project ($i = 1$) when the following conditions are met.*

$$b > \frac{\bar{\theta}_1^{\omega_t} + \sqrt{(\bar{\theta}_1^{\omega_t})^2 - 4r\sigma_{1,\omega_t}^2 c_1}}{2r\sigma_{1,\omega_t}^2}, \tag{A3}$$

$$b \leq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} - \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}, \tag{A4}$$

or when

$$1 \geq b \geq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}. \tag{A5}$$

Proof. The manager will choose the conventional project when the expected utility $EU_t(i = 1)$ exceeds the expected utility from shirking $EU_t(i = 0)$, which is represented in equation (A3) and $EU_t(i = 1)$ also exceeds the expected utility from accepting the innovative project $EU_t(i = 2)$, which guides equations (A4) and (A5). □

Appendix B. Empirical Strategy

Our main empirical model is described as

$$Innovation_{i,(t+2,t+5)} = \beta_0 + \beta_1 \times Bdist_{s,t} \times \delta ln(BSval)_{i,t} + \beta_2 \times Bdist_{s,t} + \beta_3 \times \delta ln(BSval)_{i,t} + \bar{\lambda} \times \bar{X}_{i,t} + \alpha_t + \epsilon \tag{B1}$$

where i indexes firm, t represents year, s indexes state, j is either 1 or 2. The independent variable we are mostly interested in is the interaction term between $FY\_hat\_BSval\_inc$ and $Bdist$. $FY\_hat\_BSval\_inc$ is a dummy variable that equals 1 if there is an increase in option grant value in the predicted first years and 0, otherwise. $Bdist$ is the variable measuring bank distress for each state. We use either the continuous value of the variable or a dummy variable, which is set to be 1 if the bank distress level is above the sample median and 0 otherwise. $\bar{X}$ is a vector of controls, including firm size measured by market capitalization, R&D expenditures scaled by total assets, and contemporaneous and up to two-year lagged firm profitability.

It is common to see that, in our patent sample, some firms are extremely innovative while some firms do not file any patents at all. For example, in our sample, some firms file thousands of patents in a year; whereas, some firms file zero. The maximum number of patents filed by a firm-year is 4,168 while the minimal number is zero.

Heteroscedasticity, or uneven variability of elements in the regression model, occurs often in datasets such as ours that have a large range between the largest and smallest observed values or are affected by trends in variables. To account for the possible heteroscedastic structure of residuals, we employ the Generalized least squares (GLS) regression model, which enables us to estimate the maximum likelihood of regression coefficients even when the regression residual is of unequal variance.

Our sample is restricted to include only firm-year observations on identified plans and predicted first years of option plans. We acknowledge that the level of the increase or decrease of the option grant value in the predicted first years could be endogenously correlated with firm and CEO characteristics. Moreover, the identification methodology of realized option plans may be affected by a measurement error. In particular, we are aware of a potential identification error if the firm did not intend to adopt a multiyear plan but awarded the same number or value of options across consecutive years for potentially endogenous reasons.

To test the robustness of our results to this potential measurement bias, we run the main regression tests using the unrestricted sample that does not include option plans only. Next, we also run the same tests using the original predicted first-year dummy variables proposed by Shue and Townsend (2017), which does not distinguish between the option grant increases and decreases that occur on predicted first years.

Our main measure of an exogenous shock to option pay compensation is the predicted first-year dummy variable. In this paper, our main focus of attention is on the interaction between option compensation and the business cycle, measured using bank distress levels ($Bdist$).

To identify the variation in option pay ($\Delta ln(BSval)$) and the interaction term between option pay and bank distress ($\Delta ln(BSval) \times Bdist$), we build and estimate the following two first-stage regression models:

$$\begin{aligned}\Delta ln(BSval)_{i,t} = \beta_0 + \beta_1 \times FY\_hat_{i,t} \times Bdist_{s,t} \\ +\beta_2 \times FY\_hat_{i,t} + \beta_3 \times Bdist_{s,t} + \bar{\gamma} \times \bar{X}_{i,t} + \alpha_t + \epsilon\end{aligned} \tag{B2}$$

$$\begin{aligned}\Delta ln(BSval)_{i,t} \times Bdist_{s,t} = \delta_0 + \delta_1 \times FY\_hat_{i,t} \times Bdist_{s,t} \\ +\delta_2 \times FY\_hat_{i,t} + \delta_3 \times Bdist_{s,t} + \bar{\eta} \times \bar{X}_{i,t} + \alpha_t + \epsilon,\end{aligned} \tag{B3}$$

where the second stage regression is described as

$$\begin{aligned}Innovation_{i,(t+j,t+j+3)} = \psi_0 + \psi_1 \times \overline{Bdist_{s,t} \times \Delta ln(BSval)_{i,t}} + \\ \psi_2 \times \overline{\Delta ln(BSval)_{i,t}} + \psi_3 \times Bdist_{s,t} + \bar{\mu} \times \bar{X}_{i,t} + \alpha_t + \epsilon,\end{aligned} \tag{B4}$$

where i indexes firm, t represents year, s indexes state, j is either 1 or 2. We control for firm size, innovation input (i.e. R&D scaled by total assets), and firm profitability as well as year-fixed effects.

Table A1: **Description of Variables**

Variables	Definition	Source
Patent data		
# Patents$_{t+1,t+4}$	log(number of patents filed in years (t+1) to (t+4) +1)	Bena et al. (2017), WRDS
# Citations$_{t+1,t+4}$	log(total citations of patents filed in years (t+1) to (t+4) +1)	USPTO
Max # Citations$_{t+1,t+4}$	log(maximum citations of patents filed in years (t+1) to (t+4)+1)	As above
# Cit. per Patent$_{t+1,t+4}$	log(average citations of patents filed in years (t+1) to (t+4)+1)	As above
Firm Characteristics		
R&D	R&D expenditure (xrd) divided by book value of total assets (at) If R&D expenditure is missing, set it to be zero	Compustat
Tobin's Q	(PRCC˙C*CSHO+AT-SEQ+TXDITC)/AT	As above
MKTCAP	log(PRCC˙C*CSHO)	As above
Profitability	OIBDP/AT	As above
Fin. Constraints (SA index)	$-0.737 \times Assets + 0.043 \times Assets^2 - 0.040 \times Age$	As above
Compensation		
ΔBS Value$_t$	Change of log(Black Scholes value of total option pay) in the predicted first years	As above
ΔBS Value$_t^{Max}$	Change of log(Black Scholes value of maximum option pay) in the predicted first years	As above
ΔFace Value$_t$	Change of log(face value of total option pay) in the predicted first years	ExecuComp
ΔFace Value$_t^{Max}$	Change of log(face value of maximum option pay) in the predicted first years	As above
First Year$_t$	Dummy variable, equals to 1 if a predicted first year following a fixed-cycle plan is identified	As above
Bank Distress		
BD	# of banks closed divided by # of active banks at the beginning period	FFEIC