Corporate Investment and Growth Opportunities: The Role of R&D Capital Complementarity

Anthony Sanford[a], Mu-Jeung Yang[b]

This Version: October 2021

Abstract:

How does the interaction of uncertainty and R&D impact corporate investment? We provide evidence that R&D significantly increases corporate investment responsiveness to PVGO news and uncertainty shocks. These results are consistent with predictions from the R&D-based real options model of corporate investment. To establish credible causal results we combine new measures of systematic and firm-specific PVGO shocks, for which we utilize stock price and option data, with exogenous measures of R&D capital stocks derived from panel variation in state R&D tax credits. We also rule out a number of potentially competing explanations for our results, including firm-level differences in lumpiness of investments, financial frictions, lifecycle growth opportunities or moral hazard-implied asset substitution or risk shifting.

JEL Codes: D25, G30, G31, O32

Keywords: Corporate investment, PVGO, R&D, option exercise

Acknowledgments: We would like to thank Matt Ringgenberg and an anonymous referee for helpful comments. All errors are our own.

[a] University of Maryland at College Park, College Park, [b] Eccles School of Business, University of Uta

1. Introduction

A fundamental issue in Corporate Finance is the understanding of the drivers of corporate investment decisions. One perspective that has gained increased attention over the last 30 years views corporate investments as result of the exercise of “real options”, see Dixit and Pindyck, 1994; Abel and Eberly, 1994. The growing popularity of the real options view of investment is in part rooted in the rise of economic and policy uncertainty during the last 20 years, and the ability of the real options framework to explain delayed investments in response to higher uncertainty, see Bloom, 2009; Bloom, Baker and Davis, 2016; Gulen and Ion 2015, Kim and Kung, 2016. At the same time, technological progress and structural change have driven corporations to increasingly invest in R&D, intellectual property and related intangible assets, see Edmans, 2011; Crouzet and Eberly, 2018a; 2018b; Ewans, Peters and Wang, 2021. Joining these two trends of the increasing importance of uncertainty shocks as well as rise in corporate R&D, a natural question is: How does the interaction of uncertainty and R&D impact corporate investment?

In this study, we provide direct empirical evidence that R&D capital is a significant determinant of corporate investment responsiveness to (uncertainty about) growth opportunities. This evidence is consistent with the R&D-based real options model, according to which R&D generates real options that are ready to be exercised through increased capital investment when growth opportunities arrive, see Berk, Green and Naik, 1999; Kumar and Li, 2016. To our knowledge, ours is the first study to provide credible causal evidence for this mechanism by addressing two issues that have prevented the prior empirical literature to establish similar results. First, shocks to the Present Value of Growth Opportunities (PVGO) are typically hard to measure, even as the Efficient Market Hypothesis suggests that higher stock market returns might be indicative of higher PVGO. The key challenge, as outlined by Fama, 1970, is that market returns might be high not just because of news of higher valuation of growth opportunities, but also due to risk compensation. We therefore employ recent advances in measuring expected returns from option prices, due to Ross, 2015 to calculate measures of abnormal returns, which are the basis for risk-adjusted PVGO news and uncertainty shocks. The second challenge is that any interaction between growth opportunities and R&D could be driven by unobservable firm-specific factors, such as CEO style (Bertrand and Schoar, 2003) or other intangibles (Edmans, 2011). To address this second issue, we use regional variation in R&D tax credits to build exogenously determined R&D

capital stocks, as in Bloom, Schankerman and Van Reenen, 2013; Homberg and Matray, 2018. Equipped with these exogenous R&D capital stocks we are in a position to investigate the causal impact of R&D capital for corporate investment responsiveness to growth opportunity shocks.

We document three key sets of results. Our first set of results focuses on our new measures of PVGO shocks and their direct impact on corporate investment. Following the recent empirical literature on real option effects in corporate investment, such as Gulen and Ion, 2015 and Kim and Kung, 2016, we measure uncertainty about growth opportunities as well as average news about PVGO. We show that our new measures of PVGO news shocks significantly stimulate corporate investment, in contrast to uncorrected average market returns, which exhibit the opposite sign. This result would be expected if uncorrected market returns mostly reflected risk-compensation instead of PVGO news. We also find evidence for substantial delay effects of PVGO uncertainty shocks, consistent with Bloom, 2009; Kim and Kung, 2016. An especially attractive feature of our analysis is that we can simultaneously control for average changes in PVGO as well as changes in the uncertainty of PVGO, thereby addressing the common criticism that times of high uncertainty are also types of bad news, see Bloom et al, 2018.

Our second set of results shows how R&D capital shapes the responsiveness of corporate investment to PVGO news and uncertainty shocks. Consistent with our R&D-based real options model of investment, firms with high R&D capital tend to be more response to PVGO shocks. They expand investment more aggressively in response to positive PVGO news shocks and contract investment more aggressively in response to PVGO uncertainty shocks. This is consistent with the view that R&D capital provides real growth options that are exercised by investing in physical capital when good news arrives; our results are also consistent with delayed exercise of real options associated with higher levels of R&D capital.

We also provide a battery of robustness checks and show that our investment response estimates are not driven by the interaction of PVGO shocks with firm-level differences in asset redeployability (or lumpy investments), financial frictions, firm lifecycle growth opportunity differences or moral hazard-implied risk shifting.

Our analysis contributes to several different empirical literatures on corporate investment behavior. We contribute to a large literature on corporate responses to uncertainty shocks, which started with theoretical work in the 1990s (Dixit and Pindyck, 1994; Abel and Eberly, 1994) and has been successfully empirically applied by studies such as Bloom, Bond and Van Reenen, 2006; Bloom, 2009; and Kim and Kung, 2016. Additionally, recent work has extended the analysis of the real options model of investment from economic uncertainty to policy uncertainty, see Gulen and Ion, 2015; Bloom, Baker and Davis, 2016. But while much of this literature has focused on the real-options implications of fixed costs of adjustment or partial irreversibility, our contribution to this literature to provide credible causal evidence for the hypothesis that R&D-based real options considerations are a significant additional channel to understand corporate investment delays in response to uncertainty.

Much of our analysis is consistent with the view that the exercise of growth options requires capital investment, an idea we share with studies such as Berk, Green and Naik, 1999; Anderson and Garcia-Feijoo, 2006; Kumar and Li, 2016.[1] However, this literature, mainly focuses on the arrival and generation of idiosyncratic or firm-specific growth options, and their implications for cross-sectional asset pricing. Our efforts complement this literature by showing how R&D-implied growth options influence the corporate investment responsiveness to systematic and idiosyncratic PVGO shocks.

We therefore also contribute to the recent fast-growing literature on heterogeneous firm investment responses to common shocks. Examples include investment response heterogeneity to monetary policy shocks due to financial frictions (Adao and Silva, 2016; Ottonello and Winberry, forth); to uncertainty shocks due to asset redeployability (Gulen and Ion, 2015; Kim and Kung, 2016); to competitive shocks due to firm size or R&D capital (Fromenteau, Schymik and Tscheke, 2016; Hombert and Matray, 2018). To our knowledge, ours is the first study to estimate the effect of R&D capital in explaining heterogeneous investment responses to common growth opportunity shocks.

2. Theory

To derive empirical predictions, we embed the generation of growth options through R&D as in Bloom and Van Reenen, 2002 into a model of growth options with idiosyncratic and systematic growth opportunities as in Babenko, Boguth and Tserlikevich, 2016. Following Babenko et al, 2016, flow profits for firm i can be written as[2]

$$\Pi_i = x_i + \rho_i y \tag{1}$$

consisting of an idiosyncratic component x_i and a non-zero exposure ρ_i to a common risk factor y. Both x_i and y follow geometric Brownian motions with mean μ_x, μ_y and dispersions σ_x, σ_y

$$\frac{dx_i}{x_i} = \mu_x \cdot dt + \sigma_x \cdot dz_i \tag{2}$$

$$\frac{dy}{y} = \mu_y \cdot dt + \sigma_y \cdot dz_y$$

with dz_i, dz_y as increments of Wiener processes and independence across these Wiener processes $E\left[dz_i dz_y\right] = 0$.

Firms can exercise growth options related to idiosyncratic and systematic opportunities. Following Babenko, Boguth and Tserlikevich, 2016, we assume that these growth options can be separately exercised to increase profits by a factor $(1+\gamma)$, with γ_x denoting the growth effect for idiosyncratic growth options and γ_y the effect for systematic growth options. Exercise of these growth options required an investment of C_x, while the cost for systematic growth options is $\rho_i C_y$.

Expected firm value at interest rate r is given by

$$V_i = E\left[\int \Pi_i \cdot e^{-rt} dt\right] \tag{3}$$

Due to option separability and our assumptions on the risk processes, Ito's Lemma implies the following Hamilton-Jacobi-Bellman equation:

$$rV_i = \Pi_i + \mu_x x_i \frac{\partial V_i}{\partial x_i} + \mu_y y \frac{\partial V_i}{\partial y} + \frac{\sigma_x^2 x_i^2}{2} \frac{\partial^2 V_i}{\partial x_i^2} + \frac{\sigma_y^2 y^2}{2} \frac{\partial^2 V_i}{\partial y^2} \tag{4}$$

Option Exercise of Growth Options

---

[2] We are grateful to an anonymous referee for suggesting to extend our methodology and analysis to capture idiosyncratic as well as systematic growth opportunity shocks.

Following Babenko et al.s' "Guess and verify" approach, one can postulate the following closed form for the value function:

$$V(x_i,\ y) = \frac{x_i}{r\ - \mu_x} + \frac{y}{r\ - \mu_y} + A \cdot y^b + B \cdot x_i^d \tag{5}$$

in which the terms $\frac{x_i}{r - \mu_x}, \frac{y}{r - \mu_y}$ capture the perpetuity value of assets-in-place, while the terms $A \cdot y^{\hat{b}}, B \cdot x_i^{\hat{d}}$ capture the option value of unexercised systematic and idiosyncratic growth options. Importantly, the coefficients $\hat{b}, \hat{d}$ are the positive roots of the following characteristic equations implied by the dynamic law of motions in (2):

$$\begin{gathered} d^2\sigma_x^2 + b(2\mu_x - \sigma_x^2) - 2r = 0 \\ b^2\sigma_y^2 + b\left(2\mu_y - \sigma_y^2\right) - 2r = 0 \end{gathered} \tag{6}$$

In other words, the changes in expected future profits μ_x, μ_y as well as changes in expected uncertainty σ_x^2, σ_y^2 change the coefficients $\hat{b}, \hat{d}$. The optimal option exercise thresholds can be derived using the appropriate value-matching and smooth-pasting conditions discussed for example in Dixit (1993). Specifically, after option exercise, the present value of the firm is

$$\hat{V}(x_i,\ y) = \frac{(1+\gamma_x)\cdot x_i}{r\ - \mu_x} + \frac{\left(1+\gamma_y\right)\cdot y}{r\ - \mu_y} \tag{7}$$

Post-exercise firm value can then be used to establish optimality conditions, such as the value matching conditions, which state that at the time of the option exercise the pre-exercise firm value has to equal to post-exercise firm value

$$\begin{gathered} V(x^*, y) = \hat{V}(x^*,\ y) - C_x \\ V(x_i, y^*) = \hat{V}(x_i,\ y^*) - \rho_i \cdot C_y \end{gathered} \tag{8}$$

and smooth-pasting conditions, which state that the marginal benefit of firm value with respect to flow profits is equalized before and after option exercise.

$$\begin{gathered} V_x(x^*, y) = \hat{V}_x(x^*,\ y) \\ V_y(x_i, y^*) = \hat{V}_y(x_i,\ y^*) \end{gathered} \tag{9}$$

Babenko et al. 2016 show that the optimal option exercise cutoffs take the form

$$x^* = \frac{\hat{d}}{\hat{d}-1} \cdot \frac{(r-\mu_x)C_x}{\gamma_x} \tag{10}$$
$$y^* = \frac{\hat{b}}{\hat{b}-1} \cdot \frac{(r-\mu_y)C_y}{\gamma_y}$$

As is well-known, $\frac{\hat{d}}{\hat{d}-1} > 1$ and $\frac{\hat{b}}{\hat{b}-1} > 1$ are the option value multiples incorporating the value of waiting. Without this multiple, growth options should be exercised whenever their present value is positive, i.e. $\frac{x^* \cdot \gamma_x}{r-\mu_x} > C_x$ and $\frac{y^* \cdot \gamma_y}{r-\mu_y} > C_y$. Additionally, the effect of risk on option exercise and therefore investment enters through these option value multiples as argued in the context of equation (6).

R&D Capital and Empirical Predictions

To introduce R&D capital in a way similar to our empirical setup. We denote by R_x, R_y the number of existing idiosyncratic and systematic growth options. These currently existing growth options are assumed to be the result of the sum of past R&D efforts. In other words, R&D capital captures eventual outcomes of past R&D projects that successfully generated growth options, even if these processes mature only with a time lag. Given an overall R&D capital stock R, we also assume that the fraction of idiosyncratic systematic growth options stays constant as firms increase their R&D capital stock, i.e. the shares $s_x = \frac{R_x}{R}$, $s_y = \frac{R_y}{R}$ stay constant.

Given the cumulative density functions for outcomes x, y are given by $F_x(.), F_{y(.)}$ overall investment from the exercise of growth options can be written as

$$I_i = \left(s_x \cdot \int_{x^*}^{\infty} dF_x(x) + s_y \cdot \int_{y^*}^{\infty} dF_y(y)\right) \cdot \mathrm{R} \tag{11}$$
$$= \left(1 - F_x\left(\frac{d}{d-1} \cdot \frac{(r-\mu_x)C_x}{\gamma_x}\right)\right) s_x \cdot R + \left(1 - F_y\left(\frac{d}{d-1} \cdot \frac{(r-\mu_y)C_y}{\gamma_y}\right)\right) s_y \cdot R$$

Equation (11) can now be used to derive our core empirical predictions on the interaction of shocks to growth opportunities and R&D capital. On the one hand, higher exogenous R&D capital should make firm investment more responsive to changes in expected average profit growth:

$$\frac{\partial^2 I_i}{\partial R \partial \mu_x} = s_x \cdot f_x(x^*) \cdot \left(\frac{\hat{d}}{\hat{d}-1}\right) \cdot \left(\frac{C_x}{\gamma_x}\right) > 0 \tag{12}$$
$$\frac{\partial I_i}{\partial R \partial \mu_y} = s_y \cdot f_y(y^*) \cdot \left(\frac{\hat{b}}{\hat{b}-1}\right) \cdot \left(\frac{C_y}{\gamma_y}\right) > 0$$

Intuitively, higher levels of R&D capital means that a firm has more accumulated growth options, which in turn will make the firm more sensitive to higher average expected profits for these growth options μ_x, μ_y.

On the other hand, higher exogenous R&D capital should make firms delay investments more in response to uncertainty shocks:

$$\frac{\partial^2 I_i}{\partial R \partial \sigma_x^2} = -s_x \cdot f_x(x^*) \cdot \frac{\partial x^*}{\partial \sigma_x^2} < 0 \tag{13}$$
$$\frac{\partial^2 I_i}{\partial R \partial \sigma_y^2} = -s_y \cdot f_y(y^*) \cdot \frac{\partial y^*}{\partial \sigma_y^2} < 0$$

with $\frac{\partial x^*}{\partial \sigma_x^2} < 0$ and $\frac{\partial y^*}{\partial \sigma_y^2}$, as increased uncertainty will increase the optimal exercise time for growth options. Intuitively, more uncertainty about the value of growth options will delay their exercise time since it increases the option value of waiting, captured by the option value multiples $\left(\frac{\hat{d}}{\hat{d}-1}\right), \left(\frac{\hat{b}}{\hat{b}-1}\right)$. This in turn will delay a larger part of investment if the firm has more growth options, i.e. has more R&D capital.

The results in (12) and (13) can also be used to hypothesize about the relative size of investment responses to changes in average growth μ and uncertainty σ. For example, one might expect that firms tend to generate more idiosyncratic growth options than systematic growth options, since such idiosyncratic growth options are more likely to provide them with a competitive advantage, see Barney, 1986. In terms of our model, $s_x > s_y$, so that all other things equal, we would expect that investment responses to idiosyncratic shocks to μ_x, σ_x are larger in absolute value than responses to systematic shocks to μ_y, σ_y.

3. Empirical Methodology

3.1 Abnormal returns

The key idea of our measures of news and uncertainty shocks mirrors the logic of event studies see Campbell, Lo, Mackinlay, 1997; Kothari and Warner 2007, which in turn builds on the efficient market hypothesis. If stock prices correctly reflect expectations of financial market participants on future fundamentals, any changes in these expectations should induce changes in stock prices. These changes in stock prices in turn, will be measured by the stock returns $r_{i,t+1} = p_{i,t+1} - p_{i,t}$, where $p_{i,t}$ are log stock prices for firm i in period t. However, this baseline logic needs to consider that even without any news, stock prices should be expected to predictably change based on time and risk compensation, captured by the expected returns $E_\tau[r_{i,\tau+1}]$. Indeed, Fama in 2012 stated that "Market Efficiency means that deviations from equilibrium expected returns are unpredictable based on currently available information. But equilibrium expected returns can vary through time in a predictable way, which means price changes need not be entirely random." (Fama and Litterman, 2012). As a result, the actual object of interest, are stock returns that are adjusted to remove predictable return, which we call abnormal returns. Following Campbell and Shiller, 1988, these abnormal returns can be approximated as

$$r_{i,t+1} - E_t\left[r_{i,t+1}\right] = (E_{t+1} - E_t)\sum_{\tau\geq 0}\rho^\tau \Delta d_{i,t+1+\tau} - (E_{t+1} - E_t)\sum_{\tau\geq 1}\rho^\tau r_{i,t+1+\tau} \tag{14}$$

Abnormal returns can therefore be interpreted to capture three types of surprises. First, abnormal returns might be high because the current dividend was surprisingly high. Second, abnormal returns can signal revisions of expectations on future dividends and therefore future profits. Third, abnormal returns can reflect surprises on the expectations of future expected discount rates. As is well-known, current dividend surprises can only explain a very small fraction of the variation of stock returns, see Campbell and Shiller, 1988; Cochrane, 2008. Abnormal returns are therefore mostly driven by expectation revisions either on future profitability and therefore future dividends, or by surprises to expected discount rates. Additionally, we directly control for changes in current profits, which directly addresses the concern that our abnormal returns capture changes in current dividends.

To extract and differentiate PVGO news and PVGO uncertainty shocks, we use time aggregation. Our abnormal returns are calculated on a weekly basis, while the investment data we are interested in is reported on a quarterly frequency. We therefore define the average surprise or abnormal return within a quarter as our measure of PVGO news. The intuition behind this definition is that if positive surprises in one week are cancelled out by negative surprises in the next week, we would not expect there not be any positive or negative news "on average" within the quarter. Formally, we define news shocks as

$$NEWS_{i,t,t+1}^{PVGO} = \frac{1}{N}\sum_{\tau=t}^{t+1}\left(r_{i,\tau+1} - E_{\tau}\left[r_{i,\tau+1}\right]\right) \tag{15}$$

In contrast, uncertainty shocks within the quarter are defined by the dispersion of surprises. In our previous example, where the positive surprises in one week are cancelled out by negative surprises in the following week, we would measure an uncertainty shock within the quarter. Formally, we define these shocks as

$$UNC_{i,t,t+1}^{PVGO} = SD_{t,t+1}\left[r_{i,\tau+1} - E_{\tau}\left[r_{i,\tau+1}\right]\right] \tag{16}$$

3.2 Normal Returns and Recovery Theorem

As mentioned before, our methodology builds on abnormal returns. While realized returns are easy to measure, it is the construction of the expected returns $E_t[r_{t+1}]$, that is the biggest challenge for calculating abnormal returns. This is especially true in the presence of time variation in risk premia, which has been widely documented to be an important aspect of the data, see Campbell and Cochrane, 1999 and Cochrane, 2008.

One particularly attractive source of information for expected returns are option prices on stock returns, in our case options on the S&P 500 index. The reason is that information on the strike levels of option portfolios, combined with option prices allows one to potentially recover data in state probabilities that can be used to construct expected returns on the underlying asset, in our case $E_t[r_{t+1}]$, see Breeden and Litzenberger, 1978. Formally, let f_{kl} denote the state probabilities of moving from state k to state l, such as a transition from an S&P 500 index value of 1000 to a value of 1200. The Breeden and Litzenberger methodology enables us to measure state prices λ_{kl}, using a Butterfly spread portfolio, that pays off \$1 in state l, given that today's state is k. State prices λ_{kl} are not enough to calculate returns $E_t[r_{t+1}]$, since they combine the effects of differences in state probabilities with the effects of risk adjustment. To extract state probabilities f_{kl} from these state prices we require the usage of some functional form assumptions on the stochastic discount factor (SDF), to separate state probabilities from risk adjustment. Our baseline assumes time separability of risk preferences of a representative investor, and closely follows Ross, 2015. Let λ_{kl} denote state prices of future state j to current state i.

$$\lambda_{kl} = \left(\frac{\delta U'_l}{U'_k}\right) \cdot f_{kl} \tag{17}$$

Where δ is the one-period discount factor and U'_k is the marginal utility of wealth in state k. Define $z_k = \frac{1}{U'_k}$ and impose $\sum_l f_{kl} = 1$ as f_{ij} are probabilities. Then we can rewrite this in matrix notation as

$$\Lambda \cdot z = \delta \cdot z \tag{18}$$

Where $z = \left(\frac{1}{U'_1}, \dots, \frac{1}{U'_S}\right)$, so the recovery of state probabilities reduces to an eigenvector problem. The intuition for this approach is that for the matrix of state prices Λ is a sufficient statistic for the valuation effects of discounting, incorporating both the time discounting δ as well as the risk adjustment $\frac{U'_j}{U'_i}$ under separable preferences. Therefore, once the state price matrix is measured, and under the additional assumptions of time homogeneity and time separable preferences, recovering marginal utilities across states reduces to the stated eigenvector problem. Once one calculated the eigenvectors, one can calculate the state probabilities from state prices by

$$f_{kl} = \left(\frac{1}{\delta}\right) \cdot \left[\frac{z_l}{z_k}\right] \lambda_{kl} \tag{19}$$

With these state probabilities at hand, we can calculate $E_t[r_{t+1}]$.

3.3 Extension to Firm-Specific Abnormal Returns

Until now, our methodology only allows us to construct $E_t[r_{t+1}]$ and therefore systematic abnormal returns $r_{t+1} - E_t[r_{t+1}]$, but does not cover firm-specific abnormal returns $r_{i,t+1} - E_t[r_{i,t+1}]$. In this section we extend our method to enable us to measure such firm-specific PVGO shocks. Under the same assumptions as in the last section, we can write the stochastic discount factor (SDF) as

$$M_{t+1} = M_{kl} = \delta \frac{U_l'}{U_k'} = \delta \left[\frac{z_k}{z_l}\right] \tag{20}$$

Furthermore, for every stock return, it is true that

$$E_t\left[M_{t+1}\left(r_{i,t+1} - r_{f,t+1}\right)\right] = 0 \tag{21}$$

where $r_{i,t+1}$ is the net stock return for firm i and $r_{f,t+1}$ is the risk-free rate. By the definition of a covariance (21) can be rewritten as $0 = E_t[M_{t+1}] \cdot \{E_t[r_{i,t+1}] - r_{f,t+1}\} + Cov_t(M_{t+1}, r_{i,t+1} - r_{f,t+1})$, which we can then in turn solve for $E_t[r_{i,t+1}]$

$$E_t\left[r_{i,t+1}\right] = r_{f,t+1} - \frac{Cov_t\left(M_{t+1}, r_{i,t+1}\right)}{E_t[M_{t+1}]} \tag{22}$$

In other words, once we have measured the SDF (20) using the solution to eigenvector problem (18), we can simply derive firm-specific expected returns $E_t[r_{i,t+1}]$ using the firm-specific covariance of stock return $r_{i,t+1}$ with the SDF to capture systematic risk. This is a generalization of CAPM, which uses information from options markets to construct the SDF M_{t+1} instead of relying on market returns and capital market equilibrium as in CAPM. We can then use the results from (22) in (14) to measure firm-specific abnormal returns.

3.4 Exogenous R&D capital stocks

To estimate the empirical counterparts of equations (12) and (13) we will need to analyze interaction effects between PVGO shocks and the number of growth options. As suggested in our theory section, we think of this number of growth options as the output of an innovation process, with R&D as the key input. At the same time, we are keenly aware that a use of current R&D expenditure would be problematic from at least two perspectives. First, R&D spending is likely to be driven by a variety of unobserved firm-level factors, such a long-term orientation (Edmans, 2011) or CEO leadership style (Bertrand and Schoar, 2003), which in turn are also likely to be directly correlated with corporate investment. We refer to this problem as the "endogeneity problem of R&D". Second, it is well-known that innovation is an uncertain, time-delayed process in which innovation results are not known until years later. Indeed, the theoretical work in asset pricing using growth options, such as Berk et al. 1999 and Kumar and Li, 2016 assumes that innovation is such a multi-stage process. We refer to this as the “time lag problem of R&D”. Our empirical strategy to proxy for the number of growth options with R&D is intended to address both of these empirical problems.

We address the “endogeneity problem of R&D” by using state-level R&D tax credits as instrument for past R&D expenditures. This empirical strategy has been used by studies on economics, such as Bloom, Schankerman and Van Reenen, 2013 as well as finance studies such as Hombert and Matray, 2018. Since the introduction of the first federal R&D tax credit in 1981, US states have increasingly adoption state-level versions of an R&D tax credit. The process started with the adoption the first state-level R&D tax credit in Minnesota in 1982 and has continued until today. During this time, the number of states adopting R&D tax credits has risen to over 30, and the value of the credits themselves has increased by a factor of more than four. At the same time, R&D tax credits strongly vary in the cross section of states, starting at a minimum value of 2.5% in states like South Carolina and Minnesota to a maximum value of 20% for states like Arizona and Hawaii. As a result, changes in the state-level R&D tax credit offer a lot of exogenous variation across states and over time, as exemplified by California, which changed its R&D tax credit five times between 1987 and 2010. This variation is especially useful, since the large corporations we analyze typically have R&D facilities in a variety of states, thereby enabling us to construct firm-specific R&D tax-credit induced R&D expenditures by exploiting the distribution of patenting across states for each firm. We follow the methodology of Bloom et al., 2013 who begin by first noting that a firm’s user cost of capital (Hall-Jorgenson user cost of capital equation) can be decomposed into two parts of an equation: one that varies by firm and one that does not. More specifically, they define the firm’s user cost of capital as:

$$\rho_{i,t}^{U} = \frac{(1 - TC_{i,t})}{(1 - T_{i,t})}\left[\tilde{r}_t + \delta_{RD} - \frac{\Delta P_t^R}{P_{t-1}^R}\right] \tag{23}$$

where $TC_{i,t}$ is the discounted value of tax credits, $T_{i,t}$ is the corporate tax rate (inclusive of both the federal and state tax rates) , $\tilde{r}_t$ is the real interest rate, δ_{RD} is the depreciation rate, and $\frac{\Delta P_t^R}{P_{t-1}^R}$ is the growth rate of the R&D capital asset price. Since Bloom et al., 2013 are interested in deriving a measure of firm-specific R&D expenditures and since $\left[\tilde{r}_t + \delta_{RD} - \frac{\Delta P_t^R}{P_{t-1}^R}\right]$ is not firm specific, they focus on the tax price component of the user cost equation: $\rho_{i,t}^{U} = \frac{(1-TC_{i,t})}{(1-T_{i,t})}$. This tax price component of the user cost can further be decomposed into a “firm-specific” portion, $\rho^{F}_{i,t}$, and a “state-level” portion, $\rho^{S}_{i,t}$. They define the state component of the tax price as:

$$\rho^{S}_{i,t} = \sum_{s} \theta_{i,s,t} \rho^{S}_{s,t} \tag{24}$$

where $\rho^{S}_{s,t}$ is the state-level tax price and $\rho^{S}_{s,t}$ is each firm i’s 10-year moving average share of inventors in a particular state, s. The state-by-year tax price data is obtained from Wilson, 2009. At the same time, Bloom et al., 2013 use the inventor location information from USPTO patent files to measure the different locations in which firms have R&D facilities that are subject to different state-level R&D tax credits. Bloom et al., 2013 then test the validity of their instrumental variable by projecting the R&D expenditure variable on their instruments and find that the state-level tax credit has considerable power as an IV for R&D expenditures.

A natural concern at this point might be that state-level R&D tax credits themselves might be driven by state-level economic environments. However, both Bloom et al., 2013 and Hombert and Matray, 2018 analyze the R&D tax credit changes and find no evidence of any systematic correlation of R&D tax credits with state-level economic variables, once state and year fixed effects are included in the analysis. Furthermore, it should be noted that even if state R&D tax credits are correlated with state-level economic fundamentals, our analysis remains well-identified as long as such state fundamentals are not systematically correlated with the unobserved firm-level factors, such as CEO style or long-termism, that we aim to exclude from the analysis. Since most of the firms we analyze have R&D facilities in multiple states, such as correlation is unlikely.

To address the “time lag problem of R&D”, we follow Bloom et al. 2013 and use a perpetual inventory method to construct exogenous capital stocks based on R&D-tax credit induced R&D expenditures. In particular, current R&D capital is the discounted sum of past R&D expenditures:

$$R^{x}_{i,t} = \widehat{XR}_{t} + (1 - \delta_{RD}) \cdot R^{x}_{t-1} = \sum_{\tau=0}^{t} (1 - \delta_{RD})^{t-\tau} \cdot \widehat{XR}_{t-\tau} \tag{25}$$

where $\widehat{XR}_{t}$ are R&D-tax credit induced R&D expenditures, and δ_{RD} is the depreciation rate of R&D capital, which we set to δ_{RD}=0.15, following the analysis of Hall, Jaffe and Trajtenberg, 2004. Using this perpetual inventory method to summarize past R&D expenditures into a current R&D capital stock has several advantages. First, it directly addresses the “time lag problem of

R&D" by using an accumulated capital stock in which past expenditures enter with geometrically declining importance. As a result, past R&D has several years to be able to impact the current stock of growth options available to the firm. Second, the use of R&D capital stocks also facilitates identification, since it is past state-level R&D tax credits that enter into current R&D capital stocks as well. As a result, even if current R&D tax credits are correlated with current unobservable firm factors, such as CEO style, such unobservable current factors are less likely to be correlated with past state-level R&D tax credits.

Additionally, to facilitate readability, we use standardized values of log R&D capital as our independent variables, so that we subtract average log R&D and divide by the standard deviation of log R&D. As a result, all coefficients on R&D will directly give us the impact of a one standard deviation change in percentage terms of R&D.

3.5 Investment regression specifications

We build on the empirical literature on the determinants of corporate investments, especially Eberly, Rebelo and Vincent (2012) for our empirical model. Specifically, our regression specification will be of the form

$$\begin{aligned}\left(\frac{I}{K}\right)_{i,t} = \beta_0 + \beta_1 \cdot \left(\frac{I}{K}\right)_{i,t-1} + \beta_2 \cdot ln\, Q_{i,t} + \beta_3 \cdot ln(CFK)_{i,t} + D_i + \epsilon_{i,t} \\ + \beta_4 \cdot ln\, R_{i,t}^{x} + \beta_N^S \cdot NEWS_{t,t+1}^{PVGO} + \beta_U^S \cdot UNC_{t,t+1}^{PVGO} \\ + \boldsymbol{\beta_{N,R}^S \cdot NEWS_{t,t+1}^{PVGO} \times ln\, R_{i,t}^{x} + \beta_{U,R}^S \cdot UNC_{t,t+1}^{PVGO} \times ln\, R_{i,t}^{x}} \\ + \beta_N^I \cdot NEWS_{i,t,t+1}^{PVGO} + \beta_U^I \cdot UNC_{i,t,t+1}^{PVGO} \\ + \boldsymbol{\beta_{N,R}^I \cdot NEWS_{i,t,t+1}^{PVGO} \times ln\, R_{i,t}^{x} + \beta_{U,R}^I \cdot UNC_{i,t,t+1}^{PVGO} \times ln\, R_{i,t}^{x}}\end{aligned} \tag{26}$$

where $\left(\frac{I}{K}\right)_{i.t}$ is the investment rate as percentage of capital, for firm i at time t, and is the dependent variable of interest. Our main independent variables are measures of news and uncertainty shocks, interacted with exogenous R&D capital stocks. We use $ln\, R_{i,t}^{x}$ to denote the log of exogenous R&D capital, calculated according to (23). Additionally, we use $NEWS_{t,t+1}^{PVGO}$ and $UNC_{t,t+1}^{PVGO}$ to denote systematic (or common) PVGO shocks and $NEWS_{i,t,t+1}^{PVGO}$ and $UNC_{i,t,t+1}^{PVGO}$ for PVGO shocks specific to firm i[3]. Importantly, when we include both systematic and firm-specific PVGO shocks, we expect the coefficients on the systematic PVGO shocks to capture the investment responses to systematic PVGO shocks, while the coefficients on firm-specific PVGO shocks should capture the responses to idiosyncratic PVGO shocks, by the Frisch-Waugh Theorem. All specifications with interaction terms will always also include the un-interacted baseline variables the interactions consist of.

In addition to these main variables of interest, we also include a number of additional variables, that have been shown to significantly influence corporate investment in the literature. The first of these additional control variables is Tobin's Q, for which we include a logged version of the variable, denoted by $ln\, Q_{i,t}$. According to standard neoclassical investment theory, as formalized in Hayashi, 1982 and Abel and Eberly, 1994, Tobin's Q should be a sufficient statistic governing corporate investment. As a result, from the perspective of neoclassical investment theory, our measures of PVGO shocks should have no additional value to explaining corporate investment behavior. However, it is well known that Tobin's Q as measured in the data does not provide such a sufficient statistic, partly due to measurement error, see Alti, 2003. Importantly, even if Tobin's Q would be measured without noise, we would expect it to reflect both the value of growth opportunities as well as the value of assets-in-place[4]. We therefore include Tobin's Q to control for the value of assets-in-place.

The second main control variable is $ln(CFA)_{i,t}$, which measures cash flow as a percentage of total assets. Cash-flow variables such as this have a long, albeit somewhat controversial tradition in the finance literature. On the one hand, a literature following Farazzi, Hubbard and Petersen, 1988 has argued that investment responses to cash-flow reflect financial frictions. On the other hand, a literature following Alti, 2003 argues that current cash flows are a signal of future profitability and should therefore be included in investment regressions, because Tobin's Q is too noisy of a measure to capture near-term profitability well. We take no particular stance on this debate, but instead add cash flow as control variable to ensure robustness.

[3] We measure these shocks in the quarter up to the reporting time of the dependent variable to approximate contemporaneous impacts news and uncertainty shocks on investment.
[4] These are the first two terms on the right hand side of equation (5).

The third main control variable is lagged investment $\left(\frac{I}{K}\right)_{i.t-1}$, following Eberly, Rebelo and Vicent, 2012, which is motivated by the macroeconomic investment literature, such as Christiano Eichenbaum and Evans, 1999, and shows that lagged investment is an important determinant of corporate investment behavior.

In addition to these control variables, our specifications also include a full set of firm fixed effects D_i, which we use to control for any time-invariant or highly persistent unobservable factors that might influence corporate investment. We note that in most specifications, we will use a combination of a lagged dependent variable $\left(\frac{I}{K}\right)_{i.t-1}$ with firm fixed effects D_i. Whenever this happens, we use Arellano-Bond Dynamic Panel estimators to correctly estimate the coefficients on all variables.[5]

We also note that our data will consist of large, public firms, which have been shown to exhibit much smoother investment patterns than the lumpy establishment level investment patterns, as emphasized by Cooper and Haltiwanger (2006). Since the degree of lumpiness firm investment patterns varies a lot, we will explicitly take account of the potentially lumpy nature of investment in our extensions in section 6.

4. Data

In this section, we give an overview of the data used to construct our PVGO news and uncertainty shock measures, our investment outcomes and our exogenous R&D capital stocks. We used three types of data: option price data, primarily obtained from the OptionMetrics database, firm-level data, primarily obtained from the merged Compustat/CRSP database, and other data (such as control variables), generally obtained directly from the FRED database.

4.1 Option price data

All option data used to construct our PVGO shocks originate from the OptionMetrics database via the Wharton Research Data Services (WRDS). To construct the shocks, we use the S&P 500 option prices with quarterly expiration at all available intervals. In order to apply the RT, several data

[5] We have also confirmed that our results are broadly similar if we do not sure Arellano-Bond estimators.

transformations are necessary. First, following Figlewski, 2008, the option price used is the midpoint of the bid-ask spread. Reported strike prices are divided by 1,000 in order to convert them from strike prices per 1,000 stocks to strike prices per stock. We convert time-to-maturity from an expiration date to a fraction of years to expiration. These transformations allow us to use the Black-Scholes (B-S) equation to convert prices to implied volatilities Black and Scholes, 1972, a required step in the estimation of state price densities (Sanford, 2021). To estimate state price densities (SPDs), we interpolate available option prices using a mixture of a b-spline with an at-the-money (ATM) knot and a linear interpolation that is dependent on firm survival probability over certain horizons as is outlined in detail in Sanford, 2021. The b-spline with ATM knots is used to interpolate a full set of option prices in the strike price dimension. The linear interpolation with firm survival probability interpolation is used to interpolate option prices in the TTM dimension. Using this method allows us to obtain a full implied volatility surface which can then be converted to option prices using the B-S equation. Once we have a complete set of option prices, we estimate the SPD by taking the second derivative of option prices with respect to strike prices (Breeden and Litzenberger, 1978). Using SPDs, we can obtain PVGO news and uncertainty shocks by applying the recovery theorem by Ross, 2015. We rely on WRDS to access S&P 500 return data (CRSP) and the treasury bill rate (Fama-French), which we use as the risk-free rate.

4.2 Firm level data

Firm-level data originate from the merged Compustat/CRSP database via WRDS. The data consist of: investment (I), capital (K), cash flows (CF), tobin's q (q), and profit. We follow Eberly, Rebelo, and Vincent (2012) to construct all variables. More specifically, investment is the expenditures on property, plant, and equipment. Capital is defined as the replacement value of capital stock for each firm using the recursion:

$$K_{i,t} = \left(K_{i,t-1} \left(\frac{P_{K,t}}{P_{K,t-1}} \right) + I_{i,t} \right) (1 - \delta_i)$$

where P_K is the price deflator for nonresidential investment, $I_{i,t}$ is the firm's capital expenditure, and δ_i is the firm's depreciation rate. Cash flow is defined as income before extraordinary events plus depreciation and amortization plus minor adjustments. Tobin's Q is defined as:

$$Q_{i,t} = \frac{Mcap_{i,t-1} + Debt_{i,t-1} + Invent_{i,t-1}}{K_{i,t}}$$

Where $Mcap_{i,t-1}$ is the market value of equity is the closing stock price times the number of common shares outstanding, $Debt_{i,t-1}$ is the firm's long-term debt, and $Invent_{i,t-1}$ is total inventories. Finally, profit is defined as operating income before amortization and depreciation.

4.3 Other data

Control variables include: unemployment, yield spread, GDP growth and GDP forecasts. The unemployment rate is the quarterly seasonally adjusted unemployment rate for the United States. GDP growth is calculated as the quarterly percentage change in the seasonally adjusted real GDP. We downloaded both indicators—unemployment rate and GDP growth—directly from the St-Louis Fed's FRED database. The quarterly GDP forecast can be found in the Survey of Professional Forecasters on the Federal Reserve Bank of Philadelphia's website. Finally, to calculate the change in aggregate profit, we sum all firms' profits quarterly and take the difference from the previous quarter.

We present basic summary statistics for all used variables in table 1.

[Table 1]

5. Results

5.1 Investment responses to PVGO Shocks

This section provides evidence on the direct impact of PVGO news and uncertainty shocks on investment. Since our PVGO shocks have not previously been used in the literature on corporate investments, we first provide a number of validation exercises before reporting our main results.

5.1.1 Validation of PVGO Shocks

We begin with an analysis of the predictive value of our measures of news and uncertainty shocks. We first focus on systematic PVGO shocks, since they most directly incorporate risk-compensation correction from option prices we use. As discussed in section 3.1, our measures of systematic PVGO news and uncertainty shocks are based on surprise movements in stock prices.

If the variation in returns we use indeed correctly measures surprises to market participants' information sets, then two implications follow. First, because these movements are surprises, they should be unforecastable using other lagged variables, such as investments. In formal terms, investments should not Granger-cause our measures of common PVGO news and uncertainty shocks. Second, because the surprises and therefore our measures of common PVGO news and uncertainty shocks capture movements in expectations of future fundamentals, our shocks should have predictive value for investment. In other words, our common PVGO shocks should Granger-cause investments.

Table 3 summarizes Granger causality tests for our measures of systematic PVGO news and uncertainty shocks. The tests show that both systematic PVGO news and uncertainty shocks cannot be rejected to Granger-cause investments. On the flipside, lagged investments have no predictive value for our measures of systematic PVGO news and uncertainty shocks, so that the hypothesis that investments do not Granger-cause news or uncertainty shocks cannot be rejected.

These Granger-causality tests only establish that our systematic PVGO shocks contain information that is helpful to predict investments, but they cannot tell us what the nature of this information is. In particular, even if our measures of systematic PVGO shocks would successfully proxy for systematic PVGO shocks, these shocks might either represent expectation revisions on future profits or expectation revisions on future discount rates. Both types of surprises potentially stimulate corporate investments. Investments might either increase in response to systematic PVGO shocks because firms anticipate higher profits from implementing growth options or because the present value of expected future profits has increased due to lower expected future discount rates. From a certain perspective, differentiating between these two potential explanations is not important for our analysis, as in both cases the present value of growth opportunities has increased. However, it is informative to analyze whether our PVGO shocks are mostly driven by discount rate news or whether they do at least partly reflect cash flow news.

We therefore directly test whether our PVGO shocks predict firm profit growth from two perspectives. First, if our PVGO shocks provide some information on future profits, they should predict future profits. Second, since PVGO shocks are surprises to market participants, they should be uncorrelated with past profit growth. Since these regressions are informative about the informational content of PVGO shocks, we will use both the systematic and firm-specific PVGO shocks we constructed. Table 3 provides evidence on the predictive value of PVGO shocks for profits. As the first two columns show, positive systematic PVGO news shocks are strongly predictive of profit growth about five quarters ahead, while PVGO uncertainty shocks are predictive of systematically lower profit. This negative relation between uncertainty shocks and profit growth is most likely the result of the systematic correlation between periods of high uncertainty and periods of bad news, as emphasized by Stock and Watson, 2012. The third column in table 3 therefore includes both uncertainty and news shocks in the profit regressions and shows that indeed uncertainty shocks are highly correlated with news shocks. Additionally, the same profit predictions hold for firm-specific PVGO shocks, with the coefficient on firm-specific PVGO news shocks an order of magnitude higher than the coefficient on systematic PVGO news shocks.

As additional validation, the last three columns of table 4 show that past profit growth is not systematically correlated with systematic PVGO news or uncertainty shocks, as should be the case if our measured indeed pick up shocks to the information sets of investors.

5.1.2 Investment Responses to PVGO Shocks and the Role of Risk-Premium Adjustments

In this section, we analyze the importance of the risk-premium adjustment discussed in section 3.2. Specifically, our the abnormal returns $r_{i,t+1} - E_t[r_{i,t+1}]$, which are the basis of our PVGO shock measures adjust for time-varying risk premia $E_t[r_{i,t+1}]$ using the option-price method outlined in section 3.2. However, a natural question is whether such a risk-premium adjustment is needed.

[Table 4]

The first column of table 4 report our baseline results. One advantage of our approach to constructing PVGO news and uncertainty shocks is that we use the same underlying data on abnormal returns. This allows us to include both uncertainty and news shocks simultaneously to ensure that the investment estimates of PVGO news shocks are not driven by PVGO uncertainty shocks and vice versa. Including both PVGO uncertainty and news shocks together therefore moves us closer to the theoretical comparative statics of section 2. As shown in the first column of table 4, including both PVGO shocks simultaneously leaves both response coefficients to PVGO news and PVGO uncertainty shocks highly significant.

Consistent with the model in section 2, investment increases in response to positive news shocks. From the perspective of the theory, better PVGO news lower the option exercise threshold and therefore stimulate investment. Furthermore, this is the case, although we directly control for Tobin's Q and cash flow, both of which have been argued to capture news about future firm profitability. This suggests that we successfully capture the effect of news on PVGO as opposed to changes in the profitability of assets-in-place, as discussed in section 3.5. These empirical results are also qualitatively consistent with our model's prediction on uncertainty shocks: increased uncertainty implies a "wait-and-see" effect by increasing the profit threshold for exercising a growth option. Correspondingly, capital expenditures systematically decline in response to positive uncertainty shocks.

The investment response to systematic PVGO news is quantitatively sizeable: a one standard deviation increase in the news shocks stimulates investment by 0.71 percentage points ($= 0.0392 \times 0.18$). This is a large effect, compared to an average investment capital ratio of 10.8 percentage points reported in table 1. Similarly, a one standard deviation increase in uncertainty reduces investments by around 0.96 percentage points ($= -0.042 \times 0.229$). Both responses are quantitatively significant but not unrealistically large, especially considering the fact that these are systematic PVGO news and uncertainty shocks.

Additionally, column 2 of table 4 adds firm-specific PVGO news and uncertainty shocks. As mentioned in section 3.5, since systematic PVGO shocks are already included, the coefficient on the firm-specific PVGO shocks should be interpreted as the additional effect of idiosyncratic PVGO news and uncertainty shocks on corporate investment. As column 2 of table 4 shows, these estimates are again consistent with the view that our risk-premium adjustment is working as expected, since positive idiosyncratic PVGO news shocks are stimulating investment, while idiosyncratic PVGO uncertainty shocks are depressing investment. The third column of table 4 re-estimates these effects on the subsample of firms with at least some R&D data, which will be the baseline sample for our main results. It confirms that our PVGO shocks show the same sign and a similar magnitude on those firms.

The investment responses to news and uncertainty shocks are also of interest for another validity check. While the statistical tests of Granger causality are consistent with the view that our shock measures really represent changes in the information set of financial market participants, another natural question is whether we really need to use abnormal returns to measure these expectation changes. In other words, how different would results be if one were willing to assume that the predictable part of realized returns is constant or zero, i.e. $E_{\tau}[r_{\tau+1}] = 0$. While we believe that such a random walk assumption is a very good approximation of stock returns in the very short run, we are also cognizant of the fact that longer run stock returns are much more predictable, see Cochrane (2008). Whether normal returns are needed to adjust realized stock returns is therefore an empirical question, depending on the frequency of the data under consideration.

Column 4 of table 4 report the results of using average market returns and the standard deviation of market returns as placebo measures of news and uncertainty shocks. As expected, these measures deliver significantly different results from our systematic PVGO news and uncertainty shock measures. Remember that the key difference here is our use of option-implied expected returns to calculate abnormal returns, from which we then calculate PVGO news or uncertainty shocks. In response to higher average, uncorrected market returns, investments decline on average. This is most likely driven by the fact that these market returns are dominated by risk compensation, instead of stock price movements in response to new information. As a result, one would expect that investment indeed declines in response to higher risk premia, due to increased costs of capital.

Interestingly, increased realized market volatility, measured as the standard deviation of uncorrected market returns within a quarter, seems to stimulate investment, which is a seeming contradiction to any "wait-and-see" effect of investment. Column 5 of table 4 extends this analysis to firm-specific average stock returns and volatility of stock returns, which seem to exhibit similar problems as the uncorrected aggregate returns. Importantly, the investment response to uncorrected average firm-specific stock returns is negative, while there is not statistically significant investment response to firm-specific stock return volatility.

5.2 Results for the R&D-based Real Options Model

In this section, we provide our empirical results testing equations (12) and (13) in section 2.

[Table 5]

Table 5 documents our main findings. Column 1 shows that firms significantly expand investment more aggressively in response to systematic PVGO news shocks if they also have high levels of R&D capital. This is exactly what our theory predicted in equation (12): firms with more R&D capital have more growth options, so that in reaction to PVGO news shocks, investment should expand more. The associated heterogeneous investment responses are quantitatively meaningful: a one standard deviation increase in R&D capital increases investment by 1.57 percentage points more for a systematic PVGO news shock of the same magnitude. This is a very large effect, compared to an average investment capital ratio of 10.8 percentage points documented on table 1. To put this effect into perspective, a one-standard deviation news shock stimulates investment by 0.8 percentage points ($= 0.0449 \cdot 0.182$) column 1 of table 5.

The second column of table 5 tests the model prediction for the investment response interaction between uncertainty and R&D capital from equation (13). In the model, firms with higher R&D capital have a higher number of growth options, so that they will delay investment on more growth options, which in turn implies a higher reduction in investment. This prediction is confirmed in column 2 of table 5. Quantitatively, PVGO uncertainty shocks have a comparable investment response heterogeneity as news shocks. A one standard deviation increase in R&D capital implies a contraction of -1.83 percentage points.

Because systematic PVGO news and uncertainty shocks tend to be correlated, the direct effect of systematic PVGO uncertainty shocks on investment weakens in the third column of table 6, when we include both systematic PVGO news and uncertainty shocks together. However, the term capturing the interaction of systematic PVGO uncertainty and exogenous R&D capital strengthens considerably in column 3 of table 5. This suggests that systematic PVGO shocks and R&D capital primarily work through the interaction of uncertainty and R&D capital, as predicted by equation (13).

In columns 4 to 6 of table 5, we then add firm-specific PVGO shocks, so that the estimated coefficients on the shocks reflect the impact of idiosyncratic PVGO news and uncertainty shocks. As expected, the magnitude of the interaction effects for idiosyncratic PVGO news and uncertainty shocks is substantially higher than the magnitude on systematic PVGO shocks. As discussed at the end of section 2, this is to be expected if the share of idiosyncratic growth opportunities s_x is much higher than the share of systematic growth opportunities s_y. Additionally, columns 4 to 6 are reassuring, since the estimates on the interaction of exogenous R&D capital and systematic PVGO shocks stay significant and are similar in magnitude to results before including firm-specific PVGO news and uncertainty shocks.

6. Robustness and Extensions

This section offers several robustness checks, for our empirical results related to the predictions of the R&D-based real options model. The following sections can be divided into three parts. First, we check the robustness of our baseline predictions of the impact of systematic PVGO news and uncertainty shocks on investment, by controlling for contemporaneous macroeconomic shocks. We then move on to check the robustness of the R&D-based real options model in equations (12) and (13), and at the same time offer additional evidence on alternative theories of corporate investment responses to PVGO shocks.

6.1 Controlling for contemporaneous macroeconomic shocks when using systematic PVGO shocks

A potential issue is the possibility that our systematic PVGO news and uncertainty shocks not only measure new information about future cash flows and discount rates, but instead are correlated with contemporaneous macroeconomic shocks. This is an issue that is specific to our systematic PVGO shocks, but is worthwhile considering, since the option-price information that is key for the construction of the systematic PVGO shocks is also used to construct the firm-specific PVGO shocks.

We therefore include quarterly unemployment and GDP growth as control variables for other macroeconomic shocks into our investment specification from section 5.1.2. Since macro shocks such as the onset of a recession can have persistent effects, we also include consensus GDP forecasts. However, we should note in this context, that ideally such persistent effects should also be reflected in changes of systematic PVGO. In other words, if we would include all possible variables forecasting future GDP growth, we would expect to eventually render our systematic PVGO shock measures insignificant as forecast measures will become multicollinear.

[Table 6]

Table 6 reports the results of including controls for contemporaneous macro shocks as well as contemporaneous profit changes in an investment model as in section 5.1.2. Contemporaneous profit is added, as abnormal returns might include contemporaneous surprise dividend changes as shown in the context of the Campbell-Shiller decomposition in equation (14). As can be seen in comparison to table 4, the investment response coefficients to systematic PVGO news and uncertainty shocks are slightly strengthened by including these controls. On the other hand, it is informative to see that among the macro variables included in the firm-level regressions, responses to our systematic PVGO news and uncertainty shocks are typically an order of magnitude bigger than for other macro variables. A one-sided hypothesis test shows that responses to the systematic PVGO news and uncertainty shocks are statistically significantly larger than responses to the macro variables, with p-values ranging from 0.0210 to effectively 0.

6.2 Investment Irreversibility and Asset Redeployability

The first alternative explanation for our interaction results in section 5.2 is related to irreversible investments in the spirit of Kim and Kung, 2016. From this perspective, firms with assets that are not easily redeployable across business areas will face frictions to disinvestment. Since R&D intensive firms might have high levels of not redeployable assets, much of our results could be driven by irreversible investments rather than the number of growth options created by R&D. For example, it is well known that higher uncertainty will lead to an expansion of inaction regions for capital expenditure under investment irreversibility, see Dixit and Pindyck, 1994; Abel and Eberly, 1994; Bloom, 2009. This prediction might explain why we find reduced investment for firms with high R&D capital. Additionally, one might expect that higher investment irreversibility leads to a more cautionary investment behavior in response to PVGO news shocks: since firms know that they cannot easily divest non-redeployable assets, they will invest less aggressively in response to growth opportunities.

To investigate this possibility, we use firm-specific measures of irreversible investments, for which we use the inverse of asset redeployability measures of Kim and Kung, 2016. These measures in turn are based on estimates of re-salability of assets across industries. We use these irreversibility measures by interacting them with systematic and idiosyncratic PVGO news and uncertainty shocks and including these interactions alongside our interactions of PVGO shocks with exogenous R&D capital. Remember that our measures of R&D capital are exogenous in the sense that they are accumulated from R&D expenditure values that are driven by state investment tax credit. To the degree that this instrumental variables strategy is successful, we would expect that including investment irreversibility does not change our baseline interaction results.

[Table 7]

Table 7 reports our results. We note that in this and the following tables, we report the coefficient estimates on the interaction terms of various alternative theories and our PVGO shock measures, but we suppress the standard errors to conserve space. Instead, significance levels are denoted by stars *. Columns 1 and 2 of table 7 documents the results of including investment irreversibility interactions with systematic and firm-specific PVGO shocks. As expected, our estimates remain highly significant. At the same time, this column shows some interesting results for investment irreversibility. In particular, the prediction that less redeployable assets lead firms to invest less aggressively in response to positive PVGO news shocks is bourne out in the data, but only for systematic PVGO news shocks. On the other hand, investment irreversibility seems to only reduce investment in response to idiosyncratic PVGO uncertainty shocks, but not for systematic PVGO uncertainty shocks – and then only at the 10% level. However, we should also note that we are focusing on the sample of firms with positive R&D data during our sample, so that the expected negative investment effect of PVGO uncertainty for firms with high investment irreversibility could still apply more broadly.

6.3 Asset Tangibility

A prominent literature in finance has shown that financial frictions are an important determinant of investment behavior. In this context, Almeida and Campello 2007 have used asset tangibility to quantify financial frictions. This is based on limited enforcement models of financial frictions like Hart and Moore, 1994, in which the ability to collateralize a higher fraction of assets, results in lower degrees of external financing frictions. At the same time, high R&D firms by definition generate a higher fraction of intangible assets, which implies higher financial frictions. Therefore, more financially constrained firms in turn might fail to expand in response to positive PVGO news shocks, due to their inability to finance large capital expenditures. Additionally, more financially constrained firms might reduce investments more in response to PVGO uncertainty shocks. This is especially the case if financing constraints are only occasionally binding, since firms can then avoid running into financial constraints in the future by delaying investment expenditures today, see Alfaro, Bloom and Lin, 2019 and Melcangi, 2019. In other words, firms will attempt to preserve their ability to rapidly expand in the future, once the uncertainty is lifted by increasing their "precautionary savings" today. This might be an alternative explanation why high R&D firms tend to systematically invest less in response to PVGO uncertainty shocks. To investigate the robustness of our results to these predictions, we follow Almeida and Campello 2007 and construct firm-level measures of asset tangibility and include their interaction with systematic and firm-specific PVGO news and uncertainty shocks to control for the effect of financial frictions on investment response heterogeneity to PVGO shocks.

[Table 8]

Columns 3 and 4 of table 7 document the results. As before it shows that our baseline results for the R&D-based real options model remain significant. However, the asset tangibility results are of interest in their own right. Remember that higher values of tangibility correspond to less financially constrained firms. The results in table 7 suggest that less financially constrained firms respond less to systematic and idiosyncratic PVGO news shocks and not more, as predicted by a basic limited enforcement financial frictions model. On the other hand, the fact that less financially constrained firms seem to cut their investments less in response to positive PVGO uncertainty shocks is fully consistent with such a theory, albeit a model with occasionally binding constraints instead of always binding constraints.

6.4 Firm Age and Lifecycle Growth Opportunities

Another plausible alternative explanation for our findings is that growth opportunities might vary by firm age. From this perspective, young firms are more dynamic and have more growth opportunities than old firms, see Adelino, Song and D. Robinson, 2017; Kueng, Yang and Hong, 2017. As a result, equation (13) would predict that younger firms cut back capital expenditures more than old firms, which could potentially explain our results if young firms also tend to be more R&D intensive. We therefore create a proxy for firm age from Compustat data on firms' IPO dates. Though admittedly only a very crude proxy for real firm age, it seems plausible that the argument on differences in growth opportunities should also apply to age as a public firm. We then include the interaction of PVGO shocks and firm age as control variables in our heterogeneous investment response regressions.

[Table 7]

The third column in table 7 reports the results. As before, the interaction coefficients of exogenous R&D capital and PVGO shocks are reasonably robust and do not change much after we include age interactions. Furthermore, the interaction effect of firm age and PVGO uncertainty seems consistent with the idea that younger firms cut investment back more than older firms, consistent with the view that younger firms have more growth opportunities. However, R&D capital is not correlated enough with firm age for this effect to explain our baseline interactions.

6.5 Risk Shifting or Asset Substitution

Our last set of potential alternative explanations for the heterogeneous investment responses to PVGO shocks are related to capital structure and bankruptcy risk. Ever since Black and Scholes, 1973 and Merton 1974, it has been well understood that firm value under limited liability can be analyzed as a call option with the value of debt liabilities as strike. Additionally, the value of this call option is potentially subject to moral hazard by self-interested managers, who can increase the riskiness of firm investments, which boosts firm value at the expense of debt holders, see Jensen, and Meckling, 1976; Leland, 2002. This “risk shifting” or “asset substitution” channel would potentially explain our results, if low R&D firms are more likely to increase risky investment and therefore exhibit higher investment than high R&D firms in times of high PVGO uncertainty. Empirically, this could be the case if high R&D firms exhibit either low levels of leverage or are further away from bankruptcy than low R&D firms or if firms close-to-bankruptcy tend to cut their R&D budgets a lot. In this case, high leverage or close to bankrupt firms would increase the riskiness of investment projects to “gamble for resurrection”, which therefore boosts investment. To proxy for this risk shifting channel, we use three separate measures. The first is firm leverage and is directly related to the idea that more leverage implies that firms may be closer to default, as in Leland, 2002.

The second is the Altman Z-score, a proxy variable used by the academic literature and practitioners alike to predict firm default, see Russ, Peffley and Greenfield, 2004 and Altman,

2018. As mentioned above, we would expect firms with high Altman Z-scores to increase investment more in response to PVGO uncertainty shock than firms with low Altman Z-scores, consistent with Leland, 2002.

The third measure is firm size, as measured by total market capitalization. This firm size measure is often used in the asset pricing literature, e.g. in Fama and French, 1992 and has been argued to reflect "financial distress risk", see Vassalou and Xing, 2004. More importantly, future continuation value or "franchise value" is theoretically a key variable that managers consider when deciding whether to increase asset substitution, see Leland, 2002. Only when franchise values are low will managers increase asset substitution, so that one might expect that higher investments in response to higher PVGO uncertainty especially for small cap firms. In other words, the interaction effect of market cap and PVGO uncertainty should be negative.

[Table 8]

As shown in of table 8, risk shifting or asset substitution is unlikely to be an explanation for the R&D interaction results we see in the data. The response of capital expenditures to systematic and idiosyncratic PVGO uncertainty shocks stays negative and significant for high R&D firms, across almost all specifications in table 8, except for column 4. Even then, the interaction between exogenous R&D capital and idiosyncratic PVGO uncertainty still remains highly significant, even though the interaction effect between exogenous R&D capital and systematic PVGO uncertainty becomes insignificant.

The results are more mixed when considering the risk-shifting hypothesis. On the one hand, the leverage results are potentially consistent with risk-shifting: in response to systematic PVGO uncertainty shocks, more leveraged firms invest more aggressively. On the other hand, when we use the Altman Z-score to measure closeness to bankruptcy, we find that firms closer to bankruptcy tend to invest less aggressively in response to systematic PVGO uncertainty shocks. Furthermore, predictions of the risk shifting channel for market cap would have been that smaller firms invest more aggressively in response to PVGO uncertainty shocks, which is not a pattern we find in the data.

7. Conclusion

In this paper, we have derived predictions from the R&D-based real options model of investment and provided estimates for the causal interaction of R&D capital and PVGO shocks on corporate investment. Our empirical contribution was made possible by new measures of PVGO news and uncertainty shocks that are derived from abnormal returns. Our results are fully consistent with the predictions of the R&D-based real options model of corporate investments, that explains why capital expenditure and R&D capital are complementary. Furthermore, we show that alternative approaches to explain investment responses to PVGO uncertainty shocks, such as investment irreversibility, financial frictions and risk shifting are not driving our results.

References

Adao, B. and A. Silva, 2020. The effect of firm cash holdings on monetary policy. *European Economic Review*, 128, 103508.

Adelino, M, Song, M. and D. Robinson. 2017. Firm Age, Investment Opportunities and Job Creation. Journal of Finance, *72*(3), pp.999-1038.

Alfaro, L., Bloom, N. and X. Lin, 2019. The Finance-Uncertainty Multiplier. Working Paper, Stanford University.

Alti, A., 2001. How Sensitive Is Investment to Cash Flow When Financing Is Frictionless? *The Journal of Finance*, *58*(2), pp.707-722.

Altman, E. 2018. A Fifty-Year Retrospective on Credit Risk Models, the Altman Z -Score Family of Models and their Applications to Financial Markets and Managerial Strategies. *Journal of Credit Risk*, 14(4).

Anderson, C. and L. Garcia-Feijoo, 2006. Empirical evidence on capital investment, growth options and security returns. *The Journal of Finance*, *61*(1), pp.171-194.

Berk, J., Green, R. and V. Naik, 1999. Optimal Investment, Growth Options, and Security Returns. *The Journal of finance*, *54*(5), pp.1553-1607.

Black, F. and M. Scholes, 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81(3), pp.637-654.

Bloom, N. 2009. The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), pp.623-685.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta, I, and S. Terry. 2018. Really Uncertain Business Cycles, *Econometrica*, *86*(3), pp.1031-1065.

Bloom, N., Schankerman, M. and J. Van Reenen, 2013. Identifying technology spillovers and product market rivalry. *Econometrica*, *81*(4), pp.1347-1393.

Breeden, D.T. and R.H. Litzenberger, 1978. Prices of State-Contingent Claims Implicit in Option Prices. *Journal of business*, pp.621-651.

Cochrane, J. 2008. Financial Markets and the Real Economy. In: Mehra, R. (ed). Handbook of the Equity Risk Premium.

Crouzet, N. and J. Eberly, 2018a. Intangibles, Investment and Efficiency. In *AEA Papers and Proceedings* (Vol. 108, pp. 426-31).

Crouzet, N. and J. Eberly, 2018b. Understanding Weak Capital Investment: the Role of Market Concentration and Intangibles. Jackson Hole Economic Policy Symposium

Eberly, J., Rebelo, S. and N. Vincent 2012. What explains the Lagged-Investment Effect? *Journal of Monetary Economics*, *59*(4), pp.370-380.

Fama, E. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25(2), pp.383-417.

Fama, E. and K. French, 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance*, *47*(2), pp.427-465.

Fama, E. and R. Litterman, 2012. An Experienced View on Markets and Investing. *Financial Analysts Journal*, *68*(6), pp.15-19.

Fazzari, S., Hubbard, G. and B. Petersen, 1988. Financing constraints and corporate investment, Brookings Papers on Economic Activity.

Fromenteau, P., Schymik, J. and J. Tscheke, 2016. Import Competition and the Composition of Firm Investments. Working Paper, University of Munich

Gulen, H. and M. Ion, 2015. Policy Uncertainty and Corporate Investment. *The Review of Financial Studies*, *29*(3), pp.523-564.

Hall, B., Jaffe, A. and M. Trajtenberg, 2004. Market Value and Patent Citations: A First Look. *The RAND Journal of Economics*, 36(1), pp.16-38.

Hart, O. and J. Moore, 1994. A Theory of Debt Based on the Inalienability of Human Capital. *The Quarterly Journal of Economics*, *109*(4), pp.841-879.

Hayashi, F. 1982. Tobin's Marginal Q and Average Q: A Neoclassical Interpretation. *Econometrica*, 50(1), pp.213-223.

Homberg, J. and A. Matray, 2018. Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China? *The Journal of Finance*, *73*(5), pp.2003-2039.

Hubbard, R. 1998. Capital-Market Imperfections and Investment. *Journal of Economic Literature,* 36(1), pp.193-225.

Jensen, M. and W. Meckling, 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of financial economics*, *3*(4), pp.305-360.

Kim, H. and H. Kung, 2016. The Asset Redeployability Channel: How Uncertainty Affects Corporate Investment. *The Review of Financial Studies*, *30*(1), pp.245-280.

Korthari, S. and J. Warner 2007. Econometrics of Event Studies. In *Handbook of empirical corporate finance* (pp. 3-36). Elsevier.

Kueng, L., Yang, M. and B. Hong 2017. Sources of Firm Life-Cycle Dynamics: Size vs Age Effects. NBER Working Paper.

Kumar, P. and D. Li, 2016. Capital Investment, Innovative Capacity, and Stock Returns. *The Journal of Finance*, *71*(5), pp.2059-2094.

Lach, S. and M. Schankerman, 1989. Dynamics of R&D and Investment in the Scientific Sector. *Journal of Political Economy*, *97*(4), pp.880-904.

Leland, H. 2002. Agency Costs, Risk Management and Capital Structure. *The Journal of Finance*, *53*(4), pp.1213-1243.

Malmendier, U. and G. Tate, 2005. CEO overconfidence and corporate investment. *The journal of finance*, *60*(6), pp.2661-2700.

Melcangi, D. 2019. Firms' Precautionary Savings and Employment during a Credit Crisis. Working Paper, Federal Reserve Bank of New York.

Merton, R. 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of finance*, *29*(2), pp.449-470.

Milgrom, P., J. Roberts. 1990. The Economics of Modern Manufacturing: Technology, Strategy, and Organization. *American Economic Review*, pp.511-528.

Ottonello, P. and T. Winberry. Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica*, *88*(6), pp.2473-2502.

Ross, S. 2015. The Recovery Theorem. *The Journal of Finance*, *70*(2), pp.615-648.

Russ, R., Peffley, W. and A. Greenfield, 2004. The Altman Z-Score Revisited. Working paper.

Sanford, A. 2021. State Price Density Estimation with an application to the Recovery Theorem. *Studies in Nonlinear Dynamics and Econometrics,* forthcoming.

Schankerman, M. 2002. Idiosyncratic and Common Shocks to Investment Decisions. *Economic Journal*, *112*(482), pp.766-785.

Shleifer, A. 1988. Implementation Cycles. *Journal of Political Economy*, *94*(6), pp.1163-1190.

Stein, J. 2003. Agency, Information and Corporate Investment. *Handbook of the Economics of Finance*, *1*, pp.111-165.

Vassalou, M. and Y. Xing, 2004. Default Risk in Equity Returns. *The Journal of Finance*, *59*(2), pp.831-868.

Table 1: Summary statistics of main variables

VARIABLES	(1) Mean	(2) SD	(3) 25th Perc	(4) Median	(5) 75th Perc
Systematic PVGO News Shock	0.0105	0.182	-0.00828	0.0182	0.0700
Systematic PVGO Uncertainty Shock	0.141	0.229	0.0343	0.0615	0.116
Uncorrected Return	0.0461	0.349	-0.0358	0.1886	0.3708
Idiosyncratic PVGO News Shock	-0.0020414	0.0265608	-0.0170319	-0.00576	0.0081237
Idiosyncratic PVGO Uncertainty Shock	0.0321934	0.0192707	0.0166981	0.027754	0.0444155
log R&D capital	-0.896	0.36	-1.002	-0.756	-0.693
log R&D expenditures	-0.0024457	0.072378	-0.02168	0	0.02133
I/K	0.108	0.115	0.0268	0.0696	0.153
log CFK	-1.961	1.793	-3.107	-1.949	-0.804
log Tobin's Q	1.180	1.693	-0.0171	1.081	2.304
Change aggregate profit	3735.481	156380.3	-96403.25	0	131452.1
Unemployment	6.37	1.681	5.161	5.921	7.444
GDP Forecast	9975.102	4440.334	5895.331	10205.4	14060.34
GDP Growth	0.0522	0.0355	0.037	0.05	0.069

Notes: Summary statistics for all main variables in our analysis. PVGO shocks are averages and volatility of stock return surprises of the S&P 500 index. Uncorrected return is return on S&P 500 index. R&D capital is calculated by accumulating exogenously identified R&D expenditures using perpetual inventory method.

Table 2: Granger causality tests of PVGO shocks and

	(1) H0: Systematic PVGO News do not G-cause investment		(2) H0: Investment does not G-cause Systematic PVGO News	
L = lags	F-Stat	P-Value	F-Stat	P-Value
1	577.7	2.20E-16	0.0833	0.7663
2	229.59	2.20E-16	0.0467	0.9544
3	123.23	2.20E-16	0.1188	0.9491
5	51.632	2.20E-16	0.0924	0.9934
10	13.338	2.20E-16	0.122	0.9996

	(3) H0: Systematic PGVO Uncertainty does not G-cause investment		(4) H0: Investment does not G-cause Systematic PVGO Uncertainty	
L = lags	F-Stat	P-Value	F-Stat	P-Value
1	1802.1	2.20E-16	0.7648	0.3818
2	719.57	2.20E-16	0.6962	0.4985
3	386.94	2.20E-16	0.465	0.7067
5	163.12	2.20E-16	0.6269	0.6793
10	41.46	2.20E-16	0.5629	0.8454

Notes: Tables provide results of Granger causality test between investment and PVGO shocks with different lag lengths. PVGO News shocks are quarterly averages of weekly abnormal S&P 500 returns, while PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns.

Table 3: Cash-flow implications of PVGO shocks.

	Future Profit Growth			Past Profit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔProfit t+5	**ΔProfit t+5**	**ΔProfit t+5**	**ΔProfit t-1**	**ΔProfit t-1**	**ΔProfit t-1**
Systematic PVGO News Shock	15.75***		14.29***	3.555		6.877
	(2.593)		(4.434)	(13.70)		(14.54)
Systematic PVGO Uncertainty Shock		-7.689***	-6.561**		-2.980	4.103
		(1.441)	(2.910)		(9.864)	(8.841)
Idiosyncratic PVGO News Shock	161.6***		193.2***	-164.7***		-162.6***
	(33.83)		(32.55)	(39.70)		(40.04)
Idiosyncratic PVGO Uncertainty Shock		48.34	-92.60		-105.3***	-33.61
		(67.62)	(71.57)		(36.89)	(50.42)
I/K	17.14	21.62*	15.72	-67.42***	-70.96***	-66.74***
	(12.04)	(11.75)	(11.93)	(14.49)	(14.84)	(14.52)
Tobin's Q	-3.848***	-4.516***	-3.971***	8.331***	8.784***	8.354***
	(1.133)	(1.144)	(1.140)	(2.049)	(2.039)	(2.032)
log CFK	-0.809	-0.699	-0.948*	1.247	1.066	1.298
	(0.521)	(0.501)	(0.521)	(1.019)	(1.068)	(1.090)
Firm FE	YES	YES	YES	YES	YES	YES
N	25699	25699	25699	29,000	29,000	29,000

Notes: Prediction of future and past profit growth using PVGO News and Uncertainty Shocks. Data frequency is quarterly. Standard errors are clustered at the firm-level.

Table 4: Comparison of PVGO shocks with moments from uncorrected realized stock returns

	(1)	(2)	(3)	(4)	(5)	(6)
	PVGO Shocks			**Uncorrected Returns**		
	Dependent Variable: Investment / Capital (I/K)					
Systematic PVGO News Shock	0.0177***	0.0222***	0.0355***			
	(0.00171)	(0.00382)	(0.00568)			
Systematic PVGO Uncertainty Shock	-0.0335***	-0.0368***	-0.0253***			
	(0.00148)	(0.00328)	(0.00478)			
Idiosyncratic PVGO News Shock		0.177***	0.192***			
		(0.0133)	(0.0225)			
Idiosyncratic PVGO Uncertainty Shock		-0.136***	-0.204***			
		(0.0274)	(0.0510)			
Average Uncorrected Realized S&P-500 Return				-0.1053***	-0.0325***	-0.105***
				(0.00690)	(0.00827)	(0.0142)
Volatility of Uncorrected Realized S&P-500 Return				0.1462*	0.0500***	0.0645***
				(0.00993)	(0.0115)	(0.0198)
Average Firm-specific Realized Stock Returns					-0.00542***	-0.0162***
					(0.00155)	(0.00350)
Volatility of Firm-specific Realized Stock Returns					0.00238	0.00284
					(0.00147)	(0.00367)
Lagged I/K	0.178***	0.183***	0.172***	0.1718***	0.161***	0.167***
	(0.00295)	(0.00692)	(0.0130)	(0.00267)	(0.00351)	(0.00614)
Tobin's Q	0.0104***	0.0108***	0.00681***	0.0168***	0.00499***	0.00371***
	(0.000410)	(0.00130)	(0.00227)	(0.00039)	(0.000473)	(0.000763)
log CFK	0.0505***	0.0497***	0.0504***	0.0517***	0.0566***	0.0543***
	(0.000250)	(0.000867)	(0.00194)	(0.00022)	(0.000294)	(0.000469)
Firm FE	YES	YES	YES	YES	YES	YES
N	118,625	118,625	26,377	118,625	118,625	26,377

Notes: PVGO News shocks are quarterly averages of weekly abnormal S&P 500 returns, while PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns. The Average Uncorrected S&P-500 Return is the quarterly average of weekly S&P 500 returns, while the Volatility of the Uncorrected S&P-500 Returns is the quarterly standard deviation of weekly S&P 500 returns. Similarly, the Average Firm-specific Realized Stock Returns is the quarterly average of firm-specific stock returns and Volatility of Firm-specific Realized Stock Returns is the standard deviation of weekly firm-specific stock returns within a quarter. Columns 1,2,4,5 use all publicly traded firms in Compustat, while columns 3 and 6 focus on the sample of firms with at least some R&D data. Data is quarterly and standard errors are clustered at the firm-level. All columns use Arellano-Bond estimators, due to presence of firm fixed effects and lagged depedent variables.

Table 5: R&D-based Real Options Model - Responses to PVGO shocks

	(1)	(2)	(3)	(4)	(5)	(6)
			Investment / Capital (I/K)			
Systematic PVGO News **X** R&D Capital	0.0157***		0.00460	0.0151***		0.0167***
	(0.00443)		(0.00370)	(0.00441)		(0.00463)
Systematic PVGO Uncertainty Shocks **X** R&D Capital		-0.0183***	-0.0435***		-0.0187***	-0.0119***
		(0.00454)	(0.0115)		(0.00455)	(0.00452)
Systematic PVGO News Shocks	0.0449***		-0.0166***	0.0450***		0.0310***
	(0.00454)		(0.00453)	(0.00457)		(0.00572)
Systematic PVGO Uncertainty Shocks		-0.0404***	-0.0289***		-0.0405***	-0.0310***
		(0.00423)	(0.00505)		(0.00422)	(0.00512)
R&D Capital	0.0265**	0.0345**	0.0318**	0.0258**	0.0444***	0.0419***
	(0.0117)	(0.0139)	(0.0132)	(0.0115)	(0.0113)	(0.0100)
Idiosyncratic PVGO News **X** R&D Capital				0.0462***		0.0878***
				(0.0176)		(0.0207)
Idiosyncratic PVGO Uncertainty Shocks **X** R&D Capital					-0.221***	-0.266***
					(0.0571)	(0.0591)
Idiosyncratic PVGO News Shocks				0.120***		0.193***
				(0.0196)		(0.0228)
Idiosyncratic PVGO Uncertainty Shocks					-0.0433	-0.210***
					(0.0440)	(0.0511)
Additional controls: lagged I/K, Tobin's Q, log CFK and all uninteracted baseline terms. See table notes						
Firm FE	YES	YES	YES	YES	YES	YES
N	26,377	26,377	26,377	26,377	26,377	26,377

Notes: Systematic (idiosyncratic) PVGO News shocks are quarterly averages of weekly abnormal returns for the S&P 500 (weekly firm specific abnormal returns). Systematic (idiosyncratic) PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns (weekly firm specific abnormal returns). R&D capital is calculated by accumulating state-level investment-tax credit driven R&D expenditures using perpetual inventory method. Data frequency is quarterly and standard errors are clustered at the firm-level. All columns use Arellano-Bond estimators, due to presence of firm fixed effects and lagged depedent variables.

Table 6: Systematic PVGO News and Uncertainty shocks with macroeconomic controls

	(1)	(2)	(3)
		PVGO Shocks	
		Dependent Variable: Investment / Capital (I/K)	
Systematic PVGO News Shock	0.0425***		0.0164***
	(0.00291)		(0.00334)
Systematic PVGO Uncertainty Shock		-0.0490***	-0.0414***
		(0.00264)	(0.00307)
GDP growth	-0.0451***	-0.0729***	-0.0780***
	(0.0154)	(0.0155)	(0.0156)
Unemployment	-0.00174***	-0.00185***	-0.00165***
	(0.000171)	(0.000167)	(0.000170)
Consensus forecast GDP growth	6.84e-07	-5.89e-07	-3.53e-07
	(4.60e-07)	(4.58e-07)	(4.59e-07)
Change aggregate profit	2.79e-08***	2.94e-08***	3.04e-08***
	(1.68e-09)	(1.72e-09)	(1.71e-09)
Lagged I/K	0.199***	0.200***	0.199***
	(0.00703)	(0.00701)	(0.00701)
Tobin's Q	0.0105***	0.0109***	0.0111***
	(0.00134)	(0.00132)	(0.00132)
log CFK	0.0499***	0.0486***	0.0485***
	(0.000898)	(0.000896)	(0.000894)
Firm FE	YES	YES	YES
N	118,625	118,625	118,625

Notes: PVGO News shocks are quarterly averages of weekly abnormal S&P 500 returns, while PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns. The Average Uncorrected return is the quarterly average of weekly S&P 500 returns, while the Volatility of the Uncorrected Return is the quarterly standard deviation of weekly S&P 500 returns. Data is quarterly and standard errors are clustered at the firm-level. All columns use Arellano-Bond estimators, due to presence of firm fixed effects and lagged depedent variables.

Table 7: Robustness of R&D-based Real Options Model - Irreversibility, Asset Tangibility and Firm age

	(1)	(2)	(3)	(4)	(5)	(6)
	Investment / Capital (I/K)					
Systematic PVGO News **X** R&D Capital	0.00281	0.0139**	0.0047	0.0144***	0.00230	0.0110***
	(0.00591)	(0.00623)	(0.004)	(0.00461)	(0.00341)	(0.00392)
Systematic PVGO Uncertainty Shocks **X** R&D Capital	-0.0172***	-0.0130***	-0.0138***	-0.00885*	-0.0167***	-0.0139***
	(0.00467)	(0.00471)	(0.0048)	(0.00476)	(0.00459)	(0.00459)
Idiosyncratic PVGO News **X** R&D Capital		0.0835***		0.0656***		0.0823***
		(0.0238)		(0.0196)		(0.0192)
Idiosyncratic PVGO Uncertainty Shocks **X** R&D Capital		-0.246***		-0.222***		-0.182***
		(0.0397)		(0.0505)		(0.0398)
Systematic PVGO News **X** Irreversibility	-0.00822***	-0.00462*				
Systematic PVGO Uncertainty Shocks **X** Irreversibility	-0.000221	-6.04e-06				
Idiosyncratic PVGO News **X** Irreversibility		0.0158				
Idiosyncratic PVGO Uncertainty Shocks **X** Irreversibility		-0.0277*				
Systematic PVGO News **X** Asset Tangibility			-0.104*	-0.162***		
Systematic PVGO Uncertainty Shocks **X** Asset Tangibility			0.293***	0.330***		
Idiosyncratic PVGO News **X** Asset Tangibility				-1.225***		
Idiosyncratic PVGO Uncertainty Shocks **X** Asset Tangibility				0.887*		
Systematic PVGO News **X** Firm age					-0.000223	-0.000383
Systematic PVGO Uncertainty Shocks **X** Firm age					0.000294**	-4.01e-05
Idiosyncratic PVGO News **X** Firm age						0.000480
Idiosyncratic PVGO Uncertainty Shocks **X** Firm age						0.00603***
Additional controls: lagged I/K, Tobin's Q, log CFK and all uninteracted baseline terms. See table notes						
Firm FE	YES	YES	YES	YES	YES	YES
N	26,377	26,377	26,377	26,377	26,377	26,377

Notes: Systematic (idiosyncratic) PVGO News shocks are quarterly averages of weekly abnormal returns for the S&P 500 (weekly firm specific abnormal returns). Systematic (idiosyncratic) PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns (weekly firm specific abnormal returns). R&D capital is calculated by accumulating state-level investment-tax credit driven R&D expenditures using perpetual inventory method. Data frequency is quarterly and standard errors are clustered at the firm-level. Irreversibility measures redeployability of assets, constructed by Kim and Kung, 2016. Asset tangibility measures fraction of assets that can be easily collateralized, as constructed by Almeida and Campello, 2007. Firm age is measured by years since IPO. Additional controls include all un-interacted baseline effects for any interaction terms as well as the additional controls of lagged (I/K), Tobin's Q and cash flow as percent of assets. Standard errors are clustered by firm. Significance levels are denoted by *: 10%, **: 5%, ***: 1%. Standard errors for interactions of shocks and various control variables are supressed to conserve space, with full results available in the online appendix. All columns use Arellano-Bond estimators, due to presence of firm fixed effects and lagged depedent variables.

Table 8: Robustness of R&D-based Real Options Model - Asset Substitution / Risk Shifting

	(1)	(2)	(3)	(4)	(5)	(6)
	Investment / Capital (I/K)					
Systematic PVGO News **X** R&D Capital	0.00401	0.0139**	0.00403	0.0128***	0.00281	0.0110***
	(0.00371)	(0.00623)	(0.00357)	(0.00449)	(0.00361)	(0.00392)
Systematic PVGO Uncertainty Shocks **X** R&D Capital	-0.0116**	-0.0130***	-0.0158***	-0.00692	-0.0175***	-0.0139***
	(0.00460)	(0.00471)	(0.00478)	(0.00478)	(0.00474)	(0.00459)
Idiosyncratic PVGO News **X** R&D Capital		0.0835***		0.0705***		0.0823***
		(0.0238)		(0.0209)		(0.0192)
Idiosyncratic PVGO Uncertainty Shocks **X** R&D Capital		-0.246***		-0.211***		-0.182***
		(0.0397)		(0.0542)		(0.0398)
Systematic PVGO News **X** Leverage	-0.00243	-0.00237				
Systematic PVGO Uncertainty Shocks **X** Leverage	0.0152***	0.0156***				
Idiosyncratic PVGO News **X** Leverage		-0.0318***				
Idiosyncratic PVGO Uncertainty Shocks **X** Leverage		-0.0143				
Systematic PVGO News **X** Altman Z-Score			0.00403***	0.00298*		
Systematic PVGO Uncertainty Shocks **X** Altman Z-Score			-0.0043***	-0.00410***		
Idiosyncratic PVGO News **X** Altman Z-Score				-0.00436		
Idiosyncratic PVGO Uncertainty Shocks **X** Altman Z-Score				-0.0193*		
Systematic PVGO News **X** Market Cap					0.00381**	0.00507**
Systematic PVGO Uncertainty Shocks **X** Market Cap					0.00245	0.00184
Idiosyncratic PVGO News **X** Market Cap						0.0189**
Idiosyncratic PVGO Uncertainty Shocks **X** Market Cap						-0.0192
Additional controls: lagged I/K, Tobin's Q, log CFK and all uninteracted baseline terms. See table notes						
Firm FE	YES	YES	YES	YES	YES	YES
N	26,377	26,377	26,377	26,377	26,377	26,377

Notes: Systematic (idiosyncratic) PVGO News shocks are quarterly averages of weekly abnormal returns for the S&P 500 (weekly firm specific abnormal returns). Systematic (idiosyncratic) PVGO Uncertainty shocks are quarterly standard deviations of weekly abnormal S&P 500 returns (weekly firm specific abnormal returns). R&D capital is calculated by accumulating state-level investment-tax credit driven R&D expenditures using perpetual inventory method. Leverage measures ratio of debt to equity. Total assets measures balance sheet value of assets. Market cap measures total stock market value of outstanding equity. Data frequency is quarterly and standard errors are clustered at the firm-level. Controls include all un-interacted baseline effects for any interaction terms as well as the additional controls of lagged (I/K), Tobin's Q and cash flow as percent of assets. Standard errors are clustered by firm. All columns use Arellano-Bond estimators, due to presence of firm fixed effects and lagged depedent variables.