Recessions, Bank Distress & Managerial Incentives to Innovate

Petra Sinagl   Jiawei (Brooke) Wang*

March 1, 2023

Abstract

Recessions shake financial markets. Are managerial incentives to innovate impacted by crises and resulting bank distress? We show that exogenous shocks to CEO option pay awarded in bad times lead to firms producing more patents in future years. These results are consistent with risk-averse managers choosing to innovate more in bad times, which is when conventional projects are riskier due to the overall higher systematic risk in markets. Benefits of choosing the 'safer' conventional project shrink in bad times. In normal times (i.e., unconditionally), increasing CEO option pay does not impact future firm innovation. We also show that when managers are more risk averse or have more 'skin in the game,' increasing their option pay reduces future firm innovation, consistent with higher risk-sharing costs.

JEL classification: G01, G34, O31

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

*Petra Sinagl: University of Iowa, petra-sinagl@uiowa.edu. Jiawei (Brooke) Wang: University of Iowa, jiawei-wang@uiowa.edu. We would like to thank Michael Ewens, Chad Jones, Joseph Kalmenovitz, Erik Lie, Timothy McQuade, Filippo Mezzanotti, Amrita Nain, and participants at the 15th Annual Corporate Governance Conference, the 28th Finance Forum, the 2021 FMA Annual Meeting and the University of Iowa seminar for their comments and suggestions.

I. Introduction

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 examine the conditions driving the link between managerial incentives and firm innovation.

Exploring the causal impact of CEO compensation on firm innovative output has not been an easy task. Biggerstaff, Blank, and Goldie (2019) exploit a one-time exogenous drop in option compensation around FAS 123R and conclude that awarding managers with options has zero impact on firm innovation. Biggerstaff, Blank, and Goldie (2019)'s methodology is built around one shock from a particular period when the regulation change occurred. It remains unclear whether the same result prevails under different conditions.

We use the Shue and Townsend (2017)'s identification strategy that utilizes identified multi-year option plans, which allows us to study the impact of CEO option compensation under different conditions over time. Unconditionally, we confirm an overall zero to mildly negative impact of CEO option pay on firm innovation. We show that in times of high bank distress, this relation becomes positive. Our findings suggest that awarding managers with options in times of economic distress provides them with stronger incentives to engage in innovative projects.

We identify a list of factors driving the relation between CEO option pay and firm innovation using a simple one-period model. Managers weigh the costs and benefits of exploring an innovative project and decide to innovate only when 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 lose undiversifiable labor income.

Economic conditions also affect managerial incentives to innovate. Bad times are associated with an overall higher systematic risk. In the proposed model, we consider that when systematic risk increases, the conventional project becomes riskier. Market conditions do not impact the volatility of the innovative project. The innovative project is unconditionally the most risky project to invest in, regardless of economic conditions. In bad times, systematic risk increases, which makes the conventional project riskier and the risk differential between the two projects, thus, decreases. This gives the risk-averse manager stronger incentives to engage in innovative activities because the conventional project becomes relatively more costly when times are bad. Consequently, we expect to see that increasing managerial incentive pay awarded in bad times is likely to work better to induce innovation as compared to being awarded in good times.

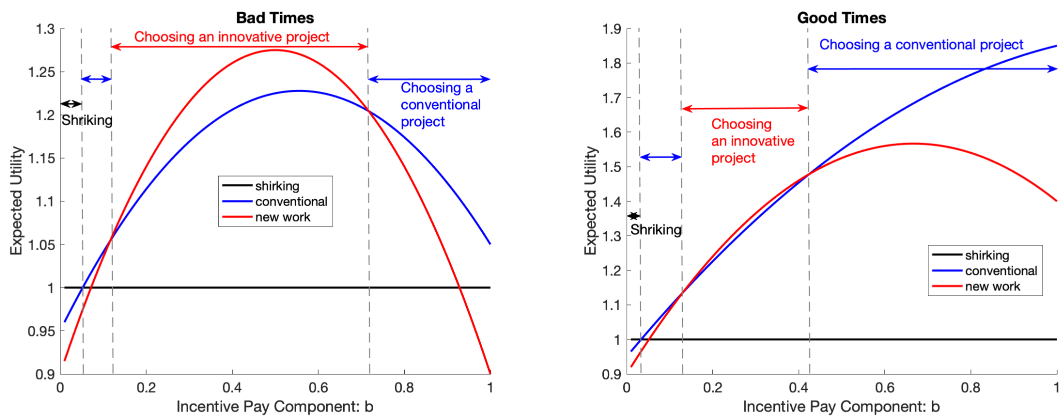


Figure 1: **Managerial expected utility from accepting a project.**

Figure 1 summarizes the main implications of the model. It compares the levels of expected utility for three possible 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 manager will choose such project that yields the highest expected utility. Expected utility is the expected project payoff shared with the manager minus the cost of risk aversion and the cost of effort.

When the incentive component (b) is the lowest and close to zero, the manager chooses to shirk. When b increases above a certain threshold, the manager is now deciding primarily between the conventional project and the innovative project. When b is high enough, i.e., with 'skin in the game', the manager is more likely to choose a conventional project over the innovative one. Choosing the riskier innovative project is optimal for reasonably low levels of the incentive component b, because for lower b the higher cost of risk sharing is less likely to exceed the higher expected firm profits from the innovative project. In bad times, when the volatility of the conventional project increases due to higher systematic risk, awarding managers with more options and increasing b creates stronger incentives to innovate, as compared to normal times when the conventional project is relatively less risky.

Our empirical findings support the model. First, we show that awarding managers who have higher portfolio delta 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 loose.

Second, we document that when firms increase their CEO's option pay in bad times, their future total innovative output increases. This innovative output is also of a higher quality as an average produced patent receives more future citations. We conclude that an exogenous increase in CEO compensation experienced during times of increased financial distress positively affects firm innovation.

We document that executive option compensation encourages firm innovation in bad times. This finding seems to be in contrast with Nanda and Rhodes-Kropf (2017), who argue that investors respond to financing risk, represented by limited future funding, by reducing their interest to finance innovative firms. We argue that both the negative external forces discouraging innovation together with the positive internal forces tied to managerial incentives may coexist during bad times. We show that the managerial incentives to innovate are likely to be countercyclical.

CEOs evaluate the costs and benefits of implementing innovative projects. We explain these results within the framework of our proposed model. In bad times, when systematic risk increases, the risk differential between the innovative and conventional project decreases. We argue that in bad times, the relative benefits of engaging in innovative projects may outweigh its relative costs, which explains why more managers may choose to invest in the riskier innovative projects.

Understanding how incentives to innovate are formed is particularly important during times of economic distress. We have seen and continue to observe in recent days that extreme circumstances, such as the World Wars, or the COVID-19 pandemic, lead to high advancements in innovation around the world. Industry practitioners argue that prioritizing innovation today, during the COVID-19 pandemic, is key to unlocking post-crisis growth. A recent survey shows that 90% of executives in the U.S. believe the COVID-19 crisis will fundamentally change the way their firm will do business in the next 5 years (McKinsey and Company, 2020). More than three-quarters of executives also agree that this crisis will create new opportunities for growth in their industry. Despite observing these spikes in demand for innovation and innovative output during extreme downturn events, there is little consensus among researchers on how economic shocks impact innovative output.

Our paper contributes to existing literature by identifying a direct channel through which crises affect future firm innovation. We study how incentives of CEOs to innovate, measured using CEO compensation data, are impacted by business cycle shocks. Specifically, we examine whether and to what extent long-term incentive compensation (i.e. stock option awards) induces CEOs to produce more (or less) innovation.

This is the first paper to focus on listing the factors influencing 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 policy makers. 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 obvious importance of managerial option compensation, much remains unknown about how and whether CEO option plans induce effort to produce innovative output. In this paper, we shed some light on which factors affect firms' innovation activities via the internal managerial incentive system. In particular, we study how efficient CEO option compensation is in inducing innovation under various conditions and different economic states.

Several studies evaluate how CEO compensation affects firm innovation. For example, Ederer and Manso (2013) provide evidence suggesting that combining tolerance for early failure and reward for long-term success is effective in motivating innovation. Manso (2011) suggest that a combination of stock options with long vesting periods, option repricing, golden parachutes, and managerial entrenchment is a useful package to motivate managers to exert effort to innovate.

This paper extends the existing literature by listing a number of factors affecting the relation between CEO option pay and firm innovation. We highlight the role of managerial 'skin in the game' and find results consistent with Ma and Tang (2019)'s who show that managers with more 'skin in the game' build less risky investment portfolios.

Managerial characteristics are considered to explain a large portion of the variation in a firm's innovation productivity. Islam and Zein (2020) show that CEOs with hands-on experience as inventors produce higher-quality innovation. Moreover, Sunder, Sunder, and Zhang (2017) find that pilot CEOs (i.e. CEOs who have a hobby of flying airplanes) are involved in projects with significantly better innovation outcomes. The authors explain that CEO pilot credentials capture the personality trait of risk-taking and a desire to pursue novel approaches.

Existing literature offers conflicting views on the overall impact of crises on innovation. On one hand, the Schumpeterian view (Schumpeter, 1942; Caballero and Hammour, 1991) argues that the process of creative destruction is an integral part of economic growth and fluctuations. Schumpeter (1934) argues in favor of the creative destruction of crises, which positively impacts innovative output: *"[..]depressions are not simply evils, which we might attempt to suppress, but–perhaps undesirable–forms of something which has to be done, namely, adjustment to previous economic change."* According to Schumpeter, typically, initial increased destruction is followed by a surge in creation during the recovery phase of the business cycle.

On the other hand, a number of papers argue that the heightened financial distress observed during crises negatively affects firms' innovative activities. For example, Nanda and Rhodes-Kropf (2017) propose an investment model forecasting that investors respond to financing risk, represented by limited future funding, by reducing their interest to finance innovative firms. Tian and Wang (2014) show that the failure tolerance of venture capital investors significantly influences firms' innovative activities.

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

(2020) 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.

All of these existing studies are primarily focused on evaluating and quantifying the total effects of crises on firm innovation. Our paper contributes to this literature by focusing on the role of option compensation in providing managers with incentives to innovate. We highlight the role of managerial 'skin in the game' and economic conditions.

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. In the beginning of the period, at time t, the manager is offered a package (w, b) that constitutes of 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).

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 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): $c_2 > c_1 > 0$.

	$i = 0$: shirking	$i = 1$: conventional project	$i = 2$: innovative project
$\omega_t =$ bad	$\theta_0 = 0$	$\theta_1 \sim N(\bar{\theta}_1^{bad}, \sigma_{1,bad}^2)$	$\theta_2 \sim N(\bar{\theta}_2^{bad}, \sigma_2^2)$
$\omega_t =$ good	$\theta_0 = 0$	$\theta_1 \sim N(\bar{\theta}_1^{good}, \sigma_{1,good}^2)$	$\theta_2 \sim N(\bar{\theta}_2^{good}, \sigma_2^2)$
Cost of effort	$c_0 = 0$	c_1	c_2

ASSUMPTION 1: *The expected payoff of both projects ($i = 1, 2$) is higher in good times than in bad times: $\bar{\theta}_1^{bad} < \bar{\theta}_1^{good}$ and $\bar{\theta}_2^{bad} < \bar{\theta}_2^{good}$.*

ASSUMPTION 2: *The standard deviation of the payoff distribution for the conventional 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.*

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

Figure 2 graphically illustrates assumptions made about the state dependence of the payoff distributions for the two projects that the managers can choose from (other than shirking). The intuition behind the assumption that the conventional project becomes more risky is based on the observation that the systematic risk increases during bad times. The conventional project is largely exposed to systematic risk, which means that it also becomes riskier when economic conditions deteriorates. 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 risker 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.

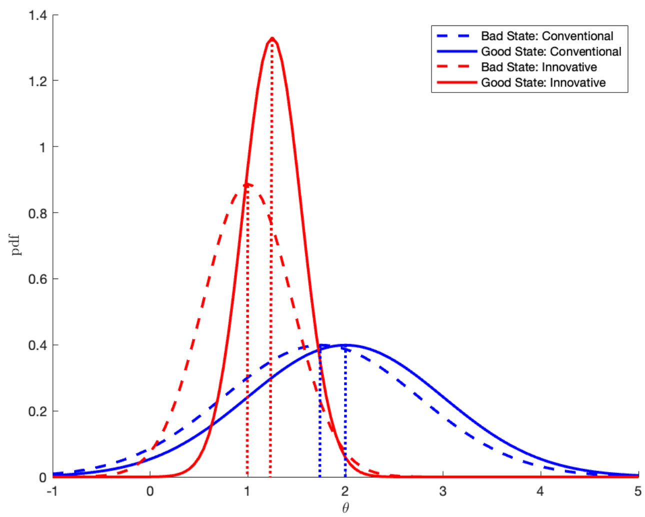


Figure 2: **Payoff distributions.** The blue (red) lines represent the payoff distributions for the innovative (conventional) project. When the expected state of economy is bad, the payoff distribution is described using dashed lines. Solid lines illustrate conditions when the expected economy is good.

B. *Choosing a project*

The manager has a constant absolute risk aversion r and her expected utility EU_t drawn from accepting the offer depends on the flat wage received, the share of expected firm profits minus the cost of risk aversion and the cost of effort.

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

with r being the manager's risk aversion coefficient and i representing the project chosen by the manager, $i = 0, 1, 2$. The manager will choose such project that maximizes her expected utility, subject to her beliefs about the expected economic state ω_t.

$$\max_i EU_t(i) \tag{3}$$

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

	$i = 0$: shirking	$i = 1$: conventional project	$i = 2$: innovative project
ω_t = bad	w	$w + b\bar{\theta}_1^{bad} - rb^2\sigma_{1,bad}^2 - c_1$	$w + b\bar{\theta}_2^{bad} - rb^2\sigma_2^2 - c_2$
ω_t = good	w	$w + b\bar{\theta}_1^{good} - rb^2\sigma_{1,good}^2 - c_1$	$w + b\bar{\theta}_2^{good} - rb^2\sigma_2^2 - c_2$

PROPOSITION 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.*

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

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.

$$\underbrace{w}_{\text{exp. utility from shirking}} > \underbrace{w + b\bar{\theta}_i^{\omega_t} - rb^2\sigma_{i,\omega_t}^2 - c_i}_{\text{exp. utility from accepting project } i}, \tag{5}$$

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.

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

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

$$b \leq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} - \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}, \tag{7}$$

or when

$$1 \geq b \geq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}. \tag{8}$$

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 (9) and $EU_t(i = 1)$ also exceeds the expected utility from accepting the innovative project $EU_t(i = 2)$, which guides equations (10) and (11). □

PROPOSITION 3 (**Manager choosing the innovative project**): *The manager will choose to invest in the innovative project ($i = 2$) when the following conditions are met.*

$$b > \frac{\bar{\theta}_2^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t})^2 - 4r\sigma_2^2 c_2}}{2r\sigma_2^2}, \tag{9}$$

$$b \geq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} - \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}, \tag{10}$$

or when

$$b \leq \frac{\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t} + \sqrt{(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})^2 - 4r(\sigma_2^2 - \sigma_{1,\omega_t}^2)(c_2 - c_1)}}{2r(\sigma_2^2 - \sigma_{1,\omega_t}^2)}. \tag{11}$$

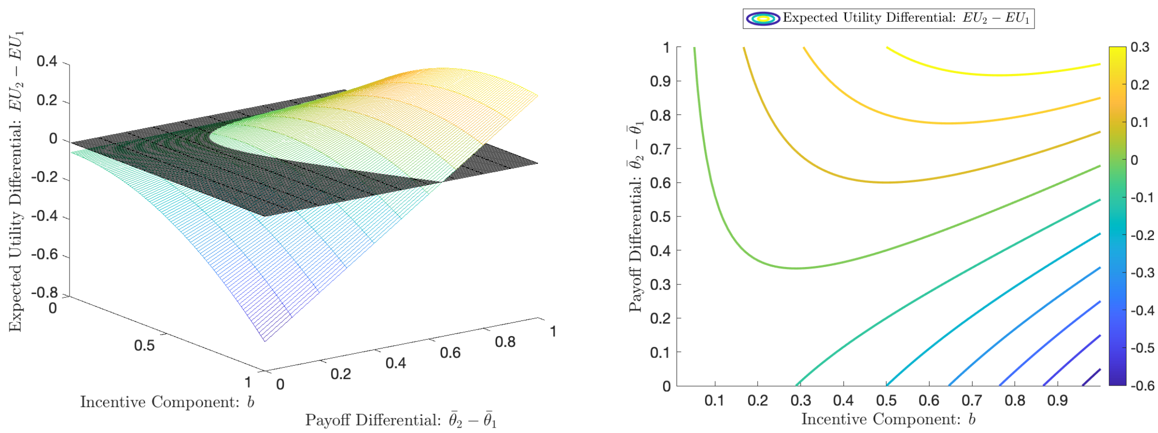


Figure 3: **Payoff differential & the expected utility differential for choosing the innovative over conventional project: $EU_2 - EU_1$.** The grey surface represents a zero value of the expected utility differential, which makes the manager indifferent from choosing between the innovative and conventional project. Any value above the grey surface indicates that the manager prefers to accept the innovative project. Figure on left shows the levels of the expected utility differential as a function of the payoff differential $(\bar{\theta}_2^{\omega_t} - \bar{\theta}_1^{\omega_t})$ and the incentive pay component b. Parameters used to create this figure are: $\sigma_1^2 = 0.3$, $\sigma_2^2 = 0.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$ and $w = 1$.

C. Testable Implications

TESTABLE IMPLICATION 1: *Increasing option pay for managers with already high incentive pay (b) can discourage innovation due to higher risk sharing.*

fig:exp˙util˙v2 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.

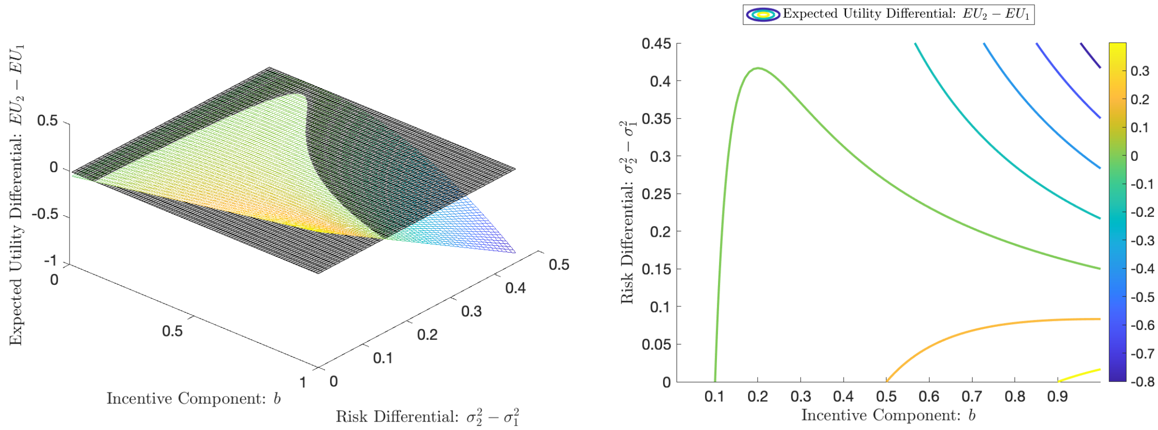


Figure 4: **Risk differential & the expected utility differential for choosing the innovative over conventional project: $EU_2 - EU_1$.** The grey surface represents a zero value of the expected utility differential, which makes the manager indifferent from choosing between the innovative and conventional project. Any value above the grey surface indicates that the manager prefers to accept the innovative project. Figure on left shows the levels of the expected utility differential as a function of the risk differential $(\sigma_2^2 - \sigma_2^1)$ and the incentive pay component b. Parameters used to create this figure are: $\bar{\theta}_1 = 1$, $\bar{\theta}_2 \bar{=} 1.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$ and $w = 1$.

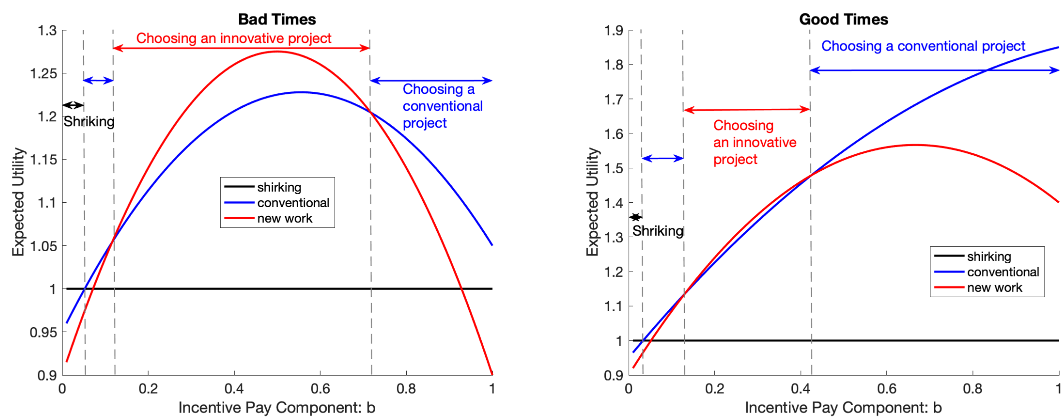


Figure 5: **Expected utility.** Parameters used to create this figure are: $\bar{\theta}_1^{bad} = 1$, $\bar{\theta}_1^{good} = 1.5$, $\bar{\theta}_2^{bad} = 1.5$, $\bar{\theta}_2^{good} = 2$, $\sigma_{1,bad}^2 = 0.3$, $\sigma_{1,good}^2 = 0.2$, $\sigma_2^2 = 0.5$, $r = 3$, $c_2 = 0.1$, $c_1 = 0.05$ and $w = 1$.

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 costs of risk sharing 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 innovative project decreases.*

In bad times, when market risk is high, conventional projects become more risky. Market risk is assumed to play 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 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.

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 a 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 a 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 of 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 patenting activity of individual entrepreneurs. Babina, Bernstein, and Mezzanotti (2020) show, however, firm-affiliated patenting represents the vast majority of total patents granted over the period that we cover in our sample.

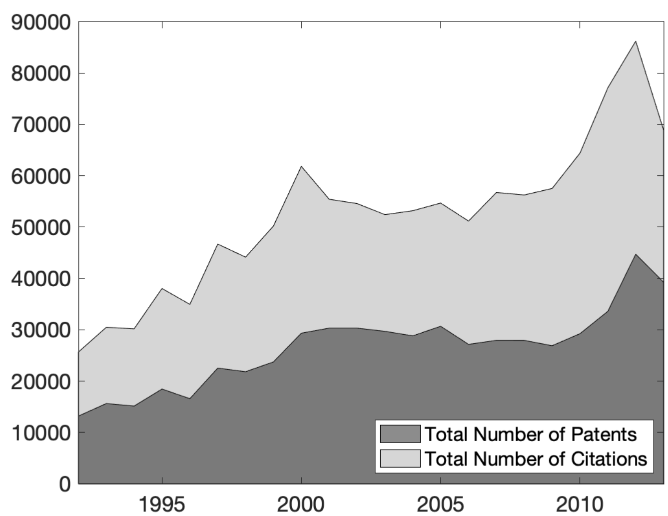


Figure 6: **Aggregate Patenting Trends.** This graph illustrates the time series trend in the annual total number of patents filed by all US firms and the total number of citations received by these patents.

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 6 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 citations records with the existing patents using the USPTO patent ID.[1]

We end our sample with patents with application date from 2013, even though WRDS US patent data is available until 2019. It typically takes three years for a patent to be 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 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 6 displays the total number of patents successfully filed between 1992 to 2013 and their received citations.

Figure 7 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 are displayed on the left figure. The figure on 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 increases steadily over time and drops in 2013. The average number of citations per patent, however, decreases 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 manager exerts effort to induce output and innovation.

In this paper, we focus on two dimensions of the total firm-level innovation output: 1)

[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.

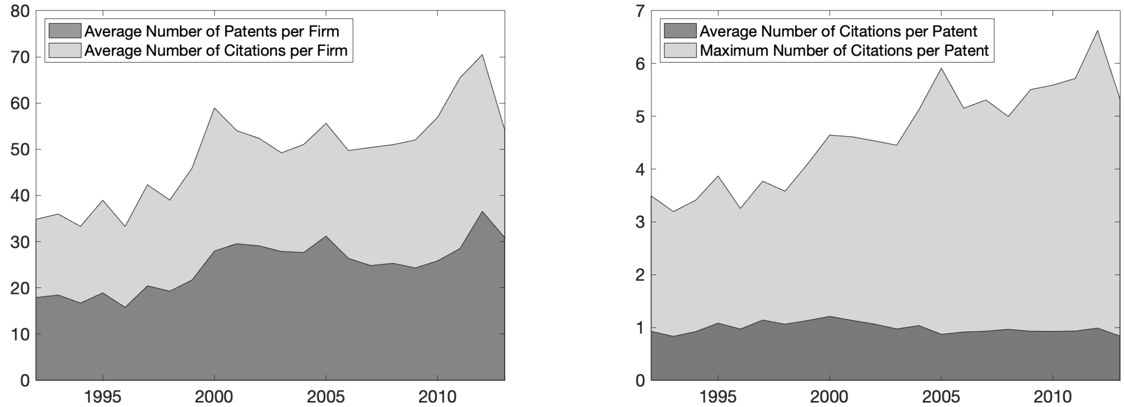


Figure 7: **Per-firm Patenting Trends.** This graph illustrates the time series trend in the annual average number of patents filed per firm and average number of firm citations received by these patents, see Panel (a). Panel (b) shows the average total number of citations received per patent and the 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.

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 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 the former one 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 among each other, we scale each patent's citation count by the average number of citations received by all patents applied at 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

$$\text{Bank Distress}_{st} = \frac{\text{\# of Banks Closed}_{s,t}}{\text{Total \# of banks}_{s,t-1}}. \tag{12}$$

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 plans or are predicted first years. Firms in our sample with identified fixed-cycle plans are very similar to an average firm in terms if 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% level.

Table I: **Summary Statistics**

This table reports the summary statistics for the main variables used in the analysis. For each variable, we present its mean, median, standard deviation, 25th and 75th percentile, as well as the numbers of observations. All variables are defined in the Appendix. The sample consists of all nonfinancial, nonutility firms with at least one patent successfully filed during 1992 to 2015. The sample is restricted to include only firm-year observations where the firm CEO is identified to be on a plan and years with predicted first year of plans. There are 786 unique firms and 2,915 firm-year observations in the sample. A description of all the variables is included in Table A1.

	N	Mean	STD	25%	Median	75%
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
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

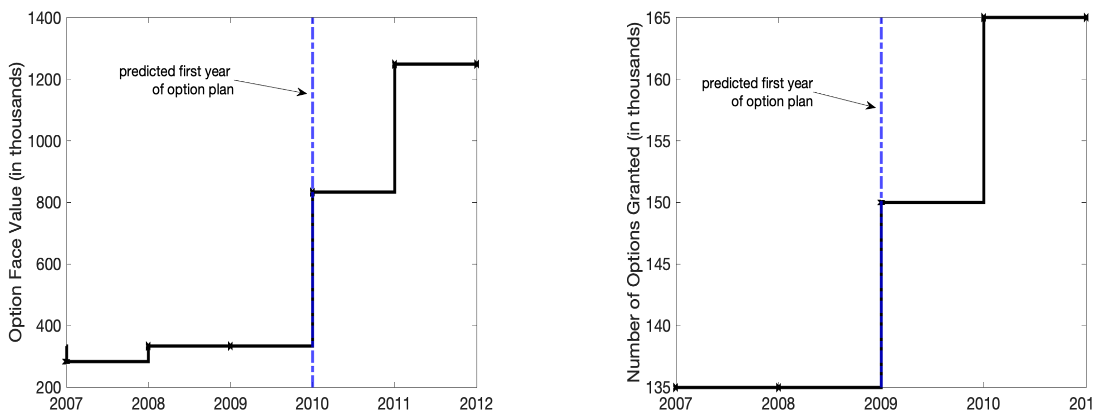
Executive multiyear option plans provide us with a tool to identify variations in managerial incentives to exert effort, that is arguably exogenous to current firm economic conditions (e.g. current firm profitability). The end of each multiyear option plan is determined years ahead, and should not be 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 in 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 the 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 8: **Two Examples of Identified Fixed Cycle Plans.** This figure shows 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 indicated by the dash-dotted vertical lines.

In Figure 8, 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 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 exactly 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 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 are able to detect 1,080 predicted first years. Among the firms which 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 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 9. 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.

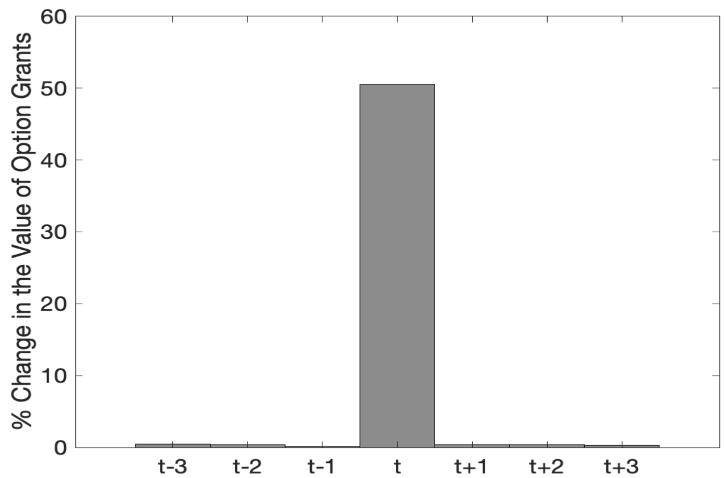


Figure 9: **Change in CEO Option Grant Value in and around Predicted First Years.** This figure shows the average percentage changes in the Black-Scholes value of option grants received in the predicted first years (t), one to three years before the predicted first year ($t-1$ to $t-3$) and one to three 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 presents the OLS regression results. The dependent variables are reported at the top of each column. The independent variable of interest is the dummy variable of the predicted first years, First Year_t. All regressions control for year fixed effects and time-varying CEO and firm characteristics, i.e. CEO tenure, log of cash compensation (salary + bonus), log sales, log assets, sales growth, Tobin's Q. The control variables are measured in the year prior to the grant. 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.

	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, despite the fact that 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 using 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 prior to the year when a 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 years 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 identifies 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 years, is staggered, we are able to control for year fixed effects. Our main results are always controlling for fixed effects and cluster standard errors by firms. Additionally, in both 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 'skin in the game' of managers, (*ii*) managerial risk aversion and (*iii*) the impact of economic conditions, namely bank distress.

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) # Patents$_{t+1,t+4}$	(2) # Citations$_{t+1,t+4}$	(3) # Cit. per Patent$_{t+1,t+4}$	(4) Max # of Citations$_{t+1,t+4}$
$\overline{\Delta \text{BS Value}}_t$	-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

Table IV: **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 patents produced over the next four-year period is analyzed.

	High WPS		Low WPS	
	(1)	(2)	(3)	(4)
Panel A	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat.}_{t+1,t+4}$	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-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	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat.}_{t+1,t+4}$	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-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	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat.}_{t+1,t+4}$	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat}_{t+1,t+4}$
$\overline{\Delta\text{BS Value}_t}$	-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

	High CEO tenure		Low CEO tenure	
	(1)	(2)	(3)	(4)
Panel D	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat.}_{t+1,t+4}$	# $\text{Pat}_{t+1,t+4}$	# 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

	High current option pay		Low current option pay	
	(1)	(2)	(3)	(4)
Panel E	# $\text{Pat}_{t+1,t+4}$	# Cit. per $\text{Pat.}_{t+1,t+4}$	# $\text{Pat}_{t+1,t+4}$	# 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

A. ‘Skin in the Game’ of Managers

Managers with more ‘skin in the game’, who are afraid of losing undiversified labor income, are generally less likely to invest in innovative projects. Ma and Tang (2019) find that managers with more ‘skin in the game’ build less risky investment portfolios. We hypothesize that CEOs in our sample may also be less likely to choose risky and innovative strategies if they have more to lose. We proxy for managerial ‘skin in the game’ using a number of 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 produced 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 a similar quality, they just choose to innovate less in total, which leads to a lower production of patents.

B. The Impact of CEO pay on Innovation in Bad Times

Next, we examine whether and when awarding CEOs with option pay impacts the innovative output produced by firms in future. We are particularly interested in studying how bank distress impact 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 A details our empirical strategy used to assess the impact of CEO pay awarded in times of high bank distress.

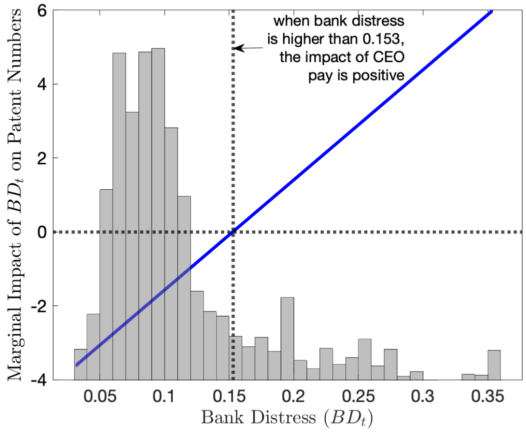
The impact of an increase in CEO pay awarded during times of high bank distress on firm innovative is positive. We find that firm innovative output, produced over next one to four years, is positively related with long-term managerial compensation awarded in bad times, see Table 3. Our results suggest 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.

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

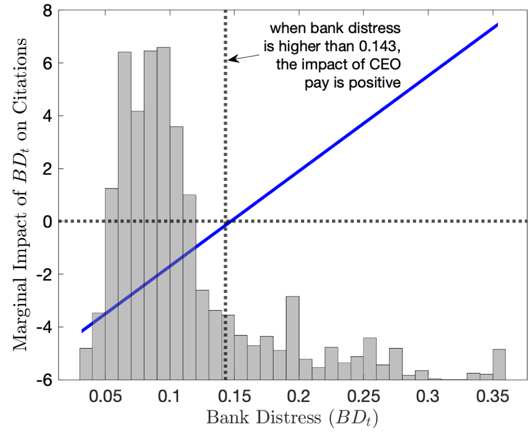
The table presents the IV 2SLS regression second-stage results. The dependent variables are reported at the top of each column. Independent variables are computed as the pooled average from years $(t+1)$ to $(t+4)$. We use First Year_t to instrument $\overline{\Delta \text{BS Value}}_t$. First Year_t 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 bank closed scaled by the total number of banks in the beginning period at 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 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)
	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\overline{\Delta \text{BS Value}_t}$	-4.551**	-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

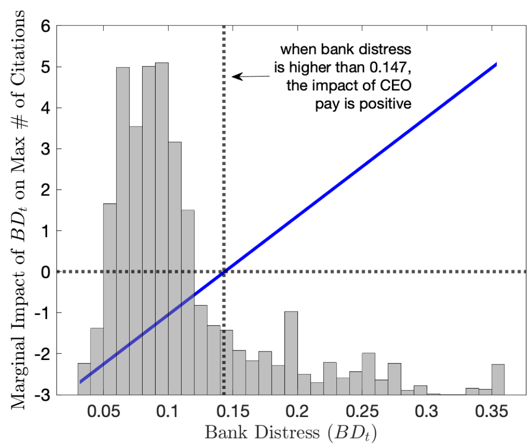
Panel B: Bank Distress Dummy				
	(1)	(2)	(3)	(4)
Variables	# $\text{Patents}_{t+1,t+4}$	# $\text{Citations}_{t+1,t+4}$	# Cit. per $\text{Patent}_{t+1,t+4}$	Max # of $\text{Citations}_{t+1,t+4}$
$\Delta ln(BSval)(t)$	-2.937**	-3.456**	-0.424	-2.157**
	(-2.19)	(-2.24)	(-0.78)	(-2.07)
Bank Distress Dummy_t (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 10: **The Marginal Impact of CEO Option Pay on Innovation.** This figure describes the marginal effects of increasing CEO option pay on the number of patent 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.

We document that when bank distress is high (i.e. the bank distress dummy variable equals 1), a one unit increase in the Black-Scholes value of the option grant leads to firms producing about 3 more patents, that receive about four more citations. The maximum number of citations also increases by three. 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.

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. This positive relation is described by the blue line from Figure 10. Our results confirm that the impact that CEO long-term compensation has on the quantity and quality of innovation strengthens in bad times. In fact, we document that the effects of CEO option pay on the number of patents produced by firms in 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. 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-existing 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.

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, which suggests that this instrument is a useful tool to measure exogenous shocks to CEO option compensation. Most importantly, we highlight how managerial 'skin in the game' and economic conditions, namely bank distress, affect the relation between CEO pay and firm innovative.

We find that awarding managers that have more 'skin in the game' with more options discourages firm innovation. This impact is consistent across a number of measures of managerial 'skin in the game' used, which includes Edmans, Gabaix, and Landier (2009)'s wealth-performance sensitivity, delta of CEO holdings, current CEO option pay, CEO tenure or CEO age.

Moreover, we report that option compensation awarded during economic downturns actually increases managerial incentives to innovate. To be specific, we document that when managers receive more option pay in bad times, their firm's innovative output increases in quantity and quality. When options are awarded to managers during normal times, this impact is non-existent. This confirms results previously shown by existing literature (Biggerstaff, Blank, and Goldie, 2019; Mao and Zhang, 2018), and is consistent with the costs of risk sharing ofsetting the benefits of engaging in innovative projects.

Given the importance new technologies have in driving the process of creative destruction and productivity growth in the economy, motivating innovation is a central issue for firms, academics and policy makers. We provide new evidence of what drives the link between incentives and innovation by studying the internal executive rewards mechanism. As a policy recommendation, we suggest that in order to promote future growth through innovation, firms should closely watch the degree of managerial 'skin in the game' to assess whether the costs of risk sharing do not outweigh the benefits of innovation perceived by managers.

REFERENCES

Babina, Tania, Asaf Bernstein, and Filippo Mezzanotti, 2020, Crisis innovation, *Working Paper.*

Bena, Jan, Miguel A Ferreira, Pedro Matos, and Pedro Pires, 2017, Are foreign investors locusts? The long-term effects of foreign institutional ownership, *Journal of Financial Economics* 126, 122 – 146.

Biggerstaff, Lee, Brian Blank, and Brad Goldie, 2019, Do incentives work? Option-based compensation and corporate innovation, *Journal of Corporate Finance* 58, 415–430.

Bitler, Marianne P, Tobias J Moskowitz, and Annette Vissing-Jørgensen, 2005, Testing agency theory with entrepreneur effort and wealth, *The Journal of Finance* 60, 539–576.

Caballero, Ricardo J, and Mohamad L Hammour, 1991, The cleansing effect of recessions, Discussion paper, National Bureau of Economic Research.

Ederer, Florian, and Gustavo Manso, 2013, Is pay-for-performance detrimental to innovation?, *Management Science* 59, 1496–1513.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter, 2017, Executive compensation: A survey of theory and evidence, *The handbook of the economics of corporate governance* 1, 383–539.

Edmans, Alex, Xavier Gabaix, and Augustin Landier, 2009, A multiplicative model of optimal ceo incentives in market equilibrium, *The Review of Financial Studies* 22, 4881–4917.

Hall, Brain, 1999, The design of multi-year stock option plans, *Journal of Applied Corporate Finance* 12, 97 – 106.

Islam, Emdad, and Jason Zein, 2020, Inventor CEOs, *Journal of Financial Economics* 135, 505–527.

Ma, Linlin, and Yuehua Tang, 2019, Portfolio manager ownership and mutual fund risk taking, *Management Science* 65, 5518–5534.

Manso, Gustavo, 2011, Motivating innovation, *Journal of Finance* 66, 1823–1860.

Mao, Connie X, and Chi Zhang, 2018, Managerial risk-taking incentive and firm innovation: Evidence from fas 123r, *Journal of Financial and Quantitative Analysis* 53, 867–898.

McKinsey, and Company, 2020, Innovation in a crisis: Why it is more critical than ever, *Report published in June 17, 2020.*

Nanda, Ramana, and Tom Nicholas, 2014, Did bank distress stifle innovation during the Great Depression?, *Journal of Financial Economics* p. 273–292.

Nanda, Ramana, and Matthew Rhodes-Kropf, 2013, Investment cycles and startup innovation, *Journal of Financial Economics* 110, 403–418.

———, 2017, Did bank distress stifle innovation during the great depression?, *Management Science* pp. 901–918.

Schumpeter, Joseph A, 1934, Depressions, *The economics of the recovery program. New York: McGraw-Hill* pp. 3–21.

———, 1942, Capitalism, socialism and democracy, .

Shue, Kelly, and Richard Townsend, 2017, How do quasi-random option grants affect CEO risk-taking?, *Journal of Finance* pp. 2551 – 2588.

Sunder, Jayanthi, Shyam V. Sunder, and Jingjing Zhang, 2017, Pilot CEOs and corporate innovation, *Journal of Financial Economics* 123, 209–224.

Tian, Xuan, and Tracy Yue Wang, 2014, Tolerance for failure and corporate innovation, *Review of Financial Studies* 27, 211–255.

Yermack, David, 2014, Tailspotting: Identifying and profiting from ceo vacation trips, *Journal of Financial Economics* 113, 252–269.

Appendix A. Empirical Strategy

Our main empirical model is described as

$$\begin{aligned} Innovation_{i,(t+2,t+5)} = \beta_0 + \beta_1 \times Bdist_{s,t} \times \delta ln(BSval)_{i,t} + \beta_2 \times Bdist_{s,t} \\ + \beta_3 \times \delta ln(BSval)_{i,t} + \bar{\lambda} \times \bar{X}_{i,t} + \alpha_t + \epsilon \end{aligned} \tag{A1}$$

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 which 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 bank distress level is above 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 patent at all. For example, in our sample, some firms file a thousand 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 ($Bdist$).

In order 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:

$$\begin{aligned} \Delta ln(BSval)_{i,t} &= \beta_0 + \beta_1 \times FY\_hat_{i,t} \times Bdist_{s,t} \\ &+\beta_2 \times FY\_hat_{i,t} + \beta_3 \times Bdist_{s,t} + \bar{\gamma} \times \bar{X}_{i,t} + \alpha_t + \epsilon \end{aligned} \tag{A2}$$

$$\begin{aligned} \Delta ln(BSval)_{i,t} \times Bdist_{s,t} &= \delta_0 + \delta_1 \times FY\_hat_{i,t} \times Bdist_{s,t} \\ &+\delta_2 \times FY\_hat_{i,t} + \delta_3 \times Bdist_{s,t} + \bar{\eta} \times \bar{X}_{i,t} + \alpha_t + \epsilon, \end{aligned} \tag{A3}$$

where the second stage regression is described as

$$\begin{aligned} Innovation_{i,(t+j,t+j+3)} &= \psi_0 + \psi_1 \times \overline{Bdist_{s,t} \times \Delta ln(BSval)_{i,t}} + \\ &\psi_2 \times \overline{\Delta ln(BSval)_{i,t}} + \psi_3 \times Bdist_{s,t} + \bar{\mu} \times \bar{X}_{i,t} + \alpha_t + \epsilon, \end{aligned} \tag{A4}$$

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