Technological Progress, Managerial Learning, and the Investment-to-Stock Price Sensitivity*

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Abstract

We develop a real options investment model in which managers learn about the unobservable characteristics of new production technologies from their most recently installed production capacity and their firm's stock price. Critically, the model predicts that managers rely more on the stock price the longer ago the firm last installed capacity. In accordance, the corporate investment-to-stock price sensitivity rises with past capacity overhang, a proxy for the time since a firm last acquired capacity. The results hold under various investment, employment, and Tobin's Q proxies and controlling for the private information in stock prices and firm financial constraints. Notably, the *dis*investment-to-stock price sensitivity falls with capacity overhang, suggesting managers also learn about liquidation values from stock prices. We shed light on the *nature* of information managers extract from markets by providing causal evidence that the managerial learning dynamics we uncover are more pronounced for firms exposed to greater technological progress.

Keywords: Managerial learning; Investment-to-stock price sensitivity; Capacity overhang; Technological progress; Innovation

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1 Introduction

Over the last few decades, a large literature has established that corporate investment is positively correlated with stock prices (see, e.g., Fama (1981), Barro (1990), Morck, Shleifer, and Vishny (1990), and Blanchard, Rhee, and Summers (1993)). Recent studies propose an explanation for this empirical relation founded on the idea that managers rely on their firms' stock market valuation to aid them in their real investment decisions. In a seminal paper, Chen, Goldstein, and Jiang (2007) show that the corporate investment-to-stock price sensitivity rises with the amount of private investor information in stock prices. Building on that work, Bakke and Whited (2010), Foucault and Frésard (2012), and Edmans, Jayaraman, and Schneemeier (2017), among others, provide support for the notion that the positive investment–stock price relation is, at least in part, driven by managerial learning. Despite the strong evidence that managers use stock prices to guide their investment decisions, the literature is notably silent on the *nature* of information managers learn from markets.

In this paper, we argue that managers use stock prices as an important source of information about the characteristics of *new* assets which they contemplate investing in. They do so since, in a world with unobservable technological progress, a firm's *existing* assets offer managers limited information about those characteristics, especially if the installed assets were acquired a long time ago. Conversely, stock investors continuously monitor a large set of similar firms, some of which may already be operating modern assets embodying the latest technological advances. As such, it is plausible that investors have incremental information about the characteristics of those assets, which, in turn, is reflected in their valuation of the firm. Accordingly, when market valuations reveal that information, managers are able to rely on stock prices in guiding their investment decisions. The information embedded in stock prices is particularly valuable when the firm's installed assets give managers a poor signal on latest technological advances due to the assets' age and likely obsolescence.

We begin our investigation by developing a real options investment model that formalizes this intuition. The firm in the model owns several production units ("factories") that enable it to produce a homogeneous output good and sell that at a stochastic price. The firm further owns a "growth option" allowing it to acquire a modern factory. Due to technological progress, the cost at which the firm can use modern factories to produce output evolves randomly with negative drift. Critically, the manager may only directly observe that cost upon acquiring a modern factory. The manager, however, forms expectations about the unobserved cost of modern capacity using information obtained from two sources. First, the manager can use the cost at which the firm's most recently installed factory produces output to infer the cost at which the modern factory would do so. Second, the manager can back out stock investors' estimate of the modern factory's production cost from the firm's stock price.

We next show that the firm optimally invests in the modern factory when the manager's *best estimate* for its value is sufficiently high relative to the investment outlay. Naturally, the manager's best estimate is a function of both the production cost of its most recently installed factory and stock investors' cost estimate, as reflected in the firm's stock price. The crux of our model is that the longer ago the firm last acquired a factory, the more it relies on the stock market's cost estimate—and the less it relies on the cost of its most recently installed factory—to learn about the modern factory's value, making the firm's investments more sensitive to the stock price. The learning-based dynamic that the firm's investment-to-stock price sensitivity rises with the time since it last acquired capacity intuitively emerges from our model and results from the logic that while the stock market's cost estimate may be poor, we assume that its predictive ability remains stable over time.[1] In contrast, the accuracy with which the cost of modern capacity can be predicted using the costs of installed factories naturally declines with the length of time since the firm acquired its most recent production capacity.

We next take several testable predictions of our theoretical framework to the data. Our empirical analysis is designed to test the model's central insight that a firm's investment-to-stock price sensitivity increases with the time since it last acquired capacity. Finding an empirical counterpart to the latter theoretical construct is challenging since the timing of firms' invest-

[1]This assumption is plausible, reflecting the notion that stock investors form their estimate from a large set of similar firms they hold in their portfolios, some of which may already be operating modern factories.

ments into *new capacity* is not observable via conventional data sources (e.g., Compustat).[2] A key innovation of our empirical approach is that we overcome this challenge by using past "capacity overhang," defined as the extent to which a firm's installed capacity exceeds its optimal capacity, as a proxy for the length of time since a firm last acquired capacity. As we explain later, capacity overhang serves as an effective proxy for the time since a firm last invested in capacity as it reflects the extent to which a firm's current demand deviates from the demand threshold at which the firm would optimally invest into additional capacity. As a result, a firm with a persistently high capacity overhang over some recent past period will optimally not have invested into capacity over that period, implying that its managers will have little hands-on experience with recent advances in production technology. We create a time-varying measure of firms' capacity overhang using the stochastic frontier model estimation technique proposed in Aretz and Pope (2018). We validate the measure using firm establishment-level data, showing that it is positively correlated with the time since a firm last opened an establishment—an observable and discrete decision to invest in new capacity. Using this measure, we estimate firms' conditional investment-to-stock price sensitivity in a panel regression specification exploiting *within-firm* variation in market valuation and capacity overhang.

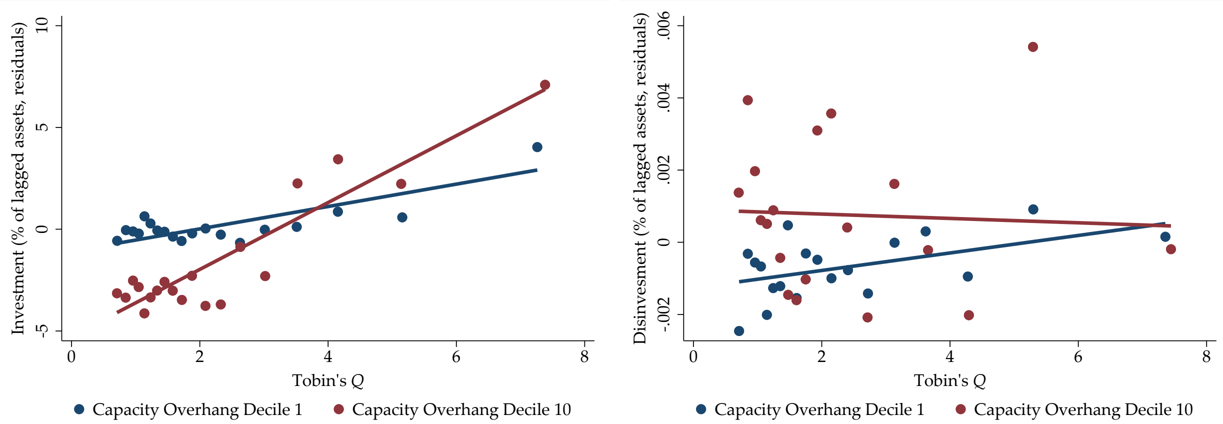
Our baseline results provide strong support for the proposed model intuition. Using the sum of capital, R&D, advertising, and acquisition expenditures scaled by lagged assets as a measure of firm investment, and regressing it on the market-to-book ratio ("Tobin's Q"), we find that while bottom capacity overhang tercile firms have a sensitivity of 1.62, the sensitivity of top tercile firms is 3.07. The difference in sensitivities is highly statistically significant and economically meaningful. A one-standard-deviation increase in Tobin's Q is associated with a 2.15 percentage point increase in the investment ratio (13.6% of the sample mean investment ratio of 15.8%) for firms in the bottom capacity overhang tercile, while the same increase is associated with a 4.09 points increase (25.9% of the sample mean) for firms in the top tercile. Our results are robust to the use of a wide range of alternative investment and market valuation

[2] The typically-used proxy for a firm's investment, reported capital expenditures, intermingles spending on new assets with outlays for maintenance, repairs, and improvements to installed assets.

metrics. Notably, we are the first to show that firms' investment in human capital—measured through employment growth at the establishments they operate—is sensitive to stock prices when capacity overhang is high. Taken together, the results suggest that the rate at which managers are guided by stock prices in making their investment decisions is an increasing function of capacity overhang, reflecting the time since the firm last invested into new capacity.

We supplement our base analyses with a host of tests aimed at ruling out that our findings are driven by other omitted yet well-known determinants of the investment-to-stock price sensitivity. We show that our main findings survive the inclusion of controls that proxy for the extent to which stock prices contain private information (as in Chen, Goldstein, and Jiang (2007)). We further explore the possibility that managers may have access to alternative sources of information on the characteristics of new production technologies, specifically through industry trade and professional associations. Notably, in tests conditioning on the presence of such associations, we show that the learning dynamics predicted by our model are more pronounced when managers lack access to these alternative information channels.

We next consider whether variation in our capacity overhang measure may simply be capturing changes in firms' financial constraints. On this front, we show that our results hold even after accounting for changes in several metrics of a firm's ability to raise funding including equity and debt issuances, firm size and age (see Hadlock and Pierce (2010)), the Whited and Wu (2006) index, textual mentions of financial constraints in regulatory disclosures (see Hoberg and Maksimovic (2015)), and firm payouts (see Almeida and Campello (2007)). That our main results continue to obtain is reassuring in light of prior work showing that the investment-to-stock price sensitivity may also capture an easing of firm financial constraints (see, e.g., Baker, Stein, and Wurgler (2003)). We further show that managerial learning among high-capacity overhang firms is particularly pronounced for the subset of unconstrained firms, consistent with the idea that such firms have a greater ability to respond to market signals to invest than firms lacking access to capital. New to the literature, we document that the



(A) Investment-Q Sensitivity

(B) Disinvestment-Q Sensitivity

Figure 1. Investment and Disinvestment Sensitives to the Stock Price Across Capacity Overhang Deciles. This figure plots investment (Panel A) and disinvestment (Panel B) scaled by one-year lagged assets against the market-to-book ratio ("Tobin's Q") plus the predicted linear relations between the variables for firms in the first (blue) and last (red) capacity overhang decile. Both the investment and disinvestment variables are orthogonalized with respect to size and cash flow.

disinvestment-to-stock price sensitivity declines with capacity overhang, suggesting that firms which have not recently disinvested learn about asset liquidation values from the stock market.

Figure 1 offers a graphical illustration of our baseline findings. Panel A points to a notable difference in the investment-to-stock price sensitivities between firms which have recently installed capacity ("Capacity Overhang Decile 1") and those which have not ("Capacity Overhang Decile 10"). To wit, while high capacity overhang firms with high market valuations exhibit disproportionately higher investment rates as compared to otherwise identical firms with low market valuations, that same relation is remarkably muted for firms with more recently installed—and thus more modern—assets. Panel B illustrates that firms with more recently installed capacity respond more pronouncedly to market valuations in terms of their disinvestment relative to firms with more obsolete capacity. The figure confirms our model logic and motivates our empirical analysis of the underlying economic mechanism.

To further empirically validate our theoretical framework, our next set of tests aim to establish that managerial learning about technological progress is the channel through which capacity overhang influences the investment-to-stock price sensitivity. In this analysis, we allow the effect of capacity overhang to be conditional on the rate of technological progress to which either a firm or industry is exposed. Relying on the idea that highly-cited patents embody economically-important innovations (see, e.g., Hall, Jaffe, and Trajtenberg (2005) and Kogan et al. (2017)), we use the number of citations of patents filed by firms in an industry to capture inter-industry variation in technological progress. Alternatively, we use a firm's within-industry rank of the time since it last filed a patent to capture intra-industry variation. To mitigate concerns that these measures may be endogenous to firm investment opportunities, we also use Bloom, Schankerman, and van Reenen's (2013) instrument for a firm's exposure to technological progress by its peers. This instrument exploits plausibly-exogenous variation in the R&D expenditures of peer firms within the same technology space as the focal firm induced through changes in state and federal R&D tax credits. In line with our theory, these conditioning tests establish that the managers of high capacity overhang firms learn more investment-relevant information from stock prices relative to those of low capacity overhang firms when they are more exposed to technological progress. These are precisely the states in which our model would predict that stock prices are likely to be more informative than managers' own information gleaned from their firms' existing operations. Our results provide direct evidence that managers are likely to be learning about technology from stock prices, with this learning driving the corporate investment-to-stock price sensitivity.

Our study contributes to a growing literature suggesting that managers incorporate investors' information embedded in stock prices into their investment decisions. In line with that idea, Chen, Goldstein, and Jiang (2007) show that the corporate investment-to-stock price sensitivity increases with the probability of informed trading (PIN) and price non-synchronicity, proxies for the amount of private investor information in stock prices. Using a methodology disentangling investment-relevant information in stock prices from noise, Bakke and Whited (2010) offer supportive evidence. Relying on shocks to a firm's investor base, insider trading rules, disclosure rules, and price discreteness, Foucault and Frésard (2012), Edmans, Jayaraman, and Schneemeier (2017), Jayaraman and Wu (2019), and Ye, Zheng, and Zhu (2019) offer further supportive evidence. Studying merger and acquisition (M&A)

announcements, Luo (2005) finds that negative stock market reactions can push managers toward canceling deals, also in line with the former evidence. Recent work by Goldstein, Liu, and Yang (2021) provides survey evidence of managerial learning as a mechanism for the investment-to-stock price sensitivity.[3] We shed new light relative to those studies by looking into the *type* of information managers glean from stock prices, providing a theoretical framework and empirical evidence that managers learn about the operational characteristics of modern capacity from stock prices. We show that this learning is a critical factor explaining the observed sensitivity of corporate investment to stock prices.

We further contribute to the literature by linking studies on the investment-to-stock price sensitivity with those on corporate innovation. A number of prior studies provide evidence that stock markets promote innovation by enabling firms to access financing (see, e.g., Brown, Fazzari, and Petersen (2009) and Acharya and Xu (2017)). Others suggest that exposure to stock market pressures may also impede managers from investing in innovation (see, e.g., He and Tian (2013) and Fang, Tian, and Tice (2014)). Our findings uncover a novel dimension in which stock markets may influence innovation. Specifically, we show that stock markets enable the dissemination of innovation as managers learn about technological progress from market prices, which, in turn, incentivizes them to invest in modernizing their assets.

We finally add to the real options investment literature, as pioneered by Brennan and Schwartz (1985), MacDonald and Siegel (1986), as well as Pindyck (1988), by parsimoniously incorporating idiosyncratic technological progress in the cost at which capacity produces output into that literature. Assuming that managers do not directly observe that cost, and that the cost obeys a geometric Brownian motion (GBM) with negative drift, the value of modern capacity in our model is a function of managers' best estimate of that cost — and thus of predictor variables conditioning the best estimate. Since the optimal investment rule

[3] A related literature suggests that managers do not only use their own stock prices in their investment decisions but also those of their peers (see Foucault and Frésard (2014), Dessaint, Foucault, Frésard, and Matray (2018), and Ozoguz, Rebello, and Wardlaw (2018), among others). Similarly, Bustamante and Frésard (2020) show that firms' investment responds directly to their peers' investment decisions, while Bernard, Blackburne, and Thornock (2020) show that firms' acquisition of information through rival firms' disclosures influences their subsequent investment decisions.

is still to acquire capacity as soon as its value estimate sufficiently exceeds the investment cost, our model leads the predictor variables to be determinants of the firm's optimal investment policy, creating a channel for investment decisions to depend on stock prices.

Our paper proceeds as follows. Section 2 develops a real options model predicting that a firm's stock price is a more important determinant of its investment policy the longer ago the firm last acquired capacity. Section 3 presents empirical evidence supporting our model, showing that the corporate investment-to-stock price sensitivity rises with capacity overhang under alternative proxy and control variables. It also reveals that the disinvestment-to-stock price sensitivity drops with capacity overhang. Section 4 shows that our main results on the investment-to-stock price sensitivity are stronger for firms and industries more exposed to technological progress. Section 5 concludes. We relay technical material (i.e., mathematical proofs and the estimation of capacity overhang) to the appendix.

2 Theoretical Framework

In this section, we develop a real options investment model featuring unobservable technological progress in the cost at which firms are able to operate new production capacity. The main insight of the model is that managers' investment decisions depend more on investors' estimate of that cost as reflected in the stock price the longer ago they last acquired capacity and thus directly observed the cost. We first state the assumptions of the model. We next derive valuation formulas and the optimal investment rule. We finally discuss the model's main testable implications for the investment-to-stock price sensitivity.

2.1 Model Assumptions

Consider an all-equity-financed firm operating in continuous time indexed by $t \in [0, +\infty)$. The firm owns K production units ("factories"), each one allowing it to produce one output unit per time unit when it is switched on and zero output units when it is switched off. We index the factories by $k \in \{1, 2, \ldots, K\}$. We further denote by t_k the time at which the kth factory was acquired, with $t_1 < t_2 < \ldots < t_K$. Since the firm is able to instantaneously and costlessly switch on or off each factory, its output quantity per time unit is equal to $Q_t \in [0, K]$. When switched on, the kth factory incurs a production cost of C_{t_k} per time unit. The firm sells its output at a unit price, P_t, evolving according to the GBM:

$$dP_t = (\mu - \delta)P_t dt + \sigma P_t dB_t, \tag{1}$$

where $\mu > 0$ is the constant expected return of an output-price replication portfolio, $\delta > 0$ its constant dividend yield, $\sigma > 0$ its constant volatility, and B_t a Brownian motion under the physical (i.e., the real-world) measure $\mathbb{P}$. Switching to the equivalent martingale measure $\mathbb{Q}$, we can alternatively write the output price process as:

$$dP_t = (r - \delta)P_t dt + \sigma P_t dB_t^{\mathbb{Q}}, \tag{2}$$

where r is the risk-free rate and $B_t^{\mathbb{Q}}$ a Brownian motion under the $\mathbb{Q}$ measure.

The firm owns one growth option allowing it to acquire the most recent modern factory at an investment cost of I.[4] Due to technological progress, the cost at which the firm can use that factory, however, differs from those of the installed factories. To be more specific, assuming that there is a new most recent modern factory in each instant, we posit that the (constant) cost at which the firm could operate the most recent modern factory to produce one output unit per time unit, C_t, trends downward according to the GBM:

$$dC_t = \gamma C_t dt + \xi C_t dW_t, \tag{3}$$

where $\gamma < 0$ is the constant drift, $\xi > 0$ the constant volatility, and W_t a Brownian motion under the physical measure. In other words, the cost at which the firm would use the factory

[4]It would be trivial to award the firm further growth options. However, since we are exclusively interested in how the firm exercises its deepest in-the-money growth option, we ignore others for simplicity.

after its installation is the "frozen-in value" of the GBM in Equation (3) at the time the factory is acquired.[5] The upshot is that the costs at which the firm operates its installed factories, C_{t_k}, are simply past values of the GBM, with, for example, C_{t_K} equal to the value of the process at the time the firm last acquired a factory. For simplicity, we assume that technological progress is idiosyncratic, so W_t is also a Brownian motion under the equivalent martingale measure, and that it is uncorrelated with the output price, P_t.

We next posit that neither managers nor stock investors directly observe the cost at which the firm would use the most recent modern factory. Managers can, however, infer that cost using two sources. First, they can infer it from the cost at which their most recently installed factory produces output, C_{t_K}. Second, they can infer it from investors' best estimate of the log cost at which the firm could operate modern capacity, $c_t \equiv \ln(C_t)$, embedded in the firm's stock price, $\mathbb{E}_t^S(c_t)$. To parsimoniously model investors' best estimate of that log cost, we introduce the auxiliary variable X_t obeying the GBM:

$$dX_t = \lambda X_t dt + \psi X_t dY_t, \tag{4}$$

where λ and $\psi > 0$ are the constant drift and volatility, respectively, and $dY_t = \rho_t dW_t + \sqrt{1-\rho_t^2} dZ_t$. Conversely, ρ_t is a deterministic function of time t and Z_t a Brownian motion independent of W_t under the physical measure. It follows that Y_t is a Brownian motion itself, that W_t and Y_t are bivariate lognormal at each time t, and that the covariance between W_t and Y_t, $\text{cov}(W_t, Y_t)$, is given by $\int_0^t \rho_s ds$.[6] We next assume that:

$$\mathbb{E}_t^S(c_t) = \alpha_t + \beta_t x_t, \tag{5}$$

[5]Due to the fact that Equation (3) gives the cost at which the firm under consideration would use modern capacity to produce output, that cost can sometimes increase over time, consistent with the insight that some technological advances may actually not help, and in fact hurt, firms. Setting the drift rate γ to a sufficiently negative number, we can however make such situations unlikely to occur.

[6]We can use the Lévy theorem to show that Y_t is a Brownian motion, and the moment generating function to show that W_t and Y_t are bivariate lognormal at each time t.

where $x_t \equiv \ln(X_t)$, $\alpha_t = \mathbb{E}(c_t) - \beta_t \mathbb{E}(x_t)$, and $\beta_t = \frac{\mathrm{cov}(c_t, x_t)}{\mathrm{var}(x_t)}$. In turn, the variance of investors' forecast error, $\epsilon_t \equiv c_t - \mathbb{E}_t^S(c_t)$, equals $\mathrm{var}(c_t) - \beta_t^2 \mathrm{var}(x_t)$. Critically, we choose $\mathrm{cov}(W_t, Y_t) = \int_0^t \rho_s ds$ in such a way that the variance of that error does not change over time t.[7] Under our modelling assumptions, c_t, $c_{t_K} \equiv \ln(C_{t_K})$, and $\mathbb{E}_t^S(c_t)$ are multivariate normal.

Comparing the two sources of information available to managers, we highlight that while the cost at which the firm operates its most recently installed factory, c_{t_K}, gives managers precise information about the cost at which it could operate new capacity if managers acquired the installed factory only a short while ago, the quality of that information naturally declines with the length of time since the acquisition. The underlying intuition is that, as the time since the last acquisition increases, managers have less hands-on experience with new capacity, leading their knowledge about such capacity to decrease. In contrast, assuming that investors collect their information from large sets of firms, with some of those likely to be already operating new capacity identical to that evaluated by the firm, it seems plausible that the value of their information about new capacity, $\mathbb{E}_t^S(c_t)$, is more stable over time. To be more specific, while the quality of investors' information about the cost at which the firm could operate new capacity may generally be poor, we see no reason to expect that quality to either improve or deteriorate over time.

2.2 Valuation and Optimal Investment Rule

Using standard valuation techniques, as, for example, described in Dixit and Pindyck (1994), we can easily show that the value of the k^{th} installed factory, $V_k(P_t)$, is:

$$V_k(P_t) = \begin{cases} b_1 P_t^{\beta_1}; & P_t < C_{t_k} \\ b_2 P_t^{\beta_2} + P_t/\delta - C_{t_k}/r; & P_t \geq C_{t_k}, \end{cases} \tag{6}$$

[7] We can write the variance of the forecast error made by investors as: $\mathrm{var}(\epsilon_t) = \mathrm{var}(c_t) - \beta_t^2 \mathrm{var}(x_t) = \xi^2 t - \left(\frac{\xi\psi \int_0^t \rho_s ds}{\psi^2 t}\right)^2 \psi^2 t = \xi^2 t - \frac{\xi^2 (\int_0^t \rho_s ds)^2}{t} = \xi^2 t \left(1 - (\int_0^t \rho_s ds/t)^2\right)$, where $\int_0^t \rho_s ds/t$ is the correlation between W_t and Y_t. Defining $\int_0^t \rho_s ds/t \equiv \mathrm{corr}_t(W_t, Y_t)$, we want to ensure that: $\frac{\partial \mathrm{var}(\epsilon_t)}{\partial t} = \xi^2 \left(1 - \mathrm{corr}_t(W_t, Y_t)^2\right) - 2\xi^2 t \mathrm{corr}_t(W_t, Y_t) \frac{\partial \mathrm{corr}_t(W_t, Y_t)}{\partial t} = 0$ by appropriately choosing $\frac{\partial \mathrm{corr}_t(W_t, Y_t)}{\partial t}$.

where the definitions of the β_1, β_2, b_1, and b_2 parameters are in Appendix A.

To determine the firm's best estimate for the value of the growth option and to identify its optimal investment rule, we first need to find the firm's best estimate for the value of the modern factory underlying the growth option. In Appendix A, we show that the firm's best estimate for the factory's value, $V^*(P_t, X_t; C_{t_K})$, which depends on the current output price, P_t, investors' production cost estimate as captured by X_t, and the (constant) production cost of the most recently installed factory, C_{t_K}, is equal to:

$$\begin{aligned} V^*(P_t, X_t; C_{t_K}) &= \mathbb{P}_t(P_t \geq C_t) \left(\mathbb{E}_t \left[b_2 \middle| P_t \geq C_t \right] P_t^{\beta_2} + P_t/\delta - \mathbb{E}_t \left[C_t \middle| P_t \geq C_t \right] /r \right) \\ &+ \mathbb{P}_t(P_t < C_t) \left(\mathbb{E}_t \left[b_1 \middle| P_t < C_t \right] P_t^{\beta_1} \right), \end{aligned} \tag{7}$$

where $\mathbb{P}_t(.)$ and $\mathbb{E}_t \left[. \middle| . \right]$ are, respectively, the conditional probability as well as expectation operator under the physical measure. The same appendix further reveals that all conditional probabilities and expectations in Equation (7) are functions of the firm's best estimate for the log cost at which it could use the modern factory to produce output, $\mathbb{E}_t[c_t]$, and the residual variance of that log cost, $\sigma_t^2(c_t)$. In turn, under our assumptions, the best estimate is the fitted value from the least-squares regression of c_t on c_{t_K} and $\mathbb{E}_t^S(c_t)$:

$$\mathbb{E}_t[c_t] = \mathbf{c}_t' \boldsymbol{\eta}, \tag{8}$$

where $\mathbf{c}_t = [1, c_{t_K}, \mathbb{E}_t^S(c_t)]'$, and $\boldsymbol{\eta} = E[\mathbf{c}_t \mathbf{c}_t']^{-1} E[\mathbf{c}_t c_t]$ is a $[3 \times 1]$ vector containing the optimal combination weights. Moreover, the residual variance of the log cost is:

$$\sigma_t^2(c_t) = \sigma^2(c_t) - \boldsymbol{\eta}' \text{var}(\mathbf{c}_t) \boldsymbol{\eta}, \tag{9}$$

where $\sigma^2(c_t)$ is the unconditional variance of c_t measured from time $t = 0$, and $\text{var}(\mathbf{c}_t)$ the unconditional $[3 \times 3]$ variance-covariance matrix of the $\mathbf{c}_t$ vector.

Having derived the firm's best estimate for the modern factory's value, we are now able to determine its best estimate for the growth option's value. Doing so is easy if we assume that managers only ever form an estimate of the log production cost of the modern factory at the current point in time t and do not update their estimate as time progresses. In that case, it is well known that managers optimally exercise the option when the output price P_t reaches the fixed threshold $\bar{P}$ from below. Given that insight, Appendix A shows that the firm's best estimate for the growth option's value, $F(P_t; X_t, C_{t_K})$, is:[8]

$$F(P_t; X_t, C_{t_K}) = \left(V^*(\bar{P}; X_t, C_{t_K}) - I\right) \left(\frac{P_t}{\bar{P}}\right)^{\beta_1}, \tag{10}$$

with $\bar{P}$ being the unique solution to the equation:

$$\frac{\partial V^*(\bar{P}; X_t, C_{t_K})}{\partial \bar{P}} \left(\frac{P_t}{\bar{P}}\right)^{\beta_1} - \beta_1 \frac{\left(V^*(\bar{P}; X_t, C_{t_K}) - I\right)}{\bar{P}} \left(\frac{P_t}{\bar{P}}\right)^{\beta_1} = 0. \tag{11}$$

In agreement with intuition, we can show that the optimal investment threshold $\bar{P}$ rises with investors' log cost estimate $\mathbb{E}_t^S(c_t)$, with the effect stronger the greater the weight assigned to $\mathbb{E}_t^S(c_t)$ in the firm's optimal log cost estimate $\mathbb{E}_t[c_t]$. In words, a lower log cost predicted by investors—as signalled through a higher stock price—induces the firm to invest more quickly, especially when the firm pays a lot of attention to investors' predictions.

In the more realistic case in which managers continuously track investors' log cost estimate, it is unfortunately impossible to derive a quasi-closed-form solution, forcing us to determine the firm's best estimate for the growth option's value numerically. The reason is that, in this case, we have two stochastic variables, P_t and X_t. Also, the growth option's value is then time-dependent since the firm skews its best estimate for c_t more toward $\mathbb{E}_t^S(c_t)$ and away from c_{t_K} the longer ago it last acquired capacity, as we see in subsection (2.3). Notwithstanding, Appendix A shows that, even in that case, managers exercise the option when the output price, P_t, exceeds the threshold $\bar{P}$, with the threshold now varying with t and X_t. Crucially,

[8] Notice X_t is stated in $F(.)$ after the semicolon, in line with us keeping it constant at its time t value.

the threshold now also rises with X_t and thus investors' log cost estimate, with the effect again being stronger the more attention the firm pays to investors' prediction.

2.3 Investment-to-Stock Price Sensitivity

In the prior section, we have seen that a lower investors' estimate for the log cost at which the firm could operate new capacity—as signalled through a higher stock price—induces the firm to invest more rapidly, especially when the firm pays greater attention to investors' estimate. In this section, we investigate in which situations the firm pays greater attention to investors' estimate. More technically, we look into those situations in which the firm assigns a high weight to investors' estimate, $\mathbb{E}_t^S(c_t)$, relative to the log cost of the most recently installed factory, c_{t_K}, in its optimal log cost prediction, $\mathbb{E}_t(c_t)$, raising its investment-to-stock price sensitivity. Proposition 1 summarizes the conclusions from that exercise:

PROPOSITION 1: *Let us denote the weights assigned to the log cost at which the firm operates its most recently installed capacity, c_{t_K}, and to investors' estimate of the log cost at which it could operate new capacity, $\mathbb{E}_t^S(c_t)$, in the firm's best prediction of the log cost at which it could operate new capacity, $\mathbb{E}_t(c_t)$, by $\eta_{c_{t_K}}$ and $\eta_{\mathbb{E}_t^S(c_t)}$, respectively. Let us further denote the time since the firm last acquired a factory by $\tau \equiv t - t_K$. It then holds that:*

1. *If $\tau = 0$, $\eta_{c_{t_K}} = 1$ and $\eta_{\mathbb{E}_t^S(c_t)} = 0$ (i.e., the firm exclusively relies on its own information about the production cost of new capacity when it just acquired a factory).*

2. *$\partial\eta_{c_{t_K}}/\partial\tau < 0$ and $\partial\eta_{\mathbb{E}_t^S(c_t)}/\partial\tau > 0$ (i.e., raising the time since the firm last acquired a factory, the firm progressively relies less on its own and more on investors' information).*

3. *$\lim_{\tau\to\infty} \eta_{c_{t_K}} = 0$ and $\lim_{\tau\to\infty} \eta_{\mathbb{E}_t^S(c_t)} = 1$ (i.e., raising the time since the last acquisition to infinity, the firm exclusively relies on investors' information).*

Proof: See Appendix A.

Intuitively, the proposition suggests that, if managers acquired modern capacity not so long ago, they are able to directly observe how well their firm can exploit the latest advances in technology. In that case, they are in no great need to consult outside sources about those latest advances. In contrast, if managers last acquired modern capacity a long time ago, they are less able to draw inferences from their installed capacity about modern capacity, making them more dependent on outside sources, such as their firm's stock price.

3 Empirical Analysis

In this section, we take the main prediction of our model (contained in Proposition 1) to the data. Doing so requires us to condition a firm's investment-to-stock price sensitivity on the length of time since the firm last invested in production capacity. A key challenge confronting our investigation is that conventional data sources (e.g., Compustat) do not contain information on the dates on which firms invest into particular assets. To overcome this challenge, we empirically investigate how past "capacity overhang," which we argue serves as a valid proxy for the length of time since the firm last acquired new capacity, conditions the corporate investment-to-stock price sensitivity. We first introduce our methodology, variables, and data sources. We next present our main results using alternative investment and Tobin's Q proxies as well as controls for other investment-to-stock price sensitivity determinants. We finally study how capacity overhang conditions the *dis*investment-to-stock price sensitivity.

3.1 Methodology, Variables, and Data Sources

We rely on the following panel regression model in our estimations:

$$\begin{aligned} Y_{i,t} &= \beta_1 Tobin\ Q_{i,t-1} + \beta_2 Overhang_{i,t-1} + \beta_3 (Overhang_{i,t-1} \times Tobin\ Q_{i,t-1}) \\ &\quad + \boldsymbol{\gamma}' \boldsymbol{Controls}_{i,t-1} + \alpha_i + \alpha_{k,t} + \epsilon_{i,t}, \end{aligned} \tag{12}$$

where $Y_{i,t}$ is a proxy for the investments (or disinvestments) of firm i over year t, $Tobin\ Q_{i,t-1}$ is a proxy for its Tobin's Q at the end of year $t-1$, $Overhang_{i,t-1}$ is its capacity overhang at that time, and $\boldsymbol{Controls}_{i,t-1}$ is a vector of control variables at that time. Conversely, β_1 to β_3 are parameters, $\boldsymbol{\gamma}$ is a vector of parameters, α_i is a static firm fixed effect, and $\alpha_{k,t}$ is a dynamic industry-year fixed effect based on three-digit SIC code industries.[9] Notice that while β_1 is the investment-to-stock price sensitivity of zero capacity overhang firms, β_3 reveals how a one-unit increase in capacity overhang changes that sensitivity. In estimating Equation (12) and others, we consistently dual-cluster standard errors by firm and year.

We estimate an alternative specification in order to less parametrically identify the effect of capacity overhang on the investment-to-stock price sensitivity:

$$\begin{aligned} Y_{i,t} &= \beta_1 Tobin\ Q_{i,t-1} + \beta_2 OverhangTercile1_{i,t-1} + \beta_3 OverhangTercile3_{i,t-1} \\ &\quad + (\beta_4 OverhangTercile1_{i,t-1} + \beta_5 OverhangTercile3_{i,t-1}) \times Tobin\ Q_{i,t-1} \\ &\quad + \boldsymbol{\gamma}' \boldsymbol{Controls}_{i,t-1} + \alpha_i + \alpha_{k,t} + \epsilon_{i,t}, \end{aligned} \tag{13}$$

where $OverhangTercile1_{i,t-1}$ and $OverhangTercile3_{i,t-1}$ are indicator variables equal to one if the firm's capacity overhang at the end of year $t-1$ is within the bottom and top tercile, respectively, and else zero, and β_1 to β_5 are parameters. While β_1 now gives the investment-to-stock price sensitivity of average (i.e., tercile 2) capacity overhang firms, β_4 and β_5 now reveal how the sensitivities of low (i.e., tercile 1) and high (i.e., tercile 3) capacity overhang firms differ from the sensitivity of the average firms, respectively.

Investment Measures. Our investment proxies are: (i) capital expenditures scaled by one-year lagged assets; (ii) the sum of capital expenditures and R&D expenses scaled by lagged assets; (iii) the change in assets scaled by lagged assets; (iv) the average of capital expenditures over years t, $t+1$, and $t+2$ scaled by lagged assets; (v) the first investment proxy minus its corresponding three-digit SIC industry mean; (vi) the sum of capital expenditures and acqui-

[9]We examine the robustness of our results to alternative industry classification schemes in Table C.2.

sition expenses scaled by lagged assets; and (vii) the sum of capital expenditures, acquisition expenses, advertising expenses, and R&D expenses scaled by lagged assets. Conversely, our disinvestment proxies are: (i) sales of property, plant, and equipment scaled by lagged assets; and (ii) the first disinvestment proxy minus its corresponding three-digit SIC industry mean.

Tobin's Q. To proxy for Tobin's Q, we use the ratio of the market value of equity plus the difference between the book value of assets and the book value of equity plus deferred taxes to the book value of assets. We alternatively use the "Total Q" proxy of Peters and Taylor (2017), which adds an estimate of the replacement cost of intangible capital obtained from accumulating past investments into R&D and SG&A to the denominator of the former proxy. We also examine the robustness of our results to the use of the "Patent Q" proxy of Woeppel (2021), which incorporates the intangible capital stock of firms' patents using estimates of their economic value based on stock price reactions to patent announcements (see Kogan et al. (2017)).

Capacity Overhang. We follow Aretz and Pope (2018) in using a stochastic frontier model to derive an estimate of capacity overhang. We can write their stochastic frontier model as:

$$\ln(K_{i,t}) = \alpha_k + \boldsymbol{\beta}'\mathbf{X}_{i,t} + \upsilon_{i,t} + u_{i,t}, \tag{14}$$

where $\ln(K_{i,t})$ is firm i's log installed capacity at time t, $\mathbf{X}_{i,t}$ is a vector of optimal capacity determinants, $\upsilon_{i,t} \sim N(0, \sigma_\upsilon^2)$ is the log optimal capacity residual, and $u_{i,t} \sim N^+(\boldsymbol{\gamma}'\mathbf{Z}_{i,t}, \sigma_u^2)$ is the log capacity overhang residual. In turn, $\mathbf{Z}_{i,t}$ is a vector of capacity overhang determinants, and $N(.)$ and $N^+(.)$ denote the cumulative normal distribution and the cumulative normal distribution truncated from below at zero, respectively. Finally, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are both parameter vectors, σ_υ^2 and σ_u^2 are parameters, and α_k is an industry fixed effect. Intuitively, the sum of the first three terms in Equation (14) models a firm's log optimal capacity, while the final term models the upward deviation between its log installed and its log optimal capacity. We offer more details about the estimation of the model, the model variables, and our method to back out an estimate of $u_{i,t}$ from the estimation outcomes in Appendix B.

Aretz and Pope (2018) show that in real options models, capacity overhang is a monotone positive transformation of the difference between the current demand for a firm's output and the demand threshold at which the firm would optimally expand its productive capacity. As a result, it is evident that firms with a persistently high capacity overhang over some recent past period will not have invested into new capacity over that period, leading their managers to have no hands-on experience with the latest production technologies.[10] Using capacity overhang to proxy for the time since the firm last acquired capacity has the advantage that we do not need to directly observe when firms last expanded their capacity, which is impossible to do using standard data sources (e.g., Compustat). The reason is that US accounting rules allow firms to consolidate their spending on a wide range of activities under the label of "capital expenditures." Yet, these activities include not only new capacity investments (which correspond most closely to our model construct) but also investments in updating, maintaining, and repairing existing assets. For this reason, any proxy based upon reported capital expenditures (e.g., the time since a firm reported capital expenditures above a certain threshold level) will not truly reflect the time since a firm last invested in *new* capacity.

We validate the capacity overhang measure by examining a subset of firms for which we can measure the time since last they last invested in new capacity with greater precision. To be more specific, this subset consists of firms that we are able to match to establishment-level data from YTS. The YTS data allow us to observe the year in which a new establishment affiliated to a firm appears, an event which we label as an "establishment opening." Establishment openings serve as a more discrete and direct proxy for a firm's decision to invest in new capacity compared to measures derived from firms' reported capital expenditures, which may include investments in new capacity as well as investments in maintaining or replacing existing assets. Figure 2 plots the average (standardized) capacity overhang for firms sorted by the

[10]More in line with that reasoning, we also condition a firm's investment-to-stock price sensitivity on its minimum capacity overhang over the last three years, arguing that a consistently high capacity overhang over that period implies that the firm will not have invested into new capacity over the period (see Table C.1 in the appendix). Given that the conclusions obtained from that exercise, however, completely align with those obtained from conditioning on capacity overhang at the start of the investment period, we ultimately decide to use the simpler past capacity overhang proxy as the conditioning variable in our main tests.

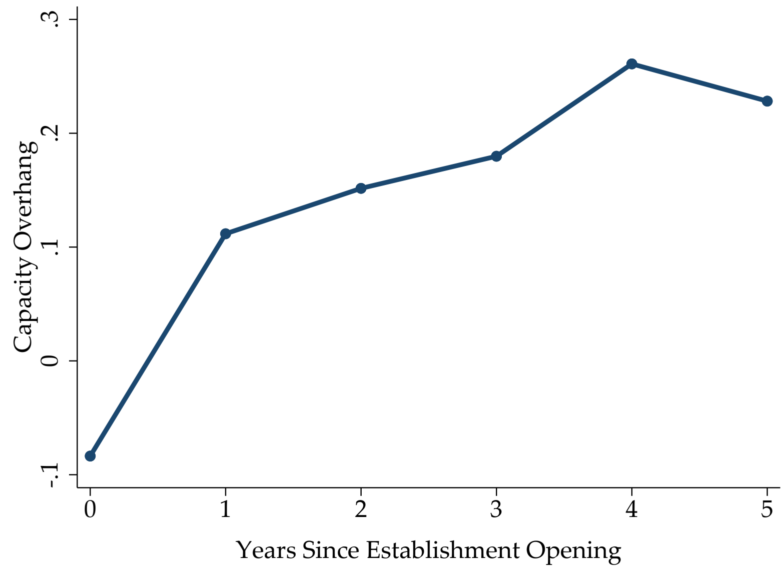


Figure 2. Capacity Overhang and Time Since Last Investment. This figure shows the relationship between the average standardized capacity overhang (y-axis) and years since a firm last opened a new establishment (x-axis). Data on plant openings is obtained for the subset of firms which we are able to match to YTS establishment-level data.

time (in years) since they opened a new establishment that we are able to observe in the YTS data. The figure shows a clear positive correlation between capacity overhang and the time since a firm's last establishment was opened.[11] Firms opening an establishment in the current year display the lowest level of capacity overhang, consistent with the fact that firms' establishment openings optimally only occur when demand is at the investment-triggering demand threshold or, equivalently, capacity overhang is zero. Conversely, a longer time since a firm last opened an establishment (i.e., since the firm last invested in new capacity) translates into a higher capacity overhang, consistent with the demand of those firms persistently being further away from the investment-triggering demand threshold. Figure 2 provides important external validation for the use of the capacity overhang measure in our tests.[12]

[11]As an alternative validation test, we also consider "net establishment openings" to account for the fact that an establishment opening may coincide with other establishments closing, signifying reallocation of productive capacity rather than capacity expansion. Doing so does not affect our conclusions.

[12]We elect to use capacity overhang as our baseline proxy for the time since a firm has last invested as we can estimate capacity overhang for the entire public-firm universe, while we can observe establishment openings only for the subset of firms matched to the YTS data (29% of the public-firm sample). Nevertheless, it is reassuring to note that the two proxies are positively correlated among the set of firms for which they are both available. In unreported tests, we further verify that our baseline results hold in the sample of public firms matched to YTS using "years since establishment opening" in place of "capacity overhang."

Control Variables. Our set of control variables includes a firm's cash flow, defined as the ratio of the sum of net income before extraordinary items, depreciation and amortization expenses, and R&D expenses to one-year lagged assets, and its size (inverse of total assets, as per Chen, Goldstein, and Jiang (2007)). Following Chen, Goldstein, and Jiang (2007), we further include a firm's value-weighted and market-adjusted forward-looking three-year cumulative equity returns. In additional tests, we include other control variables to be introduced below.

Data Sources and Summary Statistics. We obtain stock market and accounting data over the sample period from 1981 to 2019 from CRSP and Compustat, respectively. We obtain information on firm employment and establishments from the Your-Economy Time-Series (YTS) database, maintained by the Business Dynamics Research Consortium at the University of Wisconsin. The YTS database is compiled from Infogroup's historical annual business files, which are linked longitudinally to track location, employment, and sales information at the establishment level. We match the YTS data to our sample of public firms using firm names and ticker symbols. We rely on several supplemental datasets including the data on firms' *Total Q* (see Peters and Taylor (2017)) from WRDS, *Patent Q* from Woeppel (2021), and institutional ownership based on form 13-F data from the Thomson Reuters Institutional Holdings database. We winsorize all variables at the 2.5^{th} and 97.5^{th} percentiles. Table 1 offers descriptive statistics showing our sample is representative of the universe of public firms and similar to those used in prior studies (see, e.g., Chen, Goldstein, and Jiang (2007)).

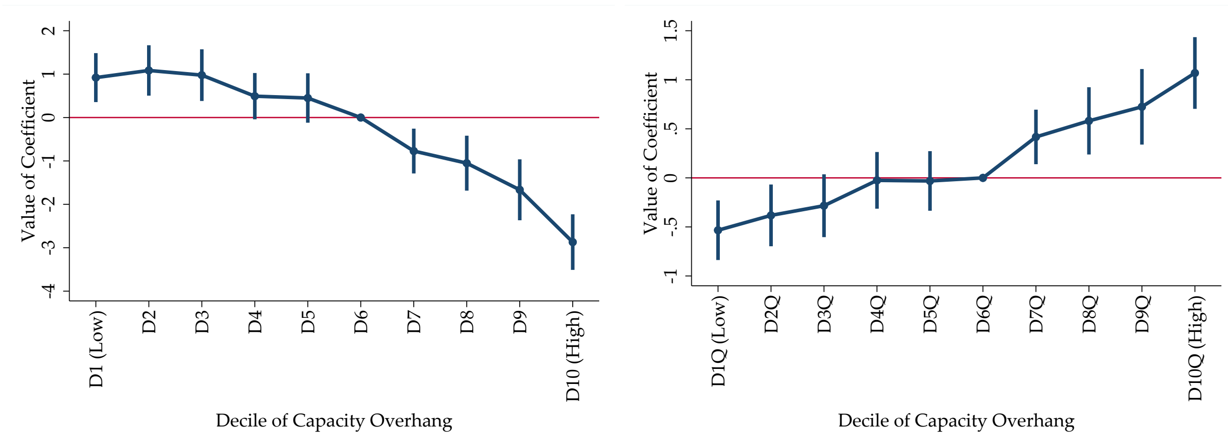
TABLE 1 ABOUT HERE.

3.2 Baseline Results

Table 2 presents the results from estimating the regression in Eq. (12), with columns (1) to (7) using each of our alternative investment proxies as dependent variable. Consistent with prior literature, the table offers strong evidence that managers condition their investments on their firm's stock price. In line with our novel theoretical predictions, it further suggests that the managers of high capacity overhang firms rely more on that price than those of low capacity overhang firms. While the Tobin's Q coeffcient in the CAPEX regression in column (1) is, for example, 0.434 (t-statistic: 3.31) for zero capacity overhang firms, an extra unit of capacity overhang raises that coefficient by 0.450 (t-statistic: 5.06) to 0.884, suggesting a significantly higher investment-to-stock price sensitivity for high capacity overhang firms. The other regressions yield similar results. In fact, the most comprehensive definition of investment (including expenditures on capital, R&D, advertising, and acquisitions; see column (7)) reveals that zero capacity overhang firms (those with relatively recent investment in capacity) have a statistically insignificant investment-to-stock price sensitivity. This sensitivity rises substantially (by 1.937) for firms with a capacity overhang value equal to one. The table also suggests that high capacity overhang firms invest less than low capacity overhang firms, in line with the idea that their start-of-year demand is further below the investment-triggering demand threshold than the demand of low capacity overhang firms.

<u>Table 2 about here.</u>

In our next set of tests in Table 3, we allow for a non-linear relationship between capacity overhang and the investment-to-stock price sensitivity, estimating the regression in Eq. (13) in which we condition the sensitivity on tercile indicator variables derived from *Overhang*, and not on *Overhang* itself. The table suggests that capacity overhang can have a stronger positive effect on the investment-to-stock price sensitivity at higher capacity overhang levels. While bottom tercile capacity overhang firms, for example, produce a 0.267 (t-statistic: –5.68) lower Tobin's Q coefficient in the CAPEX regression in column (1) than middle tercile firms, top tercile firms produce a significantly higher coefficient of 0.126 (t-statistic: 2.17) than those same firms. While the regressions in columns (4), (5), and (6) generate similar results, the effect of capacity overhang is more symmetric in those in columns (2), (3), and (7) in which our investment proxy considers assets other than physical productive capacity. In comparison to the conditioning effect of capacity overhang, the table finally suggests that the direct effect



(A) Direct Overhang Effect

(B) Investment-Q Sensitivity

Figure 3. The Effects of Capacity Overhang on Investment and the Investment-to-Stock Price Sensitivity. This figure plots the coefficients on capacity overhang decile indicator variables (Panel A) and interactions between Tobin's Q and the indicator variables (Panel B) from estimating Eq. (13) using decile (rather than tercile) indicator variables. We use the sum of capital expenditures and R&D expenses scaled by lagged assets as investment proxy and capacity overhang decile 6 as reference group. The dots are the coefficient estimates, whereas the vertical lines are the 95% confidence bounds of the coefficient estimates.

of capacity overhang is more symmetric, with bottom (top) tercile capacity overhang firms investing significantly more (less) than middle tercile firms in all seven columns.

Table 3 about here.

To graphically illustrate the effect of capacity overhang on investment and the investment-to-stock price sensitivity, Figure 3 plots the coefficients on the *Overhang* indicators (Panel A) and the interactions between *TobinQ* and the indicators (Panel B) from a regression similar to Eq. (13) but using decile (and not tercile) *Overhang* indicators. We use the sum of capital expenditures and R&D expenses scaled by lagged assets as investment proxy in that regression and *Overhang* decile 6 as reference group. Panel A confirms that this regression also suggests an almost monotonically negative relation between investment and capacity overhang. More importantly, Panel B confirms that it also suggests a close to monotonically positive relation between the investment-to-stock price sensitivity and capacity overhang. Notably, firms with the highest capacity overhang levels (decile 10) exhibit a disproportionately high investment-to-stock price sensitivity. This figure provides important support for our theoretically-motivated insight that the managers of those firms with the highest capacity overhang (i.e., the longest

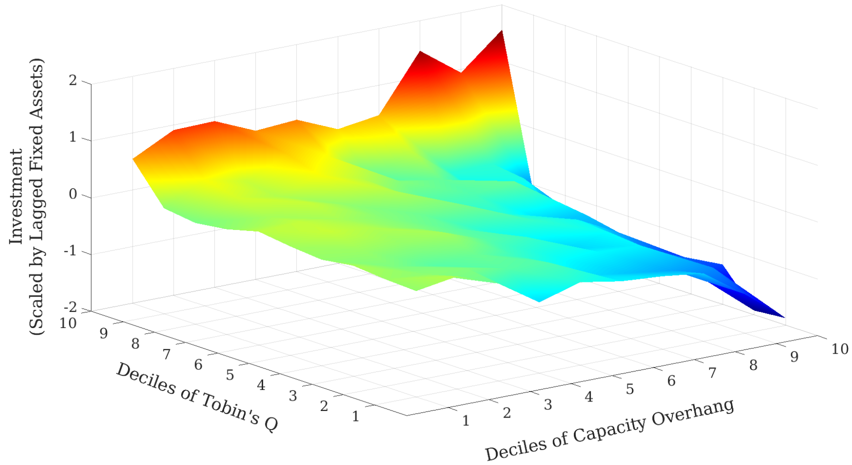


Figure 4. Investment, Tobin's Q, and Capacity Overhang. This figure shows mean investment (on the y-axis) by capacity overhang decile (on the x-axis) and Tobin's Q decile (on the z-axis). We use the sum of capital expenditures and R&D expenses scaled by lagged assets as investment proxy. The colors toward the red (blue) end of the spectrum indicate higher (lower) levels of investment.

duration since they last acquired modern capacity) guide their investment policies based on external signals (e.g., their stock market valuation) the most.

To further explore how investment, Tobin's Q, and capacity overhang are related, Figure 4 plots mean firm investment (on the y-axis) by capacity overhang decile (on the x-axis) and Tobin's Q decile (on the z-axis), where we again use the sum of capital expenditures and R&D expenses scaled by lagged assets as investment proxy. The figure clearly suggests that investment increases with Tobin's Q for each of the capacity overhang deciles. The increase is, however, only mild for the low capacity overhang deciles, while it steepens considerably for the higher deciles. Also interestingly, the figure suggests that the relation between investment and capacity overhang is negative for low and moderate Tobin's Q deciles, but positive for the highest decile. This suggests that the managerial learning effect uncovered by us can be sufficiently large to overturn the sign of the investment-capacity overhang relation.

3.3 Additional Analyses

Since our baseline results could be attributable to measurement error in our Tobin's Q proxy and/or capacity overhang proxying for omitted well-known determinants of the investment-to-stock price sensitivity, we next reestimate Eq. (12) using alternative and plausibly more accurate Tobin's Q proxies and controlling for those determinants. We first use the alternative proxies and then control for the omitted determinants. We also look into an alternative firm investment measure by considering the employment growth-to-stock price sensitivity.

3.3.1 Alternative Tobin's Q Proxies

One concern with our traditional Tobin's Q proxy is that it does not reflect a firm's intangible capital stock in the denominator. If intangible capital stock makes up a large portion of a firm's asset base, this omission would introduce measurement error into our empirical tests, potentially biasing our results. To alleviate these concerns, we next reestimate regression (13) using Peters and Taylor's (2017) $Total\ Q$ and Woeppel's (2021) *Patent* Q instead of the traditional Tobin's Q proxy. $Total\ Q$ improves upon the traditional proxy by estimating the value of a firm's intangible capital stock through capitalizing its R&D and a portion of its SG&A expenses and adding that estimate to the denominator. Similarly, *Patent* Q improves upon the traditional proxy by incorporating the replacement cost of patent capital based on patent market value estimates computed by Kogan et al. (2017). Table 4 reveals that the results from the regressions using the alternative Tobin's Q proxies completely agree with our baseline results. Thus, it is unlikely that measurement error in Tobin's Q drives our conclusions.

TABLE 4 ABOUT HERE.

3.3.2 The Employment-to-Stock Price Sensitivity

We next examine the sensitivity of firms' decisions to invest in human capital (as opposed to physical capital) as a function of stock market valuations and capacity overhang. Given that investments in physical capital generally require additional investments in human capital (e.g., to operate the new physical assets), our model predictions on fixed capital investment naturally extend to firms' decisions to invest in human capital. To empirically test our model predictions on human capital investments, we rely upon establishment-level employment data from YTS and define *Emp Growth* as the annual percentage change in the number of employees at all establishments operated by a single firm. We subsequently reestimate our baseline specification in Eq. (12) using *Emp Growth* as alternative dependent variable.

Table 5 reports the results from that exercise. The coefficient estimates in columns (1) through (3) show evidence that firms' employment-to-stock price sensitivity increases with capacity overhang in case of all our Tobin's Q proxies. The positive and statistically significant interaction coefficients on $Q \times Overhang$ suggest that firms increase their employment in response to higher stock prices when they have not invested in capacity recently (i.e., when their capacity overhang is high). Columns (4) through (6) provide further support for this idea, showing that corporate employment is insensitive to stock prices among low capacity overhang firms (i.e., those in the lowest tercile). These results completely align with our model prediction that managers learn more from stock markets when their firms have not invested in new capacity for a long time. They further corroborate our baseline findings on fixed capital investment in Tables 2 and 3 and provide novel insights into how managerial learning from stock prices affects firms' decisions to invest in physical as well as human capital.

TABLE 5 ABOUT HERE.

3.3.3 Controlling for Private Investor Information

Chen, Goldstein, and Jiang (2007) show that the investment-to-stock price sensitivity rises with the amount of private investor information in stock prices. As there could be more such information in the stock prices of high relative to low capacity overhang firms, it may be that our baseline results simply reflect a private information effect. To mitigate that concern, we reestimate regression (13) controlling for two popular private investor information proxies, namely Durnev, Morck, Yeung, and Zarowin's (2003) stock non-synchronicity and Easley, Kiefer, O'Hara, and Paperman's (1996) probability of informed trading (PIN). While stock non-synchronicity is one minus the R-squared from a regression of the stock's return on the market return and its associated-industry return, PIN is a structural model estimate of the probability of informed trading in the firm's stock. Adding both control variables and their interactions with Tobin's Q to our regressions, Table 6 shows that capacity overhang continues to condition the investment-to-stock price sensitivity as in our baseline tests. The upshot is that the effect of capacity overhang on the investment-to-stock price sensitivity still supports the predictions of our theoretical framework even after accounting for the conditioning effect of private information in stock prices on that sensitivity.

TABLE 6 ABOUT HERE.

3.3.4 Alternative Information Sources: Trade and Professional Associations

Our next analysis addresses the notion that managers may learn about the characteristics of modern production capacity through alternative sources of information apart from their own previously-installed capacity and investors' information reflected in their stock prices. A potential alternative information channel through which managers may obtain such information is an industry trade or professional association.[13] It is reasonable to expect that the presence of active trade and professional associations in a firm's industry will reduce the extent to which managers rely on stock prices to learn about technological advances in that industry. We test this idea using comprehensive information on the presence of trade and professional associations across various industries compiled by the US Department of Labor.[14] We re-estimate our baseline specification in Eq. (12) within subsamples of firms, first conditioning on the existence of a trade and professional association in a firm's industry, and second, conditioning on the existence of a trade and professional association that offers professional certification in its industry. The results are reported in Table 7.

TABLE 7 ABOUT HERE.

[13]Such associations have been shown to aid in the dissemination of information in the context of firms forming and maintaining cartels and anti-competitive agreements (see Levenstein and Suslow (2006, 2011)).

[14]We obtain the data at the level of NAICS 3-digit industry codes from the following URL: <https://www.careeronestop.org/Toolkit/Training/find-professional-associations.aspx>.

Comparing the coefficient estimates in the odd numbered columns with those in the even numbered columns, it is evident that the conditional investment-to-stock-price sensitivity is substantially higher among firms in industries without trade and professional associations. The differences in these conditional sensitivities are statistically significant in two out of three investment proxies considered in both Panels A and B of Table 7. The results imply that managerial learning from stock prices for high capacity overhang firms is muted when alternative mechanisms for information sharing are present in the industry. On the other hand, in the absence of these associations, the learning dynamics predicted by our model are particularly pronounced.

3.3.5 Controlling for Financial Constraints

Baker, Stein, and Wurgler (2003) argue that a firm's investments rise with its stock market valuation since a higher stock price enables financially constrained firms to raise more capital, easing financial constraints and promoting investment. To establish that our baseline results are not entirely driven by the easing of financial constraints, we run two sets of robustness tests. In the first, we reestimate the specification in Eq. (12) controlling for a firm's equity as well as debt issuances. In line with Hovakimian, Opler, and Titman (2001), we define an equity issuance indicator equal to one if net equity issued for cash scaled by assets exceeds 5% and else zero, and a debt issuance indicator equal to one if the annual change in short-term plus long-term debt is positive and else zero. Adding those indicators to our regressions, Table 8 suggests that investment naturally rises with equity and debt issuances. More crucially, however, the table further suggests that adding the indicators does not subsume our baseline results, with the coefficient on the interaction between the low capacity overhang tercile indicator and Tobin's Q remaining negative and highly significant for six out of seven investment proxies. Controlling for states in which firms actually issue debt and equity (which may be concurrently driven by rising stock market valuations), we thus continue to find that capacity overhang positively conditions the investment-to-stock price sensitivity.

Table 8 about here.

In our second set of tests, we rerun the specification in Eq. (12) separately on subsamples classified as constrained and unconstrained according to several well-known ex-ante financial constraints proxies from the literature. In particular, we assign firms to subsamples based on whether their (1) Hadlock and Pierce (2010) size-age index value; (2) Whited and Wu (2006) financial constraints index value; (3) Hoberg and Maksimovic (2015) text-based financial constraints measure value; or (4) total payout level lies above or below the median.[15] We use the payout level as constraints measure since Almeida and Campello (2007) argue that lower-payout firms are more financially constrained than those with higher payouts.

Table 9 reports the results from the subsample regressions. In the first six columns of the table, we report the coefficient estimates for the interaction term $Tobin\ Q \times Overhang$ for those firms classified as constrained or unconstrained according to the financial constraints indexes. Comparing across columns, it is obvious that those coefficient estimates are positive and highly significant for both types of firms. Even more remarkably, it is further obvious that the coefficient estimates are consistently higher in the subsamples of unconstrained rather than the subsamples of constrained firms. The finding that the managers of unconstrained high-capacity-overhang firms respond more to stock market signals than those of equivalent constrained firms is fully consistent with the notion that firms can only respond to stock market signals in their investment decisions when they have access to capital. In other words, the managers of constrained firms are less able to respond even when they pay close attention to the stock market and the stock market sends them a strong signal to invest. The last two columns finally show that our results are similar across high and low payout firms.

Table 9 about here.

The key insight to take away from the tests in this subsection is that our baseline results are unlikely to be entirely due to the concurrent easing of financial constraints, as signalled through

[15]We measure total payouts using the total dividends plus stock repurchases-to-operating income ratio.

equity and/or debt issuances or low financial constraint index values. Controlling for the easing of such constraints, we continue to find that capacity overhang has an almost identical effect on the investment-to-stock price sensitivity as in Tables 2 and 3. These results are also reassuring in that they suggest that our findings are unlikely to be fully explained by the idea that markets anticipate the future exercise of real options for high capacity overhang firms.

3.3.6 Controlling for Institutional Ownership

Our model's prediction that managers learn more from the stock market when their existing capacity is outdated and thus uninformative about the latest production technology advances crucially relies on the idea that investors have more stable information on such advances. That idea is plausible since most investors hold diversified portfolios of firms likely including firms which have already adopted the latest technologies. In that case, it makes sense for investors to incorporate what they know about those technologies into their valuations of firms which may still adopt them later. Critically, the ability of investors to gather information and to incorporate it into stock prices is likely higher for more sophisticated investors, as, for example, institutional investors. The upshot is that the managers of a firm with an outdated capital stock should rely more on the stock market in their investment decisions when sophisticated institutional investors hold a larger percentage of their outstanding share capital.

In Table 10, we test how institutional ownership conditions our main results, augmenting the baseline specification in Eq. (12) by including an institutional ownership proxy and its interactions with $Tobin\ Q$ and $Overhang$. The institutional ownership proxy, $High\ IO$, takes the value of one for firms whose percentage of outstanding shares held by investors filing 13-F forms is above the median and else zero. The table shows that our baseline results continue to hold controlling for institutional ownership, with the coefficient on the $Tobin\ Q$-$Overhang$ interaction term remaining positive and statistically significant for all seven investment proxies. More importantly, the coefficient on the $Tobin\ Q$-$Overhang$-$High\ IO$ interaction term is positive and significant in six out of seven cases, supporting our hypothesis that the managers of high-capacity-overhang firms extract more investment-relevant information from stock markets when there are more institutional investors holding their stock.[16]

TABLE 10 ABOUT HERE.

3.4 The Disinvestment-to-Stock Price Sensitivity

We next study an interesting twist to our main prediction. The twist is that capacity overhang also conditions the disinvestment-to-stock price sensitivity. Assuming that managers have imperfect information about what they receive both when investing and disinvesting, it seems reasonable to conjecture that, in case of disinvestments, the imperfect information is about the liquidation value of their installed assets.[17] If we further assume that managers directly observe liquidation values upon disinvesting and that stock prices reflect investors' estimates of those values, we have the prediction that the managers of firms which have disinvested capacity only recently rely less on their stock prices to guide their disinvestment decisions than those of otherwise equivalent firms which have not disinvested for some time.

Reestimating regressions (12) and (13) using our disinvestment (not investment) proxies as dependent variable, Table 11 strongly supports our prediction. Relying on sales of property, plant, and equipment scaled by lagged assets as disinvestment proxy, column (1), for example, suggests that a one-unit drop in Tobin's Q induces disinvestments to fall by 0.083 (t-statistic: –5.53), implying that high-stock-price firms disinvest less than low-price firms. Crucially, however, column (4) reveals that the disinvestment-to-Tobin's Q sensitivity of bottom capacity overhang tercile firms is 0.068 (t-statistic: 3.09) more positive than that of middle tercile firms, while showing no significant difference in that sensitivity across middle and top tercile firms. In line with our argumentation, the disinvestments of low-capacity-overhang firms (which have

[16]Consistent with Chen, Goldstein, and Jiang (2007), we confirm that the *direct* effect of high institutional ownership on the investment-to-stock price sensitivity is negative, as can be seen from the negative and significant coefficients on the interaction term between $Tobin\ Q$ and $High\ IO$.

[17]In theory, it is also conceivable that managers learn about the value of the option to reacquire the sold-off capacity in the future. In practice, however, the option to reacquire will be so far out-of-the-money on the disinvestment date that the stock price is unlikely to give a strong signal about it.

likely not disinvested capacity for some while) thus respond more positively to their stock prices than those of high-capacity-overhang firms (which have likely disinvested capacity not so long ago). Relying on the alternative regression specification or the industry-adjusted disinvestment proxy, we find consistent results in columns (2), (3), and (5).

Table 11 about here.

Overall, this section suggests a robust positive association between capacity overhang and the investment-to-stock price sensitivity, as predicted by our theoretical work in Section 2. The positive association emerges under a wide variety of investment and Tobin's Q proxies and survives controlling for other well-known determinants of the sensitivity.[18] The section also suggests a negative association between capacity overhang and the disinvestment-to-stock price sensitivity, which can be explained using an extension of our theory.

4 The Role of Technological Progress

Our theoretical analysis posits that unobserved technological progress in modern production capacity is the channel through which capacity overhang influences the investment-to-stock price sensitivity. The reason is that the managers in our model cannot directly observe the cost at which their firm is able to operate modern capacity and must thus infer that cost from the firm's installed capacity and its stock price, with the installed capacity signal, however, becoming increasingly less accurate relative to the stock price signal with the time since the firm last acquired capacity. An implication is that we expect the rate of technological progress in a firm's production capacity to condition the effect of capacity overhang on the investment-to-stock price sensitivity. In the absence of technological progress, the installed capacity signal would, for example, always be a perfect predictor of the cost at which the

[18] In an additional robustness test, we examine the possibility that changes in capacity overhang may coincide with CEO turnover events. In Table C.3, we explicitly control for whether a firm changed its CEO in a given year, and find that our baseline results continue to obtain.

firm could operate modern capacity, inducing managers to entirely rely on that signal—and to entirely ignore the stock price signal—in their investment decisions.

Motivated by these insights, we next investigate how technological progress conditions the relation between capacity overhang and the investment-to-stock price sensitivity documented in Section 3. To do so, we create an indicator variable equal to one if the number of citations for the patents issued to all firms in a firm's three-digit SIC industry over the prior year is above the third tercile and else zero ("*High Tech*"). The idea is that a large number of citations for the patents issued to the firms in an industry indicate that there were a significant number of scientifically important innovations in that industry which, presumably, also led to important innovations in the production capacity used in that industry. We obtain the patent data from Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman.[19] We then estimate the following augmented version of the regression model in Eq. (12):

$$\begin{aligned} Y_{i,t} \;=\;& \beta_1 Tobin\ Q_{i,t-1} + \beta_2 Overhang_{i,t-1} + \beta_3 (Tobin\ Q_{i,t-1} \times Overhang_{i,t-1}) \\ & + \beta_4 (Tobin\ Q_{i,t-1} \times High\ Tech_{i,t-1}) + \beta_5 (Overhang_{i,t-1} \times High\ Tech_{i,t-1}) \\ & + \beta_6 (Tobin\ Q_{i,t-1} \times Overhang_{i,t-1} \times High\ Tech_{i,t-1}) \\ & + \boldsymbol{\gamma}' \boldsymbol{Controls}_{i,t-1} + \alpha_i + \alpha_{k,t} + \epsilon_{i,t}, \end{aligned} \tag{15}$$

where β_1 to β_6 are parameters.[20] While β_3 reveals the effect of capacity overhang on the investment-to-stock price sensitivity for firms in low-technological-progress industries, β_6 shows how that effect differs for those in high-technological-progress industries.

Table 12 shows the results from estimating Eq. (15), with each column focusing on one of our seven investment proxies. Except for the regression relying on the total assets investment proxy, the table strongly supports our prediction that capacity overhang exerts a stronger positive effect on the investment-to-stock price sensitivity for firms in industries with more

[19] The URL address is: <https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data>. See Kogan, Papanikolaou, Seru, and Stoffman (2017) for details.

[20] Note that Eq. (15) does not include $High\ Tech_{i,t-1}$ since its effect is subsumed by the dynamic industry-year fixed effects.

technological progress. The CAPEX regression in column (1), for example, suggests that the effect is an insignificant 0.066 (t-statistic: 0.45) for firms in low-progress industries but rises significantly by 0.380 (t-statistic: 2.81) for those in high-progress industries. Rather remarkably, the table further shows that the effect of capacity overhang is insignificant for firms in low-progress industries in case of four of our seven investment proxies.

Table 12 about here.

While Eq. (15) exploits cross-industry variation in technological progress to condition the effect of capacity overhang on the investment-to-stock price sensitivity, we next also conduct a test exploiting within-industry variation. To do so, we recognize that each industry features technology leaders (i.e., those firms that introduce new technologies first) and followers (i.e., those that introduce the technologies later). While technology leaders quickly learn about the characteristics of modern capacity from their own operations, technology followers are less able to do so, leading them to benefit more from also considering investors' information embedded in their firms' stock prices. The implication is that, for each capacity overhang level, the investments of technology followers are expected to depend more on the stock price than those of leaders. Sorting firms into terciles based on the time since they last filed a patent by three-digit SIC industry and interpreting the top (bottom) tercile firms as technology leaders (followers), we next reestimate Eq. (13) separately by tercile to test that hypothesis. Plotting the estimation results in Figure 5, our evidence clearly supports the idea that technology followers pay more attention to the investment-relevant information included in stock prices than technology leaders at each level of capacity overhang.

Our first two tests conditioning on technological progress in Table 12 and Figure 5 could possibly suffer from endogeneity. To address those concerns, we next repeat our conditioning tests using an instrument for the amount of technological progress to which a firm is exposed developed by Bloom, Schankerman, and van Reenen (2013). The instrument, *Spill*, is the technological-proximity weighted sum taken over the exogenous R&D stocks of firms other than the current in the prior year, where the exogenous R&D stock is the capitalized value of

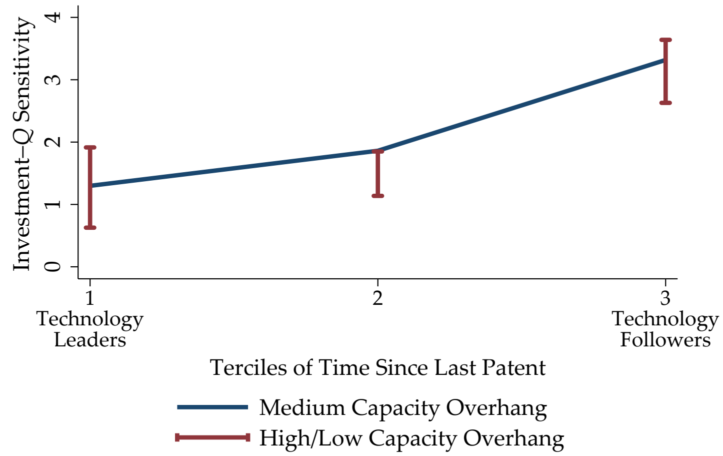


Figure 5. Investment-to-Stock Price Sensitivities Conditional on the Time Since the Last Patent. The figure plots the investment-to-stock price sensitivity at various capacity overhang levels separately by terciles sorted on the time since the firm last filed a patent. We obtain the estimates by reestimating regression (13) separately by tercile. We form the terciles separately within industry.

those portions of R&D expenses explained by state and federal tax credits.[21] As such, *Spill* is likely to be a strong instrument not only because it abstracts from the current firm but also because it only considers the exogenous parts of firms' R&D stocks.

Table 13 gives the results from estimating Eq. (12) separately for firms with high and low *Spill* values (columns (1) to (4)), Eq. (15) with *High Tech* replaced by *High Spill* (columns (5) and (6)), and an augmented version of Eq. (13) interacting Tobin's Q, the capacity overhang tercile indicators, and their interactions with *High Spill* (columns (7) and (8)).[22] We define high (low) *Spill* firms as those with a top (bottom) tercile *Spill* value. In accordance, *High Spill* is an indicator variable equal to one for firms with a *Spill* value in the top tercile and zero for those with a value in the bottom tercile. The instrumented regressions also suggest

[21] To be precise, we can write the instrumented amount of technological progress to which firm i is exposed in year t, $Spill_{it}$, as $\sum_{i \neq j} w_{ij} G_{jt}$, where the weight between firm i and j, w_{ij}, equals $\frac{(T_i T_j')}{(T_i T_i')^{1/2} (T_j T_j')^{1/2}}$ and G_{jt} is the instrumented R&D stock of firm j. In turn, T_i is a $[426 \times 1]$ vector containing the proportions of patents in 426 technology classes issued to firm i over the 1970 to 1999 period. The instrumented R&D stock of firm j in year t is calculated by capitalizing the predicted value of R&D expenses obtained from a regression of the log of those expenses on the logs of state and federal R&D tax credits.

[22] When we reestimate regression (15) with *High Tech* replaced by *High Spill* we need to add *High Spill* as separate exogenous variable since the dynamic industry-year fixed effects do not subsume its effect. We also control for possible product market spillovers (or business stealing effects) from rival firms using the corresponding variable defined by Bloom, Schankerman, and van Reenen (2013).

that the effect of capacity overhang on the investment-to-stock price sensitivity is stronger the more a firm is exposed to technological progress. Using CAPEX plus R&D expenses as investment proxy, column (5), for example, reveals that while the effect is 1.243 (t-statistic: 7.36) for low-*Spill* firms, the same effect is a significant 0.898 (t-statistic: 2.23) higher for high-*Spill* firms. The other regressions yield comparable estimation results.

Table 13 about here.

All in all, our evidence in this section suggests that firms exposed to more technological progress produce a more positive effect of capacity overhang on the investment-to-stock price sensitivity, as predicted by our theoretical work. Importantly, those conclusions emerge both in standard correlation-based as well as in causal-inference-based tests.

5 Concluding Remarks

We argue that, in a world with unobservable technological progress, managers learn investment-relevant information about the operating characteristics of modern capacity both from their installed capacity and investors' opinions about those characteristics embedded in their firm's stock price. Crucially, however, the accuracy of the installed capacity signal deteriorates relative to the accuracy of the stock price signal with the length of time since the firm last acquired capacity, leading the managers of firms which have not invested for a long time to rely more on stock prices. Using Aretz and Pope's (2018) capacity overhang estimate to proxy for the length of time since the firm last acquired capacity, we offer empirical evidence that high capacity overhang firms have a significantly higher investment-to-stock price sensitivity than low capacity overhang firms, supporting our theoretical reasoning. In line with technological progress being the channel through which capacity overhang affects the investment-to-stock price sensitivity, we further show that the effect of capacity overhang is stronger for firms or industries exposed to more technological progress. Our results provide crucial insights into the *nature* of the information that managers learn from stock prices and on how that information affects their real-side decisions. They further suggest that stock markets may play a role in the *diffusion* of innovation by facilitating managerial learning about technological developments across firms.

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Table 1. Summary Statistics

This table reports summary statistics for the main variables used in our empirical analysis. Inv_{CAPEX} is capital expenditures scaled by one-year lagged assets; $Inv_{CAPEX\ \&\ R\&D}$ is capital expenditures plus R&D expenses scaled by lagged assets; $Inv_{\Delta Assets}$ is the change in annual assets divided by lagged assets; Inv_{CAPEX3} is the average of capital expenditures over years t, $t+1$, and $t+2$ scaled by lagged assets; Inv_{IndAdj} is capital expenditures scaled by lagged asset minus the three-digit SIC industry mean at that time; $Inv_{CAPEX\ \&\ Acq}$ is capital expenditures plus acquisitions scaled by lagged assets; and Inv_{All} is capital expenditures plus R&D expenses plus acquisitions plus advertising scaled by lagged asset. $Disinv_{SPPE}$ is sale of property, plant, and equipment scaled by lagged assets, while $Disinv_{IndAdj}$ is sale of property, plant, and equipment scaled by lagged assets minus the three-digit SIC industry mean at that time. $Emp\ Growth$ is the year over year change in the total number of employees of a firm as per the YTS database. $Tobin\ Q$ is the market value of equity plus the book value of assets minus book value of equity plus deferred taxes scaled by the book value of assets. $Cash\ Flow$ is net income before extraordinary items plus depreciation and amortization expenses plus R&D expenses scaled by lagged assets. $Size$ is log total assets. Ret_{3Y} is the value-weighted and market-adjusted forward-looking three-year cumulative equity return. $Overhang$ is an estimate of capacity overhang estimated using a stochastic frontier model, as calculated by Aretz and Pope (2018). $Total\ Q$ is the market value of equity plus the book value of assets minus book value of equity plus deferred taxes scaled by the sum of the book value of assets and an estimate of the intangible capital stock's value, as calculated by Peters and Taylor (2017). $Patent\ Q$ is the market value of equity plus the book value of assets minus book value of equity plus deferred taxes scaled by the sum of the book value of assets and an estimate of the patent stock's value, as calculated by Woeppel (2021). $Async$ is stock price non-synchronicity, while PIN is the probability of informed trading from the market microstructure model of Easley et al. (1996). All variables are winsorized at the 2.5% level. The sample period is 1981 to 2019.

Variable	Mean	SD	Min	Median	Max	N
Inv_{CAPEX}	0.070	0.078	0.002	0.043	0.362	106,925
$Inv_{CAPEX\ \&\ R\&D}$	0.126	0.130	0.005	0.083	0.587	106,925
$Inv_{\Delta Assets}$	0.126	0.348	–0.422	0.056	1.447	106,925
Inv_{CAPEX3}	0.080	0.088	0.004	0.049	0.417	90,107
Inv_{IndAdj}	–0.041	0.125	–0.557	–0.021	0.189	106,925
$Inv_{CAPEX\ \&\ Acq}$	0.101	0.122	0.002	0.057	0.567	106,925
Inv_{All}	0.158	0.164	0.005	0.103	0.749	106,925
$Disinv_{SPPE}$	0.004	0.012	0.000	0.000	0.061	106,925
$Disinv_{IndAdj}$	–0.003	0.012	–0.038	–0.002	0.042	106,925
$Emp\ Growth$	0.074	0.328	–0.433	0.000	1.500	33,892
$Tobin\ Q$	1.910	1.333	0.692	1.439	6.821	107,342
$Cash\ Flow$	0.021	0.198	–0.703	0.070	0.303	106,855
$Size$	5.175	2.140	1.209	5.051	9.746	107,401
Ret_{3Y}	–0.068	0.880	–2.419	0.093	1.479	107,401
$Overhang$	0.600	0.281	0.213	0.527	1.404	107,401
$Total\ Q$	1.091	1.482	–0.348	0.625	6.954	103,228
$Patent\ Q$	2.162	3.810	–0.951	0.888	18.812	104,900
$Async$	0.796	0.251	0.056	0.911	0.999	107,401
PIN	0.207	0.109	0.031	0.191	0.467	87,030

Table 2. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, and controls, with columns (1) to (7) using different investment proxies as dependent variable. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\ \&\ R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\ \&\ Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Tobin\ Q$	0.434***	0.441*	2.675***	0.709***	0.490***	0.817***	0.579
	(0.131)	(0.235)	(0.778)	(0.175)	(0.129)	(0.225)	(0.343)
$Overhang$	–3.341***	–5.887***	–20.043***	–3.285***	–3.258***	–6.470***	–9.546***
	(0.239)	(0.338)	(1.214)	(0.317)	(0.306)	(0.353)	(0.508)
$Tobin\ Q \times Overhang$	0.450***	1.174***	1.949***	0.239**	0.434***	0.975***	1.937***
	(0.089)	(0.161)	(0.536)	(0.108)	(0.107)	(0.136)	(0.225)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,247	92,247	92,247	77,803	92,247	88,687	88,687
R^2	0.652	0.721	0.364	0.714	0.844	0.444	0.546

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 3. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: More Non-Parametric Tests

This table presents the results from regressing investment on Tobin's Q, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, interactions between Tobin's Q and the dummy variables, and controls, with columns (1) to (7) using different investment proxies as dependent variable. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\ \&\ R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\ \&\ Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Tobin\ Q$	0.945***	1.763***	7.368***	0.976***	0.969***	1.605***	2.465***
	(0.060)	(0.000)	(0.000)	(0.076)	(0.061)	(0.000)	(0.000)
$OverhangTercile1$	0.538***	0.719***	3.006***	0.457***	0.577***	1.700***	1.957***
	(0.097)	(0.152)	(0.653)	(0.121)	(0.093)	(0.197)	(0.246)
$OverhangTercile3$	–1.040***	–1.984***	–6.802***	–0.965***	–1.006***	–1.687***	–2.906***
	(0.123)	(0.182)	(0.663)	(0.143)	(0.148)	(0.193)	(0.271)
$Tobin\ Q \times OverhangTercile1$	–0.267***	–0.401***	–1.180***	–0.294***	–0.309***	–0.688***	–0.849***
	(0.047)	(0.079)	(0.340)	(0.062)	(0.044)	(0.092)	(0.125)
$Tobin\ Q \times OverhangTercile3$	0.126**	0.531***	1.452***	0.107	0.069	0.051	0.607***
	(0.058)	(0.098)	(0.362)	(0.064)	(0.060)	(0.090)	(0.137)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,161	92,161	92,161	77,731	92,247	88,687	88,687
R^2	0.657	0.731	0.387	0.731	0.846	0.450	0.558

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 4. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Using Total or Patent Q Instead of Tobin's Q

This table presents the results from regressing investment on either Total Q (Panel A) or Patent Q (Panel B), capacity overhang, an interaction between each Tobin's Q proxy and capacity overhang, and controls, with columns (1) to (7) using different investment proxies as dependent variable. Total Q is defined as per Peters and Taylor (2017) and Patent Q as per Woeppel (2021). The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Total Q							
Total Q	0.257***	0.305***	3.397***	0.345***	0.249***	0.458***	0.529***
	(0.052)	(0.092)	(0.242)	(0.059)	(0.057)	(0.074)	(0.113)
Overhang	–3.059***	–4.440***	–16.822***	–2.723***	–2.926***	–5.368***	–6.783***
	(0.233)	(0.334)	(0.959)	(0.294)	(0.280)	(0.304)	(0.452)
Total Q × *Overhang*	0.648***	0.886***	1.841***	0.420***	0.592***	1.040***	1.226***
	(0.087)	(0.164)	(0.441)	(0.087)	(0.093)	(0.139)	(0.206)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,290	90,290	90,290	77,609	90,290	90,290	90,290
R^2	0.654	0.723	0.380	0.728	0.846	0.453	0.552
Panel B. Patent Q							
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patent Q	0.020	0.041	1.084***	0.043**	0.021	0.013	0.036
	(0.018)	(0.036)	(0.086)	(0.020)	(0.020)	(0.028)	(0.047)
Overhang	–3.125***	–4.603***	–16.972***	–2.910***	–2.973***	–5.583***	–7.160***
	(0.242)	(0.320)	(0.986)	(0.293)	(0.270)	(0.289)	(0.425)
Patent Q × *Overhang*	0.251***	0.430***	0.702***	0.197***	0.228***	0.456***	0.651***
	(0.029)	(0.061)	(0.155)	(0.030)	(0.033)	(0.046)	(0.080)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,158	90,158	90,158	76,033	90,158	90,158	90,158
R^2	0.644	0.721	0.373	0.724	0.846	0.439	0.547

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 5. The Effect of Capacity Overhang on the Employment-to-Stock Price Sensitivity

This table presents the results from regressing employment growth on different combinations of the standard Tobin's Q proxy, Total Q, or Patent Q, capacity overhang, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, an interaction between each Tobin's Q proxy and capacity overhang, interactions between the Tobin's Q proxies and the capacity overhang dummies, and controls. Total Q is defined as per Peters and Taylor (2017) and Patent Q as per Woeppel (2021). The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Emp Growth					
	TobinQ	*TotalQ*	*PatentQ*	*TobinQ*	*TotalQ*	*PatentQ*
	(1)	(2)	(3)	(4)	(5)	(6)
Q	–0.625	–0.256	–0.029***	0.665*	1.012***	0.040
	(0.389)	(0.317)	(0.010)	(0.349)	(0.345)	(0.091)
$Q \times Overhang$	1.454**	1.547**	0.081**			
	(0.583)	(0.587)	(0.034)			
$OverhangTercile1$				1.338*	0.490	–0.032
				(0.710)	(0.531)	(0.555)
$OverhangTercile3$				–0.958	–0.985*	–1.242**
				(0.845)	(0.564)	(0.452)
$Q \times OverhangTercile1$				–0.732**	–0.644**	–0.043
				(0.332)	(0.303)	(0.091)
$Q \times OverhangTercile3$				–0.105	–0.136	–0.013
				(0.361)	(0.352)	(0.088)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,269	27,217	26,594	27,269	27,217	26,594
R^2	0.221	0.222	0.218	0.221	0.221	0.218

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 6. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Controlling for Private Information

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, interactions between Tobin's Q and private investor information proxies, and controls, with columns (1) to (6) using different investment proxies as dependent variable. The controls are size, cash flow, three-year stock returns, and the private investor information proxies. The private investor information proxies are the probability of informed trading (PIN) and stock price non-synchronicity ($Async$). The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment					
	$Inv_{CAPEX\ \&\ R\&D}$		$Inv_{CAPEX\ \&\ Acq}$		Inv_{All}	
	(1)	(2)	(3)	(4)	(5)	(6)
$Tobin\ Q$	0.895***	0.582**	0.655***	0.945***	1.130***	0.874**
	(0.152)	(0.227)	(0.114)	(0.222)	(0.201)	(0.328)
$Overhang$	–5.336***	–5.248***	–6.423***	–6.415***	–9.775***	–9.630***
	(0.373)	(0.371)	(0.427)	(0.415)	(0.639)	(0.630)
$Tobin\ Q \times Overhang$	1.205***	1.164***	0.948***	0.952***	1.889***	1.827***
	(0.162)	(0.169)	(0.156)	(0.154)	(0.221)	(0.227)
$Tobin\ Q \times PIN$	1.914***	1.557***	1.128**	1.613***	2.409***	2.256***
	(0.533)	(0.563)	(0.505)	(0.543)	(0.760)	(0.822)
$Tobin\ Q \times Async$		0.503*		–0.475*		0.396
		(0.290)		(0.276)		(0.411)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,254	74,254	74,254	74,254	74,254	74,254
R^2	0.757	0.757	0.451	0.451	0.567	0.568

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 7. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Role of Trade Associations

This table presents the results from regressing investment on Tobin's Q, capacity overhang and an interaction between Tobin's Q and capacity overhang and controls, while conditioning on the presence of trade and professional associations with columns (1) to (6) using different investment proxies as dependent variables. $TradeAssoc$ ($NoTradeAssoc$) is one (zero) if the firm is in an industry that has a professional association and zero (one) otherwise. $TradeCert$ ($NoTradeCert$) is one (zero) if the firm is in an industry that has a professional association, which offers a formal certification for membership and zero (one) otherwise. The controls are size, cash flow, and three-year stock returns. Panel A presents the results conditioning on the presence of a trade and professional association. Panel B presents the results conditioning on the presence of a trade and professional association, which offers formal certification for membership. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

Panel A. Trade Associations

	Inv_{CAPEX}		$Inv_{CAPEX\ \&\ R\&D}$		Inv_{All}	
Sample:	$TradAssoc$	$NoTradAssoc$	$TradAssoc$	$NoTradAssoc$	$TradAssoc$	$NoTradAssoc$
	(1)	(2)	(3)	(4)	(5)	(6)
$TobinQ$	0.688***	0.129	1.092***	0.241	1.298***	0.914**
	(0.070)	(0.197)	(0.122)	(0.273)	(0.158)	(0.448)
$Capacity\ Overhang$	-2.718***	-4.609***	-4.950***	-6.582***	-8.280***	-10.318***
	(0.247)	(0.696)	(0.349)	(1.029)	(0.498)	(1.444)
$TobinQ \times Capacity\ Overhang$	0.438***	1.226***	1.318***	2.074***	2.066***	2.497***
	(0.088)	(0.234)	(0.163)	(0.490)	(0.232)	(0.616)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,278	8,321	83,278	8,321	83,278	8,321
R^2	0.648	0.716	0.736	0.710	0.568	0.593

Panel B. Trade Associations with Certification

	Inv_{CAPEX}		$Inv_{CAPEX\ \&\ R\&D}$		Inv_{All}	
Sample:	$TradCert$	$NoTradCert$	$TradCert$	$NoTradCert$	$TradCert$	$NoTradCert$
	(1)	(2)	(3)	(4)	(5)	(6)
$TobinQ$	0.661***	0.573***	1.118***	0.659***	1.315***	1.125***
	(0.072)	(0.144)	(0.133)	(0.192)	(0.171)	(0.314)
$Capacity\ Overhang$	-2.587***	-3.937***	-4.764***	-6.151***	-7.953***	-9.900***
	(0.245)	(0.460)	(0.378)	(0.548)	(0.546)	(0.886)
$TobinQ \times Capacity\ Overhang$	0.376***	0.985***	1.254***	1.870***	2.017***	2.362***
	(0.086)	(0.204)	(0.175)	(0.287)	(0.250)	(0.413)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,418	25,850	65,418	25,850	65,418	25,850
R^2	0.650	0.678	0.740	0.698	0.575	0.543

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 8. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Controlling for Equity and Debt Issuances

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, and controls, with columns (1) to (7) using different investment proxies as dependent variable. The controls are size, cash flow, three-year stock returns, a dummy variable equal to one if a firm issued debt (issuance amount exceeding 5% when scaled by assets in the current year) and else zero, and a dummy variable equal to one of a firm issued equity (issuance amount exceeding 5% when scaled by assets in the current year) and else zero. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Tobin\ Q$	0.558***	0.875***	5.119***	0.619***	0.535***	0.643***	1.016***
	(0.064)	(0.111)	(0.306)	(0.079)	(0.074)	(0.087)	(0.147)
$Overhang$	–2.751***	–4.892***	–14.832***	–2.454***	–2.655***	–4.617***	–7.501***
	(0.231)	(0.327)	(1.038)	(0.291)	(0.291)	(0.309)	(0.455)
$Tobin\ Q \times Overhang$	0.393***	1.175***	1.891***	0.281***	0.374***	0.665***	1.632***
	(0.083)	(0.149)	(0.476)	(0.092)	(0.100)	(0.132)	(0.207)
$Equity\ Issuance$	1.551***	3.689***	23.276***	1.907***	1.432***	4.056***	6.667***
	(0.125)	(0.166)	(0.780)	(0.134)	(0.127)	(0.235)	(0.282)
$Debt\ Issuance$	2.727***	3.561***	23.606***	1.665***	2.618***	10.133***	11.416***
	(0.159)	(0.201)	(0.574)	(0.086)	(0.168)	(0.254)	(0.304)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,205	92,205	92,205	79,405	92,205	92,205	92,205
R^2	0.675	0.747	0.480	0.739	0.850	0.547	0.632

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 9. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Role of Financial Constraints

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, and controls, with Panels A through D presenting different investment proxies as dependent variable. The controls are size, cash flow, and three-year stock returns. Each pair of columns depicts results from regressions estimated in a subsample of financially unconstrained (UC) and constrained (FC) firms according to four different financial constraints proxies: (1) the Hadlock and Pierce (2010) size-age index (HP), (2) the Whited and Wu (2006) financial constraints index, (3) the Hoberg and Maksimovic (2015) text-based financial constraints index, and (4) firm payouts. Unconstrained firms are defined as those above the median value on the respective indices, while constrained firms are defined as those below the median, as of the prior year. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	HP		WW		HM		Payout	
	UC	FC	UC	FC	UC	FC	UC	FC
Panel A. $\boldsymbol{Investment_{CAPEX}}$								
Tobin Q	0.151	0.338	0.000	0.352	0.520***	0.833***	–0.150	0.492**
	(0.168)	(0.215)	(0.169)	(0.249)	(0.181)	(0.215)	(0.199)	(0.197)
Overhang	–3.502***	–3.176***	–4.073***	–2.973***	–3.101***	–2.327***	–4.777***	–3.115***
	(0.357)	(0.271)	(0.375)	(0.289)	(0.371)	(0.366)	(0.487)	(0.270)
Tobin Q × *Overhang*	0.914***	0.399***	1.138***	0.331***	0.918***	0.327***	1.472***	0.395***
	(0.189)	(0.092)	(0.206)	(0.106)	(0.165)	(0.107)	(0.269)	(0.101)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,814	42,454	39,540	36,233	19,243	18,407	43,862	44,035
R^2	0.728	0.668	0.759	0.635	0.761	0.778	0.726	0.675
Panel B. $\boldsymbol{Investment_{CAPEX\&R\&D}}$								
	HP		WW		HM		Payout	
	UC	FC	UC	FC	UC	FC	UC	FC
Tobin Q	0.317	0.755*	0.103	0.751	0.531	1.735***	0.156	1.206**
	(0.242)	(0.408)	(0.269)	(0.539)	(0.344)	(0.368)	(0.258)	(0.449)
Overhang	–4.964***	–5.708***	–5.908***	–5.809***	–5.184***	–4.948***	–5.821***	–5.759***
	(0.537)	(0.506)	(0.601)	(0.487)	(0.641)	(0.822)	(0.672)	(0.430)
Tobin Q × *Overhang*	1.471***	1.080***	1.706***	1.063***	1.837***	0.793***	1.454***	1.039***
	(0.342)	(0.172)	(0.417)	(0.205)	(0.336)	(0.238)	(0.438)	(0.171)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,814	42,454	39,540	36,233	19,243	18,407	43,862	44,035
R^2	0.727	0.751	0.757	0.750	0.795	0.821	0.723	0.746

Panel C. $\boldsymbol{Investment_{\Delta Assets}}$

	HP		WW		HM		Payout	
	UC	FC	UC	FC	UC	FC	UC	FC
Tobin Q	1.819**	4.375***	1.171	4.392***	2.845**	7.958***	–0.469	5.839***
	(0.708)	(1.353)	(0.837)	(1.596)	(1.146)	(1.369)	(0.921)	(1.307)
Overhang	–21.579***	–16.096***	–25.929***	–15.643***	–23.597***	–16.843***	–27.511***	–15.791***
	(1.371)	(1.741)	(1.894)	(1.668)	(2.359)	(2.720)	(2.252)	(1.629)
Tobin Q × *Overhang*	3.830***	1.386**	5.008***	1.340*	6.054***	0.547	7.168***	0.645
	(1.095)	(0.591)	(1.283)	(0.720)	(1.586)	(0.724)	(1.570)	(0.634)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,814	42,454	39,540	36,233	19,243	18,407	43,862	44,035
R^2	0.382	0.433	0.409	0.420	0.473	0.472	0.404	0.431

Panel D. $\boldsymbol{Investment_{All}}$

	HP		WW		HM		Payout	
	UC	FC	UC	FC	UC	FC	UC	FC
Tobin Q	0.386	0.841	0.081	0.910	0.671	2.300***	–0.423	1.412**
	(0.358)	(0.526)	(0.479)	(0.647)	(0.496)	(0.533)	(0.456)	(0.590)
Capacity Overhang	–8.959***	–8.484***	–11.634***	–8.301***	–10.696***	–8.592***	–12.166***	–8.060***
	(0.842)	(0.711)	(0.996)	(0.607)	(1.003)	(1.123)	(1.146)	(0.614)
Tobin Q × *Capacity Overhang*	2.337***	1.574***	3.161***	1.463***	2.744***	1.240***	3.412***	1.457***
	(0.493)	(0.234)	(0.652)	(0.252)	(0.495)	(0.275)	(0.725)	(0.221)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,814	42,454	39,540	36,233	19,243	18,407	43,862	44,035
R^2	0.493	0.627	0.527	0.622	0.566	0.691	0.496	0.630

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 10. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Conditioning on Institutional Ownership

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, an interaction between Tobin's Q and a high institutional ownership dummy, an interaction between Tobin's Q, capacity overhang, and the high institutional ownership dummy, and controls. The controls are size, cash flow, three-year stock returns, and the high institutional ownership dummy. The high institutional ownership dummy, $High\ IO$, takes the value of one for firms above the median of institutional ownership (fraction of shares owned by institutional investors) and zero for firms below the median. Columns (1) through (7) use different investment proxies as dependent variables. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\ \&\ R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\ \&\ Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tobin Q	0.209	0.357	2.467**	0.380**	0.287*	0.616**	0.682*
	(0.160)	(0.233)	(0.984)	(0.151)	(0.167)	(0.269)	(0.372)
Overhang	–3.023***	–4.934***	–14.658***	–2.449***	–2.815***	–5.096***	–7.722***
	(0.255)	(0.396)	(1.429)	(0.342)	(0.327)	(0.380)	(0.560)
Tobin Q × *Overhang*	0.427***	1.146***	1.663**	0.269**	0.411***	0.760***	1.643***
	(0.112)	(0.187)	(0.628)	(0.116)	(0.127)	(0.147)	(0.242)
High IO	0.265	0.966**	7.504***	0.408	0.426	2.254***	3.140***
	(0.259)	(0.382)	(1.479)	(0.289)	(0.281)	(0.469)	(0.621)
Tobin Q × *High IO*	–0.079	–0.444**	–2.851***	–0.144	–0.094	–0.523***	–1.016***
	(0.119)	(0.196)	(0.803)	(0.126)	(0.128)	(0.182)	(0.250)
Tobin Q × *Overhang* × *High IO*	0.364**	0.504	3.483***	0.392**	0.381*	1.027***	1.114**
	(0.178)	(0.336)	(1.057)	(0.175)	(0.191)	(0.278)	(0.424)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,119	89,119	89,119	76,879	89,119	89,119	89,119
R^2	0.665	0.740	0.393	0.738	0.849	0.454	0.570

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 11. The Effect of Capacity Overhang on the Disinvestment-to-Stock Price Sensitivity

This table presents the results from regressing disinvestment on various combinations of Tobin's Q, capacity overhang, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, an interaction between Tobin's Q and capacity overhang, interactions between Tobin's Q and the capacity overhang dummies, and controls. While columns (1) to (4) use sales of property, plant, and equipment scaled by lagged assets as disinvestment proxy, column (5) uses that same variable minus its mean calculated over all same-three-digit SIC industry firms at that time. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Disinvestment				
	$Disinv_{SPPE}$				$Disinv_{IndAdj}$
	(1)	(2)	(3)	(4)	(5)
$Tobin\ Q$	–0.083***	–0.076***	–0.033	–0.098***	–0.090***
	(0.015)	(0.015)	(0.028)	(0.021)	(0.021)
$Overhang$			0.375***		
			(0.131)		
$OverhangTercile1$		–0.028		–0.161**	–0.164**
		(0.042)		(0.067)	(0.068)
$OverhangTercile3$		0.120***		0.139**	0.158**
		(0.040)		(0.064)	(0.060)
$Tobin\ Q \times Overhang$			–0.067*		
			(0.037)		
$Tobin\ Q \times OverhangTercile1$				0.068***	0.062**
				(0.022)	(0.023)
$Tobin\ Q \times OverhangTercile3$				–0.017	–0.030
				(0.023)	(0.023)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	89,197	89,197	89,197	89,197	89,197
R^2	0.384	0.384	0.384	0.384	0.546

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 12. Technological Progress, Capacity Overhang, and the Investment-to-Stock Price Sensitivity

This table presents the results from regressing investment on Tobin's Q, capacity overhang, an interaction between Tobin's Q and capacity overhang, an interaction between Tobin's Q and a dummy variable equal to one for firms in industries with the number of patent citations in the top tercile in the prior year and else zero ($High\ Tech$), an interaction between capacity overhang and $High\ Tech$, an interaction between Tobin's Q, capacity overhang, and $High\ Tech$, and controls. Columns (1) to (7) use different investment proxies as dependent variable. The controls are size, cash flow, three-year stock returns, and $High\ Tech$. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\ \&\ R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\ \&\ Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Tobin\ Q$	0.736***	0.304	0.417	0.812***	0.796***	1.306***	0.603*
	(0.148)	(0.215)	(0.741)	(0.160)	(0.136)	(0.267)	(0.344)
$Overhang$	–2.969***	–4.869***	–17.067***	–2.586***	–2.905***	–5.954***	–8.223***
	(0.246)	(0.359)	(1.213)	(0.310)	(0.304)	(0.365)	(0.514)
$Tobin\ Q \times Overhang$	0.066	0.720***	2.317***	-0.073	0.001	0.412*	1.241***
	(0.147)	(0.249)	(0.822)	(0.186)	(0.192)	(0.229)	(0.318)
$Tobin\ Q \times Overhang \times High\ Tech$	0.380***	0.583**	–0.317	0.431**	0.443***	0.522**	0.705**
	(0.135)	(0.243)	(0.800)	(0.171)	(0.162)	(0.209)	(0.293)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,247	92,247	92,247	77,803	92,247	92,247	92,247
R^2	0.638	0.711	0.375	0.712	0.907	0.420	0.527

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table 13. Technological Progress, Capacity Overhang, and the Investment-to-Stock Price Sensitivity: Instrumented Regressions

This table presents the results from regressing investment on various combinations of Tobin's Q, capacity overhang, double and triple interactions between Tobin's Q, capacity overhang, and a dummy variable equal to one if the exogenous R&D stock of other firms in a firm's technology space is in the top tercile and else zero ($HighSpillovers$), and double and triple interactions between Tobin's Q, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, and $HighSpillovers$, and controls. The regressions in columns (1) and (3) ((2) and (4)) are separately run on only those firms for which $HighSpillovers$ is equal to one (zero). While columns (1), (2), (5), and (7) use the sum of CAPEX plus R&D expenses scaled by lagged assets to proxy for investment, columns (3), (4), (6), and (8) use the sum of CAPEX plus R&D expenses plus acquisition expenses scaled by lagged assets. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment							
	Spill	*No Spill*	*Spill*	*No Spill*				
	$Inv_{CAPEX\ \&\ R\&D}$		Inv_{All}		$Inv_{CAPEX\ \&\ R\&D}$	Inv_{All}	$Inv_{CAPEX\ \&\ R\&D}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tobin Q	0.604**	1.048***	0.538*	1.149***	1.001***	1.131***	1.919***	2.442***
	(0.268)	(0.120)	(0.313)	(0.163)	(0.116)	(0.159)	(0.212)	(0.255)
Overhang	−6.322***	−4.944***	−10.063***	−8.081***	−5.065***	−8.237***		
	(0.764)	(0.376)	(0.971)	(0.562)	(0.365)	(0.502)		
Tobin Q × *Overhang*	1.871***	1.214***	2.528***	1.957***	1.243***	1.987***		
	(0.425)	(0.157)	(0.514)	(0.223)	(0.169)	(0.222)		
Tobin Q × *Overhang* × *HighSpillovers*					0.898**	1.033**		
					(0.402)	(0.509)		
Tobin Q × *OverhangTercile1* × *High Spillovers*							0.230	-0.162
							(0.307)	(0.366)
Tobin Q × *OverhangTercile3* × *High Spillovers*							1.055**	1.272**
							(0.435)	(0.534)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,662	63,342	25,662	63,342	91,148	91,148	16,883	16,883
R^2	0.741	0.741	0.533	0.587	0.732	0.560	0.746	0.552

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Appendix A Mathematical Proofs

In this appendix, we derive the closed-form or quasi-closed-form solutions for the real options model introduced in Section 2. We first value the firm's installed capacity, the modern capacity underlying its growth option, and its growth option. We value the growth option assuming that the firm only observes the stock price signal at the current time or that it observes the signal continuously. We next prove Proposition 1, suggesting that the firm's investment-to-stock price sensitivity rises with the length of time since the firm last acquired capacity.

A.1 Firm Valuation

A.1.1 Valuing the Installed Capacity

We can use standard valuation techniques (see, e.g., Dixit and Pindyck (1994)) to show that the value of the installed capacity unit ("factory") indexed by k, $V_k(P_t)$, is equal to:

$$V_k(P_t) = \begin{cases} b_1 P_t^{\beta_1}; & P_t < C_{t_k} \\ b_2 P_t^{\beta_2} + P_t/\delta - C_{t_k}/r; & P_t \geq C_{t_k}, \end{cases} \tag{A.1}$$

where the β_1, β_2, b_1, and b_2 parameters are equal to:

$$\beta_1 = -\frac{(r-\delta-\sigma^2/2)}{\sigma^2} + \frac{1}{\sigma^2}\left[(r-\delta-\sigma^2/2)^2 + 2r\sigma^2\right]^{(1/2)} > 1, \tag{A.2}$$

$$\beta_2 = -\frac{(r-\delta-\sigma^2/2)}{\sigma^2} - \frac{1}{\sigma^2}\left[(r-\delta-\sigma^2/2)^2 + 2r\sigma^2\right]^{(1/2)} < 0, \tag{A.3}$$

$$b_1 = \frac{r-\beta_2(r-\delta)}{r\delta(\beta_1-\beta_2)}(C_{t_k})^{1-\beta_1} > 0, \tag{A.4}$$

$$b_2 = \frac{r-\beta_1(r-\delta)}{r\delta(\beta_1-\beta_2)}(C_{t_k})^{1-\beta_2} > 0. \tag{A.5}$$

A.1.2 Valuing the Modern Capacity Underlying the Growth Option

To value the growth option, we first need to derive the firm's best estimate of the value of the underlying modern capacity, which depends on the output price P_t and on the firm's best estimate of the log cost at which it could operate the most recent modern capacity c_t. In turn, the firm's best estimate of that log cost depends on the log cost at which it operates its most recently installed capacity, c_{t_K}, and the current value of the variable determining investors' best estimate of the log cost at which the firm can operate the most recent modern capacity, X_t. Denote the profit generated by the most recent modern capacity at time $u \geq t$ by $\psi(P_u; C_t)$. Using risk-neutral valuation techniques, we can write the firm's best estimate of the most recent modern capacity's value, $V^*(P_t, X_t; C_{t_K})$, as:

$$V^*(P_t, X_t; C_{t_K}) = \mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u; C_t)du\right]. \tag{A.6}$$

Using the law of total probability, we can rewrite Equation (A.6) as:

$$\begin{aligned} V^*(P_t, X_t; C_{t_K}) &= \mathbb{P}_t^{\mathbb{Q}}(P_t \geq C_t)\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u; C_t)du \middle| P_t \geq C_t\right] \\ &+ \mathbb{P}_t^{\mathbb{Q}}(P_t < C_t)\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u; C_t))du \middle| P_t < C_t\right], \end{aligned} \tag{A.7}$$

where $\mathbb{P}_t^{\mathbb{Q}}(.)$ is a probability under the $\mathbb{Q}$ measure. Given idiosyncratic technological progress and using the law of iterated expectations, we can rewrite Equation (A.7) as:

$$\begin{aligned} V^*(P_t, X_t; C_{t_K}) &= \mathbb{P}_t(P_t \geq C_t)\mathbb{E}_t^{\mathbb{Q}}\left[\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u; C_t))du \middle| C_t\right] \middle| P_t \geq C_t\right] \\ &+ \mathbb{P}_t(P_t < C_t)\mathbb{E}_t^{\mathbb{Q}}\left[\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u; C_t))du \middle| C_t\right] \middle| P_t < C_t\right], \end{aligned} \tag{A.8}$$

where $\mathbb{P}_t(.)$ is a probability under the $\mathbb{P}$ measure.

Conditional on $P_t \geq C_t$ and C_t, the value of modern capacity equals the value of switched-on existing capacity, with C_{t_K}, however, replaced with C_t (see the lower component solution in Equation (A.1)). Conversely, conditional on $P_t < C_t$ and C_t, its value equals the value of switched off existing capacity, with C_{t_k} replaced with C_t (see the upper component solution in the same equation). We can thus write the conditional expectations in Equation (A.8) as:

$$
\begin{aligned}
&\mathbb{E}_t^{\mathbb{Q}}\left[\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u;C_t)du\big|C_t\right]\big|P_t \geq C_t\right] = \mathbb{E}_t^{\mathbb{Q}}\left[b_2 P_t^{\beta_2} + P_t/\delta - C_t/r\big|P_t \geq C_t\right] \\
= \;& \mathbb{E}_t^{\mathbb{Q}}\left[b_2\big|P_t \geq C_t\right] P_t^{\beta_2} + P_t/\delta - \mathbb{E}_t^{\mathbb{Q}}\left[C_t\big|P_t \geq C_t\right]/r, \qquad \text{(A.9)}
\end{aligned}
$$

with $\mathbb{E}_t^{\mathbb{Q}}\left[b_2\big|P_t \geq C_t\right] = \mathbb{E}_t\left[b_2\big|P_t \geq C_t\right]$ and $\mathbb{E}_t^{\mathbb{Q}}\left[C_t\big|P_t \geq C_t\right] = \mathbb{E}_t\left[C_t\big|P_t \geq C_t\right]$ due to the fact that technological progress is idiosyncratic, and:

$$
\mathbb{E}_t^{\mathbb{Q}}\left[\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\psi(P_u;C_t)du\big|C_t\right]\big|P_t < C_t\right] = \mathbb{E}_t^{\mathbb{Q}}\left[b_1 P_t^{\beta_1}\big|P_t < C_t\right] = \mathbb{E}_t^{\mathbb{Q}}\left[b_1\big|P_t < C_t\right] P_t^{\beta_1}, \qquad \text{(A.10)}
$$

with $\mathbb{E}_t^{\mathbb{Q}}\left[b_1\big|P_t < C_t\right] = \mathbb{E}_t\left[b_1\big|P_t < C_t\right]$ due to the same fact as above. Using Equations (A.9) and (A.10), we can write the firm's best estimate of the modern capacity's value as:

$$
\begin{aligned}
V^*(P_t, X_t; C_{t_K}) \;&=\; \mathbb{P}_t(P_t \geq C_t)\left(\mathbb{E}_t\left[b_2\big|P_t \geq C_t\right] P_t^{\beta_2} + P_t/\delta - \mathbb{E}_t\left[C_t\big|P_t \geq C_t\right]/r\right) \\
&+\; \mathbb{P}_t(P_t < C_t)\left(\mathbb{E}_t\left[b_1\big|P_t < C_t\right] P_t^{\beta_1}\right), \qquad \text{(A.11)}
\end{aligned}
$$

We now notice the following relations involving the $\mathbb{P}$ probabilities in Equation (A.11):

$$
\mathbb{P}_t(P_t \geq C_t) = \mathbb{P}_t\left(\frac{c_t - \mathbb{E}_t[c_t]}{\sigma_t(c_t)} \leq \frac{p_t - \mathbb{E}_t[c_t]}{\sigma_t(c_t)}\right) = N\left(\frac{p_t - \mathbb{E}_t[c_t]}{\sigma_t(c_t)}\right), \qquad \text{(A.12)}
$$

where $p_t \equiv \ln(P_t)$ and $N(.)$ is the cumulative standard normal distribution function. The last equality in Equation (A.12) follows since c_t is normal, with conditional expectation $\mathbb{E}_t[c_t]$ and conditional variance $\sigma_t^2(c_t)$. For similar reasons, we also have the relation:

$$
\mathbb{P}_t(P_t < C_t) = N\left(\frac{\mathbb{E}_t[c_t] - p_t}{\sigma_t(c_t)}\right). \qquad \text{(A.13)}
$$

We further notice about the physical expectations in Equation (A.11):[23]

$$
\begin{aligned}
\mathbb{E}_t\left[C_t \middle| P_t \geq C_t\right] &= \mathbb{E}_t\left[e^{c_t} \middle| P_t \geq C_t\right] = e^{\mathbb{E}_t[c_t]+\frac{1}{2}\sigma_t^2(c_t)} \frac{N\left[\frac{p_t-\mathbb{E}_t[c_t]-\sigma_t^2(c_t)}{\sigma_t(c_t)}\right]}{N\left[\frac{p_t-\mathbb{E}_t[c_t]}{\sigma_t(c_t)}\right]} && \text{(A.14)}\\
\mathbb{E}_t\left[b_1 \middle| P_t < C_t\right] &= \mathbb{E}_t\left[e^{\ln\left(\frac{r-\beta_2(r-\delta)}{r\delta(\beta_1-\beta_2)}(C_t)^{1-\beta_1}\right)} \middle| P_t < C_t\right] \\
&= \mathbb{E}_t\left[e^{\ln\left(\frac{r-\beta_2(r-\delta)}{r\delta(\beta_1-\beta_2)}\right)+(1-\beta_1)c_t} \middle| P_t < C_t\right] \\
&= e^{\ln\left(\frac{r-\beta_2(r-\delta)}{r\delta(\beta_1-\beta_2)}\right)+(1-\beta_1)\mathbb{E}_t[c_t]+\frac{1}{2}(1-\beta_1)^2\sigma_t^2(c_t)} \\
&\quad \times \frac{N\left[\frac{\mathbb{E}_t[c_t]+(1-\beta_1)\sigma_t^2(c_t)-p_t}{\sigma_t(c_t)}\right]}{N\left[\frac{\mathbb{E}_t[c_t]-p_t}{\sigma_t(c_t)}\right]}, && \text{(A.15)}\\
\mathbb{E}_t\left[b_2 \middle| P_t \geq C_t\right] &= \mathbb{E}_t\left[e^{\ln\left(\frac{r-\beta_1(r-\delta)}{r\delta(\beta_1-\beta_2)}(C_t)^{1-\beta_2}\right)} \middle| P_t \geq C_t\right] \\
&= \mathbb{E}_t\left[e^{\ln\left(\frac{r-\beta_1(r-\delta)}{r\delta(\beta_1-\beta_2)}\right)+(1-\beta_2)c_t} \middle| P_t \geq C_t\right] \\
&= e^{\ln\left(\frac{r-\beta_1(r-\delta)}{r\delta(\beta_1-\beta_2)}\right)+(1-\beta_2)\mathbb{E}_t[c_t]+\frac{1}{2}(1-\beta_2)^2\sigma_t^2(c_t)} \\
&\quad \times \frac{N\left[\frac{p_t-\mathbb{E}_t[c_t]-(1-\beta_2)\sigma_t^2(c_t)}{\sigma_t(c_t)}\right]}{N\left[\frac{p_t-\mathbb{E}_t[c_t]}{\sigma_t(c_t)}\right]}. && \text{(A.16)}
\end{aligned}
$$

Equations (A.12) to (A.16) show that the firm's best estimate of the modern capacity's value hinges on the conditional expectation and conditional variance of the log of the modern-capacity cost parameter, c_t. Given that c_t, c_{t_K}, and $\mathbb{E}_t^S[c_t] = \alpha_t + \beta_t X_t$ are multivariate normal at each time t, the conditional expectation of the log cost parameter (i.e., the firm's best estimate of the value of that parameter) is equal to:

$$\mathbb{E}_t[c_t] = \mathbf{c}_t'\boldsymbol{\eta}, \tag{A.17}$$

where $\mathbf{c}_t = [1, c_{t_K}, \mathbb{E}_t^S(c_t)]'$, and $\boldsymbol{\eta} = E[\mathbf{c}_t\mathbf{c}_t']^{-1}E[\mathbf{c}_t c_t]$ is a $[3 \times 1]$ vector containing the optimal combination weights. Moreover, its conditional expectation is equal to:

$$\sigma_t^2(c_t) = \sigma^2(c_t) - \boldsymbol{\eta}'\text{var}(\mathbf{c}_t)\boldsymbol{\eta}, \tag{A.18}$$

[23]The closed-form solutions in Equations (A.15) and (A.16) can be obtained by direct evaluations of the integrals defining the conditional expectations stated in those equations.

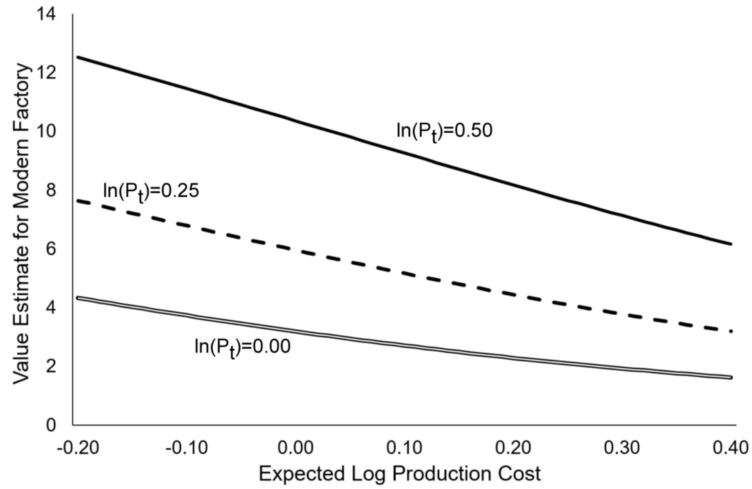

Figure A.1. The Relation Between the Modern Factory's Value Estimate and its Expected Log Production Cost The figure plots the firm's estimate of the modern capacity's value, $V^*(P_t, X_t; C_{t_K})$, against its estimate of the log cost value at which it would be able to operate that capacity, $\mathbb{E}_t[c_t]$, separately for $p_t = 0.00$, 0.25, and 0.50. The values for the other parameters are stated in the text.

where $\sigma^2(c_t)$ is the unconditional variance of c_t, and $\text{var}(\mathbf{c}_t)$ the unconditional $[3 \times 3]$ variance-covariance matrix of the predictor variable vector $\mathbf{c}_t$.

Figure A.1 plots the firm's best estimate of the modern capacity's value, $V^*(P_t, X_t; C_{t_K})$, against its estimate of that capacity's log production cost, $\mathbb{E}_t[c_t]$, for p_t equal to 0.00, 0.25, and 0.50. The figure assumes that $r = 0.04$, $\delta = 0.06$, and $\sigma = \sigma_t(c_t) = 0.20$. In line with intuition, the figure suggests that the firm assigns a lower value to modern capacity when it expects that it has to operate that capacity at a higher production cost.

A.1.3 Valuing the Growth Option

We value the firm's growth option as a binary option allowing the firm to pay the investment outlay I to obtain the underlying modern capacity. Assuming that the firm only consults the stock market at the current time t (i.e., that it only ever observes investors' estimate of the log cost of modern capacity, $\mathbb{E}_t^S(c_t)$, at that time), it is well-known that it is optimal for the firm to exercise the growth option when the output price P_t exceeds the fixed threshold $\bar{P}$. To identify that threshold, denote by $\tau(P_t)$ the random amount of time until the output price reaches the threshold. We can then compute the growth option's value conditional on the current best estimate of c_t, $F(P_t; X_t, C_{t_K})$, using the risk-neutral expectation:

$$\begin{aligned} F(P_t; X_t, C_{t_K}) &= \mathbb{E}_t^{\mathbb{Q}}\left[e^{-r\tau(P_t)}\left(V^*(\bar{P}; X_t, C_{t_K}) - I\right)\right] \\ &= \left(V^*(\bar{P}; X_t, C_{t_K}) - I\right)\left(\frac{P_t}{\bar{P}}\right)^{\beta_1}, \end{aligned} \tag{A.19}$$

where the last equality follows from $\mathbb{E}_t^{\mathbb{Q}}\left[e^{-r\tau(P_t)}\right] = \left(P_t/\bar{P}\right)^{\beta_1}$. The firm chooses $\bar{P}$ so as to maximize the value of the growth option. As a result, $\bar{P}$ solves the equation:

$$\frac{\partial V^*(\bar{P}; X_t, C_{t_K})}{\partial \bar{P}}\left(\frac{P_t}{\bar{P}}\right)^{\beta_1} - \beta_1 \frac{\left(V^*(\bar{P}; X_t, C_{t_K}) - I\right)}{\bar{P}}\left(\frac{P_t}{\bar{P}}\right)^{\beta_1} = 0. \tag{A.20}$$

Since Equation (A.20) cannot be solved for $\bar{P}$ in closed-form, we need to numerically derive the optimal output-price value at which the firm exercises the option.

Under the more realistic assumption that the firm continuously tracks the evolution of investors' best estimate of the log cost at which it could operate modern capacity, $\mathbb{E}_t^S(c_t)$, the valuation of the growth option becomes significantly more challenging. The first reason is that the growth option's value now depends on two stochastic variables, P_t and X_t.[24] The second is that the option's value is now time-dependent since the firm continuously adjusts the weights in its optimal log cost prediction, $\mathbb{E}_t(c_t)$, associated with the log cost at which operates its most recently installed capacity, c_{t_K}, and investors' estimate of the log cost at which it could operate modern capacity, $\mathbb{E}_t^S(c_t)$. We shed more light on how the firm adjusts the weights in the next section. Under these assumptions, the value of the growth option, now denoted by $F(P_t, X_t; C_{t_K})$, needs to fulfill the partial differential equation (PDE):

$$\frac{\partial F}{\partial t} + \frac{1}{2}\sigma^2 P_t^2 \frac{\partial F^2}{\partial^2 P_t} + \frac{1}{2}\psi^2 X^2 \frac{\partial F^2}{\partial^2 X_t} + (r - \delta) P_t \frac{\partial F}{\partial P_t} + \lambda X_t \frac{\partial F}{\partial X_t} - rF = 0, \tag{A.21}$$

which includes no cross-term since $dP_t dX_t = 0$ by assumption.

[24] Notice that c_K does not change until the firm exercises the growth option.

We can use a finite difference method to find the growth option's value under the new assumptions, approximating PDE (A.21) and solving it subject to boundary conditions. In particular, we could assume that $F(P_t, X_t; C_{t_K}) = \max(V^*(P_t, X_t; C_{t_K}) - I, 0)$ at a sufficiently high time t (upper time boundary). Next, we could rely on $\lim_{P_t \to 0} F = 0$ and $\lim_{P_t \to +\infty} F = V^*(P_t, X_t; C_{t_K}) - I$ at the upper and lower output price boundary, respectively. We could use $\lim_{X_t \to 0} F = F(P_t, X_t; 0)$ and $\lim_{X_t \to +\infty} F = 0$ at the upper and lower optimal investors' estimation variable boundaries, respectively.[25] Moving backward from the terminal date, we could then always first find the continuation value and second replace that with the early exercise payoff, $V^*(P_t, X_t; C_{t_K}) - I$, if the payoff exceeded the continuation value.

Valuing the growth option using the above approach, we obtain conclusions in complete agreement with those obtained assuming that the firm only consults the stock market at the current time t. In particular, fixing time t and plotting the areas in which the firm invests and does not invest in P_t-X_t space, we find that the threshold drops more rapidly with X_t the more attention the firm pays to investors' log cost estimate. More intuitively, a higher investors' log cost estimate makes the firm more reluctant to invest into modern capacity especially in those times in which the firm assigns a lot of weight to that estimate.

A.2 Proof of Proposition 1

In the last section, we have established that the firm optimally uses a least-squares regression to combine the log cost at which it operates its most recently installed capacity, c_{t_K}, and investors' estimate of the log cost at which it could operate modern capacity, $\mathbb{E}_t^S[c_t]$, into its own prediction of the log cost at which could operate modern capacity, $\mathbb{E}_t[c_t]$. More technically, we have shown that: $\mathbb{E}_t[c_t] = \mathbf{c}_t'\boldsymbol{\eta}$, where, as we indicated, $\mathbf{c}_t$ is a vector containing one and the two predictors and $\boldsymbol{\eta}$ is a vector containing the optimal combination weights. In this

[25] To understand the $\lim_{X_t \to 0} F = F(P_t, X_t; 0)$ boundary condition, notice that $X_t = 0$ implies that investors are certain that the cost at which the firm could operate modern capacity is consistently zero, leading the firm to consistently set its optimal log cost estimate to zero, too. In that case, $F(P_t, X_t; 0)$ is simply the value of a growth option on modern capacity producing output without costs. We can easily find the value of such a growth option using standard techniques (see again Dixit and Pindyck (1994)).

section, we now study under which circumstances the firm optimally decides to overweight one predictor at the cost of the other. To do so, we first derive closed-form solutions for the optimal combination weights $\boldsymbol{\eta}$. We then study the effect of the length of time since the firm acquired its most recently installed capacity on those closed-form solutions.

A.2.1 The Optimal Combination Weights

Let us denote the optimal weights on the log cost at which the firm operates its most recently installed capacity, c_{t_K}, and on investors' estimate of the log cost at which it could operate modern capacity, $\mathbb{E}_t^S[c_t]$, by $\eta_{c_{t_K}}$ and $\eta_{\mathbb{E}_t^S[c_t]}$, respectively, and collect those weights in the vector $\boldsymbol{\eta}^s = [\eta_{c_{t_K}}, \eta_{\mathbb{E}_t^S[c_t]}]'$. Using the Frisch-Waugh-Lovell theorem, we can show that:

$$\boldsymbol{\eta}^s = \text{var}(\mathbf{c}_t^s)^{-1}\text{cov}(c_t, \mathbf{c}_t^s), \tag{A.22}$$

where $\mathbf{c}_t^s = [c_{t_K}, \mathbb{E}_t^S[c_t]]'$, $\text{var}(\mathbf{c}_t^s)$ is the $[2 \times 2]$ variance-covariance matrix of $\mathbf{c}_t^s$, and $\text{cov}(c_t, \mathbf{c}_t^s)$ the $[2 \times 1]$ covariances vector between c_t and $\mathbf{c}_t^s$. Writing out Equation (A.22), we obtain:

$$\eta_{c_{t_K}} = \frac{\text{var}(\mathbb{E}_t^S(c_t))\text{cov}(c_t, c_{t_K}) - \text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t))\text{cov}(c_t, \mathbb{E}_t^S(c_t))}{\text{var}(c_{t_K})\text{var}(\mathbb{E}_t^S(c_t)) - \text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t))^2}, \tag{A.23}$$

$$\eta_{\mathbb{E}_t^S(c_t)} = \frac{\text{var}(c_{t_K})\text{cov}(c_t, \mathbb{E}_t^S(c_t)) - \text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t))\text{cov}(c_t, c_{t_K})}{\text{var}(c_{t_K})\text{var}(\mathbb{E}_t^S(c_t)) - \text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t))^2}. \tag{A.24}$$

We next denote the date on which the firm last acquired capacity (namely, the Kth factory) by t_K, with $t_K \leq t$. Using that definition, we are able to write c_t as:

$$c_t = c_0 + (\gamma - \frac{1}{2}\xi^2)t + \xi W_t = c_{t_K} + (\gamma - \frac{1}{2}\xi^2)(t - t_K) + \xi(W_t - W_{t_K}). \tag{A.25}$$

Using Equation (A.25) in $\text{cov}(c_t, c_{t_K})$, we obtain:

$$\begin{aligned} \text{cov}(c_t, c_{t_K}) &= \text{cov}(c_{t_K} + (\gamma - \frac{1}{2}\xi^2)(t - t_K) + \xi(W_t - W_{t_K}), c_{t_K}) \\ &= \text{cov}(c_{t_K}, c_{t_K}) = \text{var}(c_{t_K}). \end{aligned} \tag{A.26}$$

We next recall that c_t and X_t are multivariate normal, allowing us to write X_t as a linear combination of c_t and some independent normal variable. Denote the weight on c_t in that linear combination by φ_t, we are able to rewrite $\text{cov}(c_t, \mathbb{E}_t^S(c_t))$ as:

$$\begin{aligned} \text{cov}(c_t, \mathbb{E}_t^S(c_t)) &= \text{cov}(c_t, \alpha_t + \beta_t X_t) = \text{cov}(c_t, \beta_t \varphi_t c_t) \\ &= \beta_t \varphi_t \text{cov}(c_t, c_t) = \beta_t \varphi_t \text{var}(c_t). \end{aligned} \tag{A.27}$$

We are finally able to rewrite $\text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t))$ as:

$$\begin{aligned} \text{cov}(c_{t_K}, \mathbb{E}_t^S(c_t)) &= \text{cov}(c_{t_K}, \alpha_t + \beta_t X_t) = \text{cov}(c_{t_K}, \beta_t \varphi_t c_t) \\ &= \beta_t \varphi_t \text{cov}(c_{t_K}, c_{t_K}) = \beta_t \varphi_t \text{var}(c_{t_K}). \end{aligned} \tag{A.28}$$

Plugging Equations (A.26), (A.27), and (A.28) into $\eta_{c_{t_K}}$ and $\eta_{\mathbb{E}_t^S(c_t)}$ in, respectively, Equations (A.23) and (A.24), we can rewrite those solutions as:

$$\eta_{c_{t_K}} = \frac{\text{var}(\mathbb{E}_t^S(c_t)) - (\beta_t \varphi_t)^2 \text{var}(c_t)}{\text{var}(\mathbb{E}_t^S(c_t)) - (\beta_t \varphi_t)^2 \text{var}(c_{t_K})}, \tag{A.29}$$

$$\eta_{\mathbb{E}_t^S(c_t)} = \frac{\beta_t \varphi_t (\text{var}(c_t) - \text{var}(c_{t_K}))}{\text{var}(\mathbb{E}_t^S(c_t)) - (\beta_t \varphi_t)^2 \text{var}(c_{t_K})}. \tag{A.30}$$

A.2.2 Varying the Time Since the Firm Last Acquired Capacity

In this section, we examine how the length of time since the firm last installed capacity affects the combination weights, $\eta_{c_{t_K}}$ and $\eta_{\mathbb{E}_t^S(c_t)}$, in its optimal forecast of the log cost at which it could operate modern capacity, $\mathbb{E}_t(c_t)$. To that end, we fix the current time t but allow the time at which the firm last installed capacity, t_K, to vary. Doing so, we alter the variance of c_{t_K} and its covariances with both c_t and $\mathbb{E}_t^S(c_t)$ due to the fact that:

$$\text{var}(c_{t_K}) = \text{var}\left(c_0 + (\gamma - \frac{1}{2}\xi^2)t_K + \xi W_{t_K}\right) = \xi^2 t_K, \tag{A.31}$$

but do not alter the variances of c_t and $\mathbb{E}_t^S(c_t)$ or their cross-covariance.

Starting with the case in which the firm just acquired its most recent capacity unit (i.e., the production unit indexed by K), we have $t = t_K$ and $c_t = c_{t_K}$. In turn, Equations (A.29) and (A.30) then show that $\eta_{c_{t_K}} = 1$ and $\eta_{\mathbb{E}_t^S(c_t)} = 0$, leading to the intuitive conclusion that the firm pays no attention to investors' prediction when it can perfectly infer the cost at which it can use modern capacity from its most recently installed capacity.

To establish how $\eta_{c_{t_K}}$ changes as we let t_K fall relative to t and thus raise the time since the firm last acquired capacity, we take the partial derivative of $\eta_{c_{t_K}}$ with respect to t_K:

$$\frac{\partial \eta_{c_{t_K}}}{\partial t_K} = \frac{(\beta_t\varphi_t)^2\xi^2(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_t))}{(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_{t_K}))^2}. \tag{A.32}$$

We now notice that since Equation (A.27) implies that $\mathrm{var}(c_t)$ times $\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_t)$ is equal to $\mathrm{var}(c_t)\mathrm{var}(\mathbb{E}_t^S(c_t)) - \mathrm{cov}(c_t, \mathbb{E}_t^S(c_t))^2$ and as it also holds that:

$$\mathrm{var}(c_t)\mathrm{var}(\mathbb{E}_t^S(c_t)) - \mathrm{cov}(c_t, \mathbb{E}_t^S(c_t))^2 = \mathrm{var}(c_t)\mathrm{var}(\mathbb{E}_t^S(c_t))(1 - \rho^2_{c_t,\mathbb{E}_t^S(c_t)}) \geq 0, \tag{A.33}$$

with $\rho^2_{c_t,\mathbb{E}_t^S(c_t)}$ the squared correlation between c_t and $\mathbb{E}_t^S(c_t)$, the numerator and the denominator on the right-hand side of Equation (A.32) is positive. The upshot is that the partial derivative is positive, implying that a longer time since the firm last acquired capacity leads it to pay less attention to its own information and more to investors' information.

To see how $\eta_{\mathbb{E}_t^S(c_t)}$ changes as we let t_K fall relative to t and thus raise the time since the firm last acquired capacity, we take the partial derivative of $\eta_{\mathbb{E}_t^S(c_t)}$ with respect to t_K:

$$\begin{aligned} \frac{\partial \eta_{\mathbb{E}_t^S(c_t)}}{\partial t_K} &= \frac{-\beta_t\varphi_t(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_{t_K})) + (\beta_t\varphi_t)^3(\mathrm{var}(c_t) - \mathrm{var}(c_{t_K}))}{(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_{t_K}))^2} \\ &= \frac{-\beta_t\varphi_t(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_t))}{(\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_{t_K}))^2}. \end{aligned} \tag{A.34}$$

We now notice that $\mathbb{E}_t^S(c_t) = \alpha_t + \beta_t X_t$ and that X_t can be written as a linear combination of c_t and an independent normal variable. It follows that $\mathrm{var}(\mathbb{E}_t^S(c_t))$ is equal to $(\beta_t\varphi_t)^2\mathrm{var}(c_t)$ plus some positive summand. Thus, $\mathrm{var}(\mathbb{E}_t^S(c_t)) - (\beta_t\varphi_t)^2\mathrm{var}(c_t) > 0$, implying that the sign of the partial derivative is identical to the sign of $-\beta_t\varphi_t$. Under the assumption that X_t correlates positively with c_t, the sign of $-\beta_t\varphi_t$ is negative, rendering the partial derivative in Equation (A.34) negative. The implication is that a longer time since the firm last acquired capacity leads it to pay more attention to investors' log cost information.

We finally confirm that $\eta_{c_{t_K}}$ ($\eta_{\mathbb{E}_t^S(c_t)}$) moves toward zero (one) as we choose a high current time t and then let the time since the firm last acquired capacity go to infinity. To establish $\lim_{t_K\to 0}\eta_{c_{t_K}} = 0$, we notice that a lower t_K does not influence the numerator on the right-hand side of Equation (A.29) but increases the positive denominator, moving $\eta_{c_{t_K}}$ toward zero. To establish $\lim_{t_K\to 0}\eta_{\mathbb{E}_t^S(c_t)} = 1$, we notice that a lower t_K makes the right-hand side of Equation (A.30) move toward $\beta_t\varphi_t \text{var}(c_t)/\text{var}(\mathbb{E}_t^S(c_t))$, which, according to Equation (A.27), is equivalent to $\text{cov}(c_t, \mathbb{E}_t^S(c_t))/\text{var}(\mathbb{E}_t^S(c_t))$. Since $\mathbb{E}_t^S(c_t))$ is an unbiased predictor, we finally have $\text{cov}(c_t, \mathbb{E}_t^S(c_t))/\text{var}(\mathbb{E}_t^S(c_t)) = \text{var}(\mathbb{E}_t^S(c_t))/\text{var}(\mathbb{E}_t^S(c_t)) = 1$.

Appendix B Estimating Capacity Overhang

In this appendix, we offer more details about how we estimate capacity overhang using the stochastic frontier model methodology advocated in Aretz and Pope (2018). To do so, recall that Section (3.1) states that their stochastic frontier model can be written as:

$$\ln(K_{i,t}) = \alpha_k + \boldsymbol{\beta}'\mathbf{X}_{i,t} + \upsilon_{i,t} + u_{i,t}, \tag{B.1}$$

where $\ln(K_{i,t})$ is firm i's log installed capacity at time t, $\mathbf{X}_{i,t}$ is a vector of optimal capacity determinants, $\upsilon_{i,t} \sim N(0, \sigma_\upsilon^2)$ is the log optimal capacity residual, and $u_{i,t} \sim N^+(\boldsymbol{\gamma}'\mathbf{Z}_{i,t}, \sigma_u^2)$ is the log capacity overhang residual. In turn, $\mathbf{Z}_{i,t}$ is a vector of capacity overhang determinants, and $N(.)$ and $N^+(.)$ denote the cumulative normal distribution and the cumulative normal distribution truncated from below at zero, respectively. Finally, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are both parameter vectors, σ_υ^2 and σ_u^2 are parameters, and α_k is an industry fixed effect.

We use maximum likelihood methods to estimate the parameters of stochastic frontier model (B.1) on a recursive basis (see Kumbhakar and Lovell (2000)). The first estimation window stretches from July 1963 to December 1980 (which is directly before the start of our sample period). We roll forward the end dates of the windows on an annual basis, so that the second window stretches from July 1963 to December 1981. Equipped with the estimates from the window ending in December of year $t-1$, we next calculate $\mu^*_{i,t} = \frac{\epsilon_{i,t}\sigma_u^2 + \boldsymbol{\gamma}'\mathbf{Z}_{i,t}\sigma_v^2}{\sigma_u^2+\sigma_v^2}$ and $\sigma^*_{i,t} = \sigma_u\sigma_v/\sqrt{\sigma_u^2+\sigma_v^2}$ for each firm i and each month in year t, where $\epsilon_{i,t} = u_{i,t} + v_{i,t}$. We finally calculate an estimate of the capacity overhang of firm i in month t from:

$$\hat{u}_{i,t} = E[u_{i,t}|\epsilon_{i,t}, \mathbf{Z}_{i,t}] = \mu^*_{i,t} + \sigma^*_{i,t}\left(\frac{n(-\mu^*_{i,t}/\sigma^*_{i,t})}{N(-\mu^*_{i,t}/\sigma^*_{i,t})}\right), \tag{B.2}$$

where $n(.)$ and $N(.)$ are the standard normal density function and the cumulative standard normal distribution function evaluated at their input arguments, respectively.

In line with Aretz and Pope's (2018) main specification, we proxy for the log of installed capacity, $\ln(K_{i,t})$, using the log sum of gross property, plant, and equipment and long-term intangible assets. Conversely, we choose as optimal capacity determinants in $\mathbf{X}_{i,t}$ the log of sales over the prior four fiscal quarters; the log of costs of goods sold over that period; the log of selling, general, and administrative expenses over that period; the log of annualized volatility estimated from daily returns over the prior twelve months; the conditional market beta obtained from a regression of the daily excess stock return on the contemporaneous, the one-day lagged, and the sum of the two, three, and four day lagged excess market return over the prior twelve months, with the market beta estimate being the sum of the three slope coefficient estimates; and the log risk-free rate of return. As capacity overhang determinants in $\mathbf{Z}_{i,t}$, we choose the maximum of the sales decline over the prior four fiscal quarters and zero; the maximum of the sales decline from a stock's historical maximum sales to its sales four fiscal quarters ago and zero; and a dummy variable equal to one if net income is negative over the prior four fiscal quarters and else zero. We finally choose Kenneth French's 49 SIC code industry classification scheme to construct the industry fixed effects, α_k.[26]

To improve the timeliness of the capacity overhang estimate, we follow Aretz and Pope (2018) in using quarterly accounting data whenever possible. To be specific, whenever quarterly data are available, we use the sum of gross property, plant, and equipment and long-term intangibles from the most recent prior fiscal quarter and the trailing sums of costs of goods sold and selling, general, and administrative expenses over the prior four most recent quarters. Whenever those data are not available, we use the sum of gross property, plant, and equipment and long-term intangibles, costs of goods sold, and selling, general, and administrative expenses from the prior most recent fiscal year. In line with standard conventions, we assume that quarterly data are reported with a two-month accounting gap, while annual data are reported with a three-month gap. We obtain the market data required to calculate capacity overhang from CRSP, the accounting data from Compustat, and the market return and risk-free rate of return data from Kenneth's French's website. We winsorize all variables used in stochastic frontier model (B.1) at the first and last percentiles per month.

[26] See <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/> for details.

Appendix C Additional Robustness Tests

Table C.1. The Effect of Capacity Overhang on the Investment-to-Stock Price Sensitivity: Using Minimum Capacity Overhang

This table presents the results from regressing investment on Tobin's Q, minimum capacity overhang, an interaction between Tobin's Q and minimum capacity overhang, and controls, with columns (1) to (7) using different investment proxies as dependent variable. Minimum capacity overhang is defined as the minimum value of the capacity overhang proxy in the past three years. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Investment						
	Inv_{CAPEX}	$Inv_{CAPEX\ \&\ R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\ \&\ Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$TobinQ$	0.726***	1.377***	6.749***	0.785***	0.743***	0.979***	1.746***
	(0.080)	(0.131)	(0.438)	(0.106)	(0.084)	(0.114)	(0.181)
$Overhang_{3YMin}$	–2.806***	–4.601***	–18.468***	–3.143***	–2.427***	–6.147***	–8.798***
	(0.434)	(0.656)	(2.001)	(0.491)	(0.475)	(0.605)	(0.852)
$TobinQ \times Overhang_{3YMin}$	0.464***	1.243***	2.891***	0.448***	0.413***	1.046***	2.091***
	(0.137)	(0.217)	(0.803)	(0.162)	(0.149)	(0.186)	(0.302)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,642	68,642	68,642	59,682	68,642	68,642	68,642
R^2	0.673	0.735	0.357	0.737	0.867	0.442	0.554

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table C.2. Effect of Capacity Overhang on Investment-to-Stock Price Sensitivity: Different Fixed Effect Specifications

This table presents the results from regressing investment on various combinations of Tobin's Q, capacity overhang, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, an interaction between Tobin's Q and capacity overhang, interactions between Tobin's Q and the dummy variables, and controls using different fixed effect specifications. Panel A uses SIC4 industry classification to calculate fixed effects, while Panels B and C use FIC100 industry classification (Hoberg and Phillips (2016)) to the same end. The controls are size, cash flow, and three-year stock returns. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Panel A. Linear Effects With SIC4 Industries						
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tobin Q	0.684***	1.198***	6.397***	0.865***	0.662***	0.862***	1.471***
	(0.071)	(0.123)	(0.355)	(0.090)	(0.082)	(0.095)	(0.156)
Overhang	–3.272***	–5.858***	–20.430***	–3.087***	–3.182***	–6.414***	–9.931***
	(0.240)	(0.346)	(1.265)	(0.291)	(0.306)	(0.348)	(0.512)
Overhang × *Tobin Q*	0.458***	1.227***	2.396***	0.240**	0.447***	0.955***	1.925***
	(0.086)	(0.157)	(0.542)	(0.103)	(0.106)	(0.135)	(0.216)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,150	91,150	91,150	78,241	91,150	91,150	91,150
R^2	0.669	0.733	0.389	0.729	0.848	0.471	0.573

	Panel B. Linear Effects With FIC 100 Industries						
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tobin Q	0.620***	1.181***	6.295***	0.775***	0.463***	0.819***	1.438***
	(0.072)	(0.127)	(0.348)	(0.091)	(0.107)	(0.101)	(0.158)
Overhang	–2.998***	–5.447***	–20.863***	–2.894***	–2.866***	–6.417***	–9.861***
	(0.234)	(0.342)	(1.406)	(0.295)	(0.391)	(0.427)	(0.608)
Overhang × *Tobin Q*	0.499***	1.210***	2.500***	0.322***	0.515***	0.980***	1.950***
	(0.095)	(0.164)	(0.551)	(0.104)	(0.136)	(0.157)	(0.222)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,456	75,456	75,456	65,251	75,456	75,456	75,456
R^2	0.660	0.738	0.347	0.721	0.551	0.422	0.544

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

	Panel C. Tercile Effects With FIC 100 Industries						
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	$Inv_{\Delta Assets}$	Inv_{CAPEX3}	Inv_{IndAdj}	$Inv_{CAPEX\&Acq}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Tobin\ Q$	0.893***	1.758***	7.332***	0.892***	0.725***	1.544***	2.550***
	(0.062)	(0.090)	(0.305)	(0.000)	(0.062)	(0.094)	(0.126)
$OverhangTercile1$	0.468***	0.609***	3.792***	0.451***	0.181	1.892***	2.180***
	(0.109)	(0.159)	(0.628)	(0.119)	(0.173)	(0.209)	(0.276)
$OverhangTercile3$	–0.930***	–1.799***	–6.545***	–0.830***	–1.022***	–1.597***	–2.847***
	(0.131)	(0.180)	(0.690)	(0.153)	(0.206)	(0.200)	(0.280)
$OverhangTercile1 \times Tobin\ Q$	–0.228***	–0.381***	–1.362***	–0.256***	–0.167**	–0.679***	–0.824***
	(0.050)	(0.085)	(0.330)	(0.057)	(0.072)	(0.092)	(0.135)
$OverhangTercile3 \times Tobin\ Q$	0.141**	0.509***	1.468***	0.135*	0.164*	0.054	0.591***
	(0.064)	(0.103)	(0.338)	(0.067)	(0.092)	(0.098)	(0.139)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,372	75,372	75,372	65,182	75,372	75,372	75,456
R^2	0.665	0.748	0.375	0.740	0.553	0.430	0.559

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.

Table C.3. Effect of Capacity Overhang on Investment-to-Stock Price Sensitivity: Controlling for CEO Changes

This table presents the results from regressing investment on various combinations of Tobin's Q, capacity overhang, a dummy variable equal to one if capacity overhang is in the bottom tercile and else zero, a dummy variable equal to one if capacity overhang is in the top tercile and else zero, an interaction between Tobin's Q and capacity overhang, interactions between Tobin's Q and the dummies, an interaction between Tobin's Q and a CEO dummy equal to one in years in which there is a CEO change and else zero, and controls. Columns (1) to (3) (alternatively, (4) to (6)) use different investment proxies as dependent variable. The controls are size, cash flow, three-year stock returns, and the CEO change dummy. The plain numbers are parameter estimates, while those in parentheses are standard errors dual-clustered at both the firm and year level. Note that the table shows only the parameter estimates and t-statistics for the most relevant regressors. All regressions include static firm fixed effects and dynamic industry-year fixed effects derived from three-digit SIC industries. The final rows of the table also show the number of observations and the adjusted R-squared (R^2). The definitions of the regression variables are provided in the caption of Table 1. The sample period is 1981 to 2019.

	Panel A. Linear Effects			**Panel B. Tercile Effects**		
	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	Inv_{All}	Inv_{CAPEX}	$Inv_{CAPEX\&R\&D}$	Inv_{All}
	(1)	(2)	(3)	(4)	(5)	(6)
Tobin Q	0.450***	1.008***	1.411***	0.705***	1.709***	2.479***
	(0.069)	(0.165)	(0.170)	(0.045)	(0.114)	(0.172)
Overhang	–2.289***	–4.871***	–9.423***			
	(0.237)	(0.506)	(0.935)			
Overhang × *Tobin Q*	0.448***	1.190***	1.662***			
	(0.087)	(0.204)	(0.252)			
CEO Change	0.028	0.046	–0.863*	–0.027	–0.158	–1.160**
	(0.137)	(0.287)	(0.440)	(0.126)	(0.269)	(0.450)
CEO Change × *Tobin Q*	–0.046	–0.157	0.084	–0.030	–0.105	0.144
	(0.069)	(0.149)	(0.204)	(0.064)	(0.141)	(0.192)
OverhangTercile1				0.488***	0.817***	2.566***
				(0.117)	(0.188)	(0.313)
OverhangTercile3				–0.591***	–1.354***	–2.427***
				(0.094)	(0.226)	(0.420)
OverhangTercile1 × *Tobin Q*				–0.159***	–0.478***	–0.898***
				(0.039)	(0.092)	(0.154)
OverhangTercile3 × *Tobin Q*				0.114**	0.433***	0.438**
				(0.045)	(0.119)	(0.165)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,990	46,990	46,990	46,990	46,990	46,990
R^2	0.732	0.797	0.591	0.735	0.804	0.603

Statistical significance levels: *** p–value<0.01, ** p–value<0.05, * p–value<0.10.