Corporate Investments and Learning

Nathalie Moyen and Stefan Platikanov

July 2012

Abstract

Using age as a proxy for learning within a firm, we show that the investments of firms with younger projects react more to profit realizations. With time, firms learn about their long-term quality, and their investment decisions become less influenced by the random shocks they receive. We also show that the learning process depends on the volatility of the economic environment. In more volatile industries, firms observe more noise and less signal from profit realizations. Their investments are therefore less influenced by profits. These new empirical results are consistent with a Tobin's q framework augmented with Bayesian learning.

JEL classifications: G31, G32

Keywords: Investment, learning

Moyen is from the Leeds School of Business at the University of Colorado and Platikanov is from the Sawyer Business School at Suffolk University. We thank Sanjai Bhagat, Martin Boileau, Eric Hughson, Chris Leach, Jiaping Qiu, Mike Stutzer, Toni Whited, Jaime Zender, the editor (Holger Mueller), an anonymous referee, as well as presentation participants at Charles River Associates International, the Financial Management Association Meetings, the Northern Finance Association Meetings, the Paris Finance International Meetings, Simon Fraser University, Suffolk University, University of Colorado, the University of Scranton, and the University of Waterloo for helpful comments.

1. Introduction

New businesses account for a significant portion of the economy. In our sample of COMPUSTAT firms, more than a fifth of U.S. businesses each year are either at most three years old or newly restructured by major investments that increased their capital stock by more than 75 percent.¹ From 1988 to 1994, an average of 21.7 percent of U.S. businesses were at most three years old or newly restructured by major investments. In the new economy of the 1995-1999 period, there were on average 29.7 percent such businesses. In the aftermath of the technology “bubble” up to 2007, the average portion of new businesses returned to 21.9 percent, but decreased to 20.5 percent during the financial crisis years 2008-2009.

The empirical literature on corporate investments is focused primarily on established businesses.² Not all results from this literature necessarily apply to young businesses. In contrast to established businesses, young businesses may not fully know about their long-run prospects. Young businesses learn with time, and meanwhile they invest to the best of their knowledge. The learning process of young businesses may produce investments that differ from those of established businesses. There is indeed some evidence that young businesses behave differently. For example, Evans (1987) and Hall (1987) document that young businesses grow faster and are more volatile. Keeping these considerations in mind, we study an environment in which young businesses learn about their long-run profitability and grow their assets. First, we investigate how young firms may invest differently than mature ones in response to similar profit realizations. Second, we investigate whether economic environments with less uncertainty facilitate young firms’ inferences about their long-run prospects as detected in their investment responses. Finally, we recognize that younger firms

¹These statistics are computed from the universe of COMPUSTAT firms for the 1988-2009 period, excluding financials, utilities and public administrations, firms with negative values for total assets, sales, Tobin’s Q , or operating income before depreciation, and firms with gross property, plant, and equipment less than three million.

²For example, Cooper and Haltiwanger (2006) estimate important capital adjustment costs for the sample of large manufacturing plants operating continually between 1972 and 1988. Eberly et al. (2009) find that investment models based on Hayashi (1982) or decreasing returns to scale in production best fit the data based on a balanced COMPUSTAT sample from 1981 to 2003. Fazzari et al. (1988) first documented cash flow effects on investments using a balanced panel of firms from 1969 to 1984.

may often be more financially constrained and investigate how such constraints limit their investments.

Our investigation proceeds in two steps: we first derive testable predictions from a model and then test them in the data. In the first step, we use a dynamic Tobin’s q framework, where firms decide how much to invest each period to maximize the expected discounted sum of future payouts. Our learning framework builds on Jovanovic (1982) which describes firms’ production decisions in a competitive entry and exit setting, and on Alti (2003) which examines a firm’s investment decisions in a frictionless setting. Learning provides interesting firm dynamics in our simple incomplete information environment, where all information is public and anyone can learn by observing profit realizations. Managers neither have an informational advantage (as in Myers and Majluf, 1984), nor learn about the firm prospects from investors’ information embedded in stock prices (as in Dow and Gorton, 1997; and Subrahmanyam and Titman, 1999). In this symmetric information environment, a firm’s current profit is determined by its capital stock and its productivity level. While firms observe their productivity levels, young firms cannot distinguish their long-run quality from the short-run shocks. Similar to Alti (2003), firms learn with time about their long-run quality as they observe profit realizations. Moving beyond Alti (2003), we extend the theoretical framework and investigate the effects of the underlying economic uncertainty and possible financial constraints on learning.

The second step of our investigation yields new empirical results about firm age, industry volatility, and financial constraints. We test our theoretical predictions using firm-level data from 1988 to 2009. One difficulty we encounter empirically is how to disentangle young firms from financially constrained ones. We follow Alti’s (2003) call for “a more general context where young firms are those that have recently discovered major growth opportunities relative to the size of their existing operations.”³ We reset firm age from the time of an important increase in capital stock. Firms that have recently taken on large-scale projects have much learning going on, but they are not associated with any particular level of constraints. They may have established various ties to external markets. These major-growth opportunity firms therefore act as a good instrument for learning, in contrast with newly founded firms that are often saddled with financial constraints.⁴ For this reason, we identify young firms as those that have recently increased their capital

³Page 718.

⁴We thank the referee for suggesting to exclude historically young firms and to focus on firms with recent large increases in capital stock as a way to identify learning separately from financial constraints.

stock by at least 75 percent. Another difficulty we encounter is to account for possible errors in measuring Tobin's q , for which we use the standard Erickson and Whited's (2000) Generalized Method of Moments (GMM) estimation model.

Our first theoretical prediction describes the difference in investment-to-profit responses between young and mature firms. As in Alti (2003), young firms infer their long-run prospects from current profit realizations, and consequently invest more in response to higher profit realizations than older firms do. As firms mature, they learn about their long-run quality and temper their inferences from current profit realizations. With time, their investments become less responsive to profit shocks. Through this learning process, the model endogenously generates more volatility in the investments of younger firms.

The test of the first theoretical prediction generates a new empirical finding relating firm age to investment-to-profit responses. We find that young firms invest more in response to profit realizations than mature firms do. This empirical finding is new to the literature and it is consistent with our theoretical prediction and that of Alti (2003).⁵

Our second theoretical prediction shows that firms' investment response to profits is affected by the volatility of the underlying economic environment. Young firms operating in more volatile industries have a harder time inferring their long-term productivity from all the industry uncertainty. They observe profit realizations that contain more noise and less signal, and therefore attach less weight to the observed profit realizations when deciding how much to invest.

The test of the second theoretical prediction uses Comin and Philippon's (2005) finding that research and development (R&D) activities drive firm volatility. Industries characterized by a higher R&D intensity naturally face more technical uncertainty. Controlling for firm age, we find that firms operating in high-volatility industries have investments that respond less to profits. In contrast, firms operating in low-volatility industries benefit from more precise information, and they invest more in response to profits. This empirical finding is also new to the literature.

⁵We note, however, that our empirical finding is different from that of Oliner and Rudebusch (1992). In a small sample of 120 firms during the period of 1977 to 1983, they find that younger firms have investment-to-profit responses that are similar to those of older firms.

Our third theoretical prediction warns that a firm's financial status can potentially affect its investment response to profits. In the model-simulated data, the response of investment to profits is higher for less financially constrained firms. Because unconstrained firms have an easier access to external markets, they raise extra funds and invest more than constrained firms. Constrained firms behave more cautiously, which translates into a lower response of investment to profits.

The test of the third theoretical prediction qualifies the importance of financial constraints. We follow Erickson and Whited (2000) and measure financial constraints using firm size. As predicted, we find that young firms' investment response to profits in the COMPUSTAT data is lower for those that are more constrained. However, there is no difference in investment responses among mature firms. It is intuitively appealing that support for the financial constraint prediction is associated only with young firms where learning is taking place. More importantly, we find that the first two results are not influenced by financial constraints: when controlling for financial constraints, we verify theoretically and empirically that young firms still invest more in response to profits than mature firms, and firms in low-volatility industries still invest more in response to profits than firms in high-volatility industries.

The above empirical results are robust to different definitions of firm age, industry volatility, and financial constraints, as well as other regression variable definitions. Throughout all robustness checks, the largest response of investment to profits originate from young firms in low-volatility industries.

On the theoretical front, we recognize that other mechanisms than learning have also proven successful in explaining firm dynamics, including persistent technological shocks à la Hopenhayn (1992), or such shocks coupled with financial frictions à la Cooley and Quadrini (2001). Since Cooley and Quadrini (2001), a number of studies have made important strides in explaining firm dynamics by endogenizing various financial frictions. These studies include those by Albuquerque and Hopenhayn (2004), Clementi and Hopenhayn (2006), Cooley et al. (2004), DeMarzo and Fishman (2007), Marcet and Marimon (1992), and Quadrini (2003), among others.

More generally, our paper is related to a growing literature describing how learning affects financial markets other than through firms' investment decisions.⁶ For example, Pástor and Veronesi (2003) show that resolving the uncertainty about a firm's average dividend growth rate decreases the stock price over

⁶See Pástor and Veronesi (2009a) for a literature survey.

time and therefore the market-to-book ratio. Johnson (2007) and Pástor and Veronesi (2009b) argue that new-technology firms, where the uncertainty about future profitability is especially high, are susceptible to large stock price movements and overinvestment. Learning can also explain other behaviors, including predictability in returns, mutual fund flows, managerial turnover, and venture capital funding.⁷

On the empirical side, a few papers perform structural tests of learning models, including those by Linnainmaa (2010), Sorensen (2008), and Taylor (2010). In the literature where managers learn about investors' information imbedded in stock prices, there is abundant empirical evidence linking private information measures to the response of investment to stock prices (for example, see Bakke and Whited, 2010; Chen et al. 2007; and Luo, 2005). Our results linking firm age to the response of investment to profits complement this related learning literature. We know of one previous study testing the link with firm age, albeit with statistically insignificant results. In a small sample of 120 firms during the 1977 to 1983 period, Oliner and Rudebusch (1992) investigate the financing motives of firms, and in the process of their analysis, they also report that the investment-to-profit response of newly public firms is not statistically different from the response of firms that went public long ago. Using a larger sample, our new empirical results robustly indicate that investment-to-profit responses do differ with age.

The paper is organized as follows. The next section presents the model. Section 3 discusses the theoretical predictions. Section 4 describes the empirical data. Section 5 reports the results and all robustness checks. The last section concludes.

2. The Model

The model builds on Tobin's q framework in an environment that is dynamic and stochastic, with an infinite horizon and discrete time periods. To maximize its value, a firm must decide how much to invest I_t every period. Before making its decision, the firm observes the capital stock K_t and the random shock θ_t that give rise to profits $\Pi(K_t; \theta_t)$. The firm also faces capital adjustment costs $\Psi(I_t, K_t)$. The firm's intertemporal

⁷According to Croce et al. (2006), Johnson (2004), Lewellen and Shanken (2002), and Veronesi (1999), learning can generate some predictability in returns. Berk and Green (2004) use a learning model to explain why mutual fund flows are related to past performance, and Dangl et al. (2008) use a similar model to explain why managers are more likely to be fired after bad performance. Hochberg et al. (2008) explain venture capital investments through learning.

problem can be written as

$$V(K_t; \theta_t) = \max_{\{K_{t+1}, I_t, D_t\}} D_t + \frac{1}{1+r} \mathbb{E}_t[V(K_{t+1}; \theta_{t+1})], \quad (1)$$

subject to the sources and uses of funds equation

$$D_t = \Pi(K_t; \theta_t) - I_t - \Psi(I_t, K_t), \quad (2)$$

where r is the deterministic discount rate and D_t denotes the dividend.

The profit function,

$$\Pi(K_t; \theta_t) = \theta_t K_t^\alpha, \quad (3)$$

exhibits decreasing returns to scale in capital $0 < \alpha < 1$.

The standard capital accumulation equation, according to which this period's investment I_t takes one period to build into the capital stock K_{t+1} , is

$$K_{t+1} = (1 - \delta)K_t + I_t, \quad (4)$$

where δ is the depreciation rate. Tobin's marginal q_t is the multiplier on the capital accumulation constraint, i.e., the shadow price of capital.

Following the production-based conditional asset pricing model of Cochrane (1991), we specify the capital adjustment cost function as

$$\Psi(I_t, K_t) = \frac{a}{2} \left(\frac{I_t}{K_t} - \delta \right)^2 K_t, \quad (5)$$

where a is the capital adjustment cost parameter.

We augment the above standard Tobin's q framework with learning. Firms can observe the shock θ_t , which is given by

$$\theta_t = \exp(z_t), \quad (6)$$

where z_t follows a mean-reverting process

$$z_t = (1 - \rho)\tilde{\tau} + \rho z_{t-1} + \sigma \epsilon_t, \quad \epsilon_t \sim iidN(0, 1). \quad (7)$$

For simplicity, a firm's long-run quality $\tilde{\tau}$ is assumed to be high τ^H or low τ^L .⁸ Firms cannot directly observe their quality. At inception, firms assign equal probabilities of being high or low quality. Firms infer current

⁸In reality, there may be a continuum of possible values for a firm's quality, with firms in the lower tail of the distribution

shocks θ_t from profit realizations $\Pi(K_t; \theta_t)$, and they update beliefs about their quality. Under Bayes' rule, the probability that a firm is of high quality given the information at time t is

$$Prob_t \{ \tilde{\tau} = \tau^H \} = b_t = \frac{b_{t-1} \phi \left(\frac{z_t - (1-\rho)\tau^H - \rho z_{t-1}}{\sigma} \right)}{b_{t-1} \phi \left(\frac{z_t - (1-\rho)\tau^H - \rho z_{t-1}}{\sigma} \right) + (1 - b_{t-1}) \phi \left(\frac{z_t - (1-\rho)\tau^L - \rho z_{t-1}}{\sigma} \right)}, \quad (8)$$

where $\phi(\cdot)$ is the standard normal probability density function. The numerator is the product of b_{t-1} , the probability that the firm is of high quality at time $t-1$, and the probability that the current shock z_t is drawn from the high-quality process. The denominator is the probability of observing the current shock z_t from either the low-quality process or the high-quality process.

With learning, the behavior of young firms is more volatile than that of mature firms. For example, beginning-of-the-period Tobin's Q can be expressed as

$$Q_{t-1} = \frac{V_{t-1}}{K_t} = \frac{D_{t-1} + \frac{1}{1+r} E_{t-1} [V(K_t; \theta_t)]}{K_t} \quad (9)$$

or

$$Q_{t-1} = \frac{D_{t-1}}{K_t} + \frac{\frac{1}{1+r} \left\{ b_{t-1} E_{t-1}^H [V(K_t; e^{(1-\rho)\tau^H + \rho z_{t-1} + \sigma \tilde{\epsilon}_t})] + (1 - b_{t-1}) E_{t-1}^L [V(K_t; e^{(1-\rho)\tau^L + \rho z_{t-1} + \sigma \tilde{\epsilon}_t})] \right\}}{K_t}}. \quad (10)$$

A firm starts with equal beliefs of being of a high or low quality. Each period it observes a profit realization and updates its beliefs about its long-run quality. Beliefs become more accurate with each realization, and the uncertainty about the firm's quality decreases over time. In other words, with the gradual flow of information brought by profit realizations, the belief of being of a certain quality converges to its true probability. The younger a firm is, the further away the belief b_{t-1} is from the true probability, which is either zero or one. Equation (10) shows that those beliefs weigh in the numerator of Q_{t-1} . They introduce more volatility into the behavior of young firms.

To describe constrained firms, we add a constraint to the model. In their extreme form, financial constraints can be viewed as restricting access to external financial markets. Payouts must flow from the firm to its claimants ($D_t \geq 0$), ruling out any equity issues from claimants to the firm ($D_t < 0$).

being more likely to exit. For our purpose, we can abstract from entry and exit issues and concentrate on the partial equilibrium setting where both the high type (τ^H) and the low type (τ^L) are assumed to be economically viable.

The Euler equations characterizing the solutions for constrained and unconstrained firms are

$$\begin{aligned} \frac{1}{1+r} \text{E}_t \left[\left(\theta_{t+1} \alpha K_{t+1}^c \alpha^{-1} + (1-\delta) + \frac{a}{2} \left\{ \left(\frac{K_{t+2}^c}{K_{t+1}^c} \right)^2 - 1 \right\} \right) [1 + \lambda_{t+1}] \right] \\ = \left(1 + a \left\{ \frac{K_{t+1}^c}{K_t^c} - 1 \right\} \right) (1 + \lambda_t) \end{aligned} \quad (11)$$

and

$$\frac{1}{1+r} \text{E}_t \left[\theta_{t+1} \alpha K_{t+1}^u \alpha^{-1} + (1-\delta) + \frac{a}{2} \left\{ \left(\frac{K_{t+2}^u}{K_{t+1}^u} \right)^2 - 1 \right\} \right] = 1 + a \left\{ \frac{K_{t+1}^u}{K_t^u} - 1 \right\}, \quad (12)$$

where λ is the financial constraint multiplier, and the superscripts c and u identify constrained and unconstrained firms.

The constrained and unconstrained models cannot be solved analytically, but the solutions are obtained using the numerical method outlined in Coleman (1990) and described in the appendix. We calibrate the models following Gomes (2001). We set the intertemporal discount factor at $r = 0.065$, reflecting the average real interest rate during the last century. The capital depreciation rate is set to $\delta = 0.12$, and the capital share is calibrated to $\alpha = 0.3$. We set the adjustment cost parameter to $a = 0.5$, which approximates the value of 0.455 estimated by Cooper and Haltiwanger (2006). The persistence of the stochastic shock process is set to $\rho = 0.62$. For the volatility, we are interested in considering two environments: $\sigma = 0.12$ for low-volatility and $\sigma = 0.35$ for high-volatility. For the two types of long-run quality, we use $\tau^H = 0.25$ and $\tau^L = -0.25$.

Each of the two models (for constrained and unconstrained firms) is solved under the two alternative calibrations (low-volatility $\sigma = 0.12$ and high-volatility $\sigma = 0.35$). We simulate series for key variables, including the productivity shock θ , capital stock K , investment I , profits Π , firm value V , and Tobin's average $Q = V/K$. Under each calibration and model, we simulate 2,000 series for 500 periods. From the first 1,000 simulated series, we keep the first five periods and designate this sample as belonging to young firms. From the other 1,000 simulated series, we keep the last five periods and designate this sample as belonging to mature firms. The sample therefore consists of different subsets of firms, based on all combinations of firm age, industry volatility, and financial status.

3. Theoretical Predictions

Using the simulated panel of firms, we investigate predictions generated from the models. We focus on investment-to-profit responses for various subsets of firms differing with respect to firm age, industry

volatility, and financial status. We estimate the investment-to-profit responses as the coefficients on profit terms included in the row vector $\mathbf{z}_{it}$ in the standard investment regression specification suggested in Fazzari et al. (1988):

$$\frac{I_{it}}{K_{it}} = \mathbf{z}_{it}\boldsymbol{\alpha} + \beta Q_{it-1} + \text{error}_{it}. \quad (13)$$

The row vector $\mathbf{z}_{it}$ contains a constant, dummy variables, and profit terms $\Pi(K_t, \theta_t)/K_t$ interacted with the different dummy variables identifying different subsets of firms. More specifically, we define the following dummy variables:

$$\begin{aligned} d_{1it} &= \begin{cases} 1, & \text{if firm } i \text{ is young in year } t \\ 0, & \text{otherwise} \end{cases} \\ d_{2it} &= \begin{cases} 1, & \text{if firm } i \text{ is in a low-volatility industry in year } t \\ 0, & \text{otherwise} \end{cases} \\ d_{3it} &= \begin{cases} 1, & \text{if firm } i \text{ is financially unconstrained in year } t \\ 0, & \text{otherwise} \end{cases} \\ d_{4it} &= \begin{cases} 1, & \text{if firm } i \text{ has a negative income in year } t \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

The first three dummy variables identify firm-year observations at the center of our theoretical predictions. The fourth dummy variable recognizes the empirical literature documenting a distinct investment behavior for firms with negative income (see Allayannis and Mozumdar, 2004; Bhagat et al. 2005; and Cleary et al. 2004). The fourth dummy variable plays a role in the data only, as there is no firm with negative income generated from the model.

We estimate one specification that pools all observations into one sample, and we use dummy variables to group firm-year observations. We do not estimate separate investment regressions. Erickson and Whited (2000) attempt to estimate separate regressions for each of their two subsets of financially constrained and unconstrained firms, but they report that the model is not identified for the subset of unconstrained firms and only partially identified for the subset of constrained firms. We experience similar identification problems with the separate estimation on the different COMPUSTAT subsets.⁹

⁹After splitting the sample across all dimensions (with respect to firm age, industry volatility, financial constraints, and negative income) and testing the identification of the model in each of these subsets, we find that the model is not well

The full specification simultaneously testing all three model predictions on firm age, industry volatility, and financial constraint is written as

$$\begin{aligned}
\frac{I_{it}}{K_{it}} = & \alpha_1 \frac{\Pi_{it}}{K_{it}} d_{1it} d_{2it} d_{3it} (1 - d_{4it}) + \alpha_2 \frac{\Pi_{it}}{K_{it}} d_{1it} d_{2it} (1 - d_{3it}) (1 - d_{4it}) \\
& + \alpha_3 \frac{\Pi_{it}}{K_{it}} d_{1it} (1 - d_{2it}) d_{3it} (1 - d_{4it}) + \alpha_4 \frac{\Pi_{it}}{K_{it}} d_{1it} (1 - d_{2it}) (1 - d_{3it}) (1 - d_{4it}) \\
& + \alpha_5 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) d_{2it} d_{3it} (1 - d_{4it}) + \alpha_6 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) d_{2it} (1 - d_{3it}) (1 - d_{4it}) \\
& + \alpha_7 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) (1 - d_{2it}) d_{3it} (1 - d_{4it}) + \alpha_8 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) (1 - d_{2it}) (1 - d_{3it}) (1 - d_{4it}) \\
& + \alpha_9 \frac{\Pi_{it}}{K_{it}} d_{4it} + \beta Q_{it-1} + \gamma_1 d_{1it} + \gamma_2 d_{2it} + \gamma_3 d_{3it} + \gamma_4 d_{4it} + \gamma_0 + \text{error}_{it}.
\end{aligned} \tag{14}$$

As is standard, the dummy variables are applied to profit terms to form (nine) mutually exclusive investment-to-profit responses. The four dummy variables also appear on their own to capture the four effects on the level of investment. We test whether young firms have investment-to-profit responses that are larger than those of mature firms by verifying that $\alpha_1 > \alpha_5$, $\alpha_2 > \alpha_6$, $\alpha_3 > \alpha_7$, and $\alpha_4 > \alpha_8$. Similarly, we test whether firms in low-volatility industries have larger responses than those of firms in high-volatility industries by verifying that $\alpha_1 > \alpha_3$, $\alpha_2 > \alpha_4$, $\alpha_5 > \alpha_7$, and $\alpha_6 > \alpha_8$. Finally, we test whether financially unconstrained firms have larger responses than those of constrained firms by verifying that $\alpha_1 > \alpha_2$, $\alpha_3 > \alpha_4$, $\alpha_5 > \alpha_6$, and $\alpha_7 > \alpha_8$.

In the regression specification, investment I_t/K_t and profits Π_t/K_t are realized within the same period, while Tobin's Q_{t-1} is measured at the beginning of the period. Including the current Tobin's $Q_t = V_t/K_{t+1}$ would introduce an endogeneity problem, as the firm value V_t takes into account the firm's investment I_t decision. Because of the lag, Tobin's Q_{t-1} does not capture the most current information, so that current profits Π_t/K_t become a significant explanatory variable for investment.

Table I presents results from a regression specification with profit realizations grouped by firm age only. More specifically, the explanatory variables include two profit terms interacted with dummies identifying young and mature firms, Tobin's Q , a dummy for young firms, and a constant, so that Equation (14) reduces identified in most subsets. In addition, after the sample is split along the four dimensions, the sample size of each separate subset becomes relatively small, especially for subsets of young firms. In addition, Erickson and Whited (2000) report results from a Monte Carlo study of the power of the identification test that indicates low power at small sample sizes.

to

$$\frac{I_{it}}{K_{it}} = \alpha_1 \frac{\Pi_{it}}{K_{it}} d_{1it} + \alpha_2 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) + \beta Q_{it-1} + \gamma_1 d_{1it} + \gamma_0 + \text{error}_{it}. \quad (15)$$

There is no identification difficulty between firm age (t) and the presence of a constraint ($D_t \geq 0$) in the simulated series, and we therefore identify learning simply by firm age. Table I shows that the profit coefficient for young firms is larger (0.224) than the coefficient for mature firms (0.144), indicating that young firms react more to profit realizations than mature firms. The panel-corrected standard errors reported in parentheses indicate that the two investment-to-profit responses are statistically different from zero. The difference in responses between young and mature firms is also statistically significant.

Table II presents results from a specification with profit realizations grouped by age and industry volatility. Explanatory variables include four profit terms interacted with dummies identifying the four subsets of firms based on firm age and industry volatility, Tobin's average Q , two dummies identifying young firms and low-volatility industries, and a constant, so that Equation (14) reduces to

$$\begin{aligned} \frac{I_{it}}{K_{it}} = & \alpha_1 \frac{\Pi_{it}}{K_{it}} d_{1it} d_{2it} + \alpha_2 \frac{\Pi_{it}}{K_{it}} d_{1it} (1 - d_{2it}) + \alpha_3 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) d_{2it} + \alpha_4 \frac{\Pi_{it}}{K_{it}} (1 - d_{1it}) (1 - d_{2it}) \\ & + \beta Q_{it-1} + \gamma_1 d_{1it} + \gamma_2 d_{2it} + \gamma_0 + \text{error}_{it}. \end{aligned} \quad (16)$$

Controlling for age, we find in Table II that firms operating in low-volatility industries invest more in response to profit realizations than firms operating in high-volatility industries. The coefficients for low-volatility versus high-volatility industries are $0.429 > 0.268$ for young firms, and $0.361 > 0.189$ for mature firms. Compared to a low-volatility environment, the high-volatility calibration increases the variance of all simulated series. Not surprisingly, the variance of profits $\Pi(K_t; \theta_t)/K_t$ increases the most, as the volatility affects the productivity θ_t directly. Firms of a similar age operating in a more volatile environment observe profit realizations containing more noise and less signal. They have a harder time distinguishing whether larger profit realizations are due to being of a high quality τ^H or to receiving larger shocks $\sigma \epsilon_t$. These firms therefore attach a lower weight to profits in determining their investments. As a consequence, the investment-to-profit response is smaller for firms operating in more volatile environments.

Controlling for volatility, Table II also shows that young firms still have profit responses that are larger than those of mature firms. The responses for young versus mature firms are $0.429 > 0.361$ in low-volatility industries, and $0.268 > 0.189$ in high-volatility industries.

Table III presents results from the full specification of Equation (14) with profit realizations grouped by age, industry volatility, and financial status. Explanatory variables include a constant; Tobin's Q ; three dummies identifying young firms, low-volatility industries, and unconstrained firms; and eight profit terms interacted with dummies identifying all subsets of firms based on firm age, industry volatility, and financial status.

Table III shows that unconstrained firms invest more in response to profits than constrained firms of similar age and industry volatility. The financial constraint result is similar to that of Hennessy and Whited (2007) and Moyen (2004), where constrained firms must self-finance their investment at all times because they cannot raise external funds. In contrast, unconstrained firms raise external capital and invest more in periods of high productivity. Unconstrained firms therefore exhibit a larger correlation between investment and profits.

We note that firm age and financial constraints have opposite effects on investment responses to profits. Being young magnifies investment responses while being constrained reduces them. It is difficult to distinguish empirically between young and financially constrained firms from examining descriptive statistics only, but it is helpful that the two predictions have opposite effects on investment responses.

Table III also reassures us that the results of Tables I and II still hold. Controlling for financial status and industry volatility, young firms still invest more in response to profit realizations than mature firms. Controlling for financial status and firm age, firms in low-volatility industries still invest more in response to profits than firms in high-volatility industries.

4. Data

We test the above theoretical predictions on firm age, industry volatility, and financial status in the data. Empirically, we recognize that young firms are often financially constrained. We seek an instrument for learning inside a firm that is not related to financial status. Rather than focusing on newly founded firms which are often saddled with constraints, we turn to firms that have taken on new large-scale projects. There is much learning going on, but these firms are not associated with any particular level of constraints. They are not new to financial markets. We identify young firms as at most three years from an increase of 75 percent or more in capital stock, while mature firms are more than three years from such a large-scale project

or a foundation date. We exclude firm-year observations within three years of foundation from our sample in an effort to avoid the muddle between age and constraints.

Major increases in capital stock may introduce a great deal of uncertainty about the future success of the firm as a whole. For example, take the case of MSC Software Corporation, a leader in the computer-aided engineering industry at the height of the technology bubble. Founded in 1963, MSC undertook an important acquisition in 1999 of MARC Analysis Research Corporation, along with other smaller acquisitions (Universal Analytics Inc. and Computerized Structural Analysis and Research Corporation). As a result of these acquisitions, the capital stock of the company increased by 75.2 percent. The company states “...there is risk associated with the completion, marketing and integration of these MARC products into MSC. There is no assurance that the in-process technology will meet with either technological or commercial success. The substantial or outright failure of this integration could adversely impact MSC’s financial condition.”¹⁰ The acquisitions led to a significant increase in uncertainty, which would otherwise be typical for a new business.

Identifying young firms as those at most three years of a major change in capital stock represents a novel proxy for learning. Screening out observations based on large enough changes in capital stock, however, is not new. It is routinely applied in the investment literature. The idea is to exclude firms which may have undergone a significant change in business, where the economic environment may be different. For example, Fazzari, Hubbard, and Petersen (1988) exclude firm-year observations where mergers account for more than 10% of the capital stock, while Erickson and Whited (2000) and Hennessy (2004) excluded mergers accounting for more than 15% of book value. We note that our identification of young firms does not rely uniquely on merger events. Slightly less than half (47.1%) of our firms with new large-scale projects are related to an acquisition event according to COMPUSTAT (mnemonic aqc). Slightly more than half (52.9%) arise simply from major capital expenditures.

In addition to including firms with more than three years from a major change in capital stock, mature firms also include those that are more than three years from foundation. See the appendix for more details on how the foundation dates were determined. We were able to determine the foundation dates of 4,048 firms out of 10,603 firms in the sample. When the foundation date information was not available, we used the year of incorporation as the next best measure. We determined the year of incorporation for 1,563 firms in

¹⁰Page 19 of the 1999 annual report.

the sample. Together, we were able to collect the year of foundation or incorporation for 52.9 percent of all firms in the sample, accounting for a large majority (76.2%) of firm-year observations. Firms for which more information is publicly available – including the foundation year – tend to be the ones with more years of data available in COMPUSTAT. For the remaining 47.1 percent of firms for which we have neither the year of foundation nor the year of incorporation, we used the first year these firms appear in COMPUSTAT.¹¹

We measure industry volatility using the median intensity of R&D expenses in a given industry. Industries with more R&D activity obviously face more technical uncertainty. The choice of industry volatility measure is motivated by Comin and Philippon (2005), who show that high R&D activity explains firm volatility. Each year we rank the 48 Fama and French (1997) industries by the intensity of R&D expenses of the median firm in each industry. The bottom two quintiles of the industries are considered low-volatility and the top two quintiles are considered high-volatility. Observations belonging to the industries from the middle quintile are excluded in order to avoid possible misclassifications. In a robustness check below (see Table XIV), we confirm our main results under alternative measures including the standard deviation of profits and the industry maturity.

A firm’s financial constraint status is not directly observable, and many proxies have been proposed to measure it. Some proxies rely on a single variable, e.g., firm size, dividend payout ratio, or the availability of credit rating.¹² Other proxies encompass multiple aspects of the firm, e.g., the Kaplan and Zingales (1997) index and the Whited and Wu (2006) index.¹³

¹¹Using COMPUSTAT rather than CRSP to determine firm age when foundation and incorporation dates cannot be found is advantageous because COMPUSTAT covers private firms with public debt. As a result, firm age can be tracked from an earlier time.

¹²A low dividend payout ratio may no longer convey much information about financial constraints, as Fama and French (2001) document disappearing dividends in a majority of firms (only 20.8% of U.S. firms paid dividends in 1999).

¹³Whited and Wu (2006) document that firms classified as financially constrained by the Kaplan and Zingales index are followed by a larger number of analysts and are more often in the possession of a credit rating, which is typically associated with lower levels of information asymmetry. Whited and Wu (2006) also document that firms classified as least constrained by the Kaplan and Zingales index are the smallest and have the highest cash balances, which seems counterintuitive. In addition,

We control for firms' financial constraints using firm size. The choice of financial constraint proxy is motivated by Hennessy and Whited (2007) documenting that smaller firms are associated with larger costs of external finance. Following Erickson and Whited (2000), we classify a firm-year observation as more-constrained if the firm falls in the bottom third of the distribution of total assets and in the bottom third of the distribution of capital stock for the year. A firm is classified as financially less-constrained if it falls in the upper half of the distribution of total assets and the upper half of the distribution of capital stock for the year. The bottom third versus upper half classification implies that there are fewer firms identified as more-constrained. A number of medium-sized firms fall outside of these two extreme groups. We exclude these observations in order to mitigate any possible misclassification.¹⁴

To alleviate any concerns that firm size might not adequately capture the degree of financial constraint, a robustness check below (see Table XIV) produces similar results using credit ratings. It is however difficult to find young firms operating in high-volatility industries that have been granted a credit rating, especially in the early 1990's. COMPUSTAT provides monthly data on credit ratings granted by Standard and Poor's for three categories of debt: long term debt, short term debt, and subordinated debt. We identify a firm in a given year as less-constrained if it has been granted a rating in at least one of the three debt categories for at least one month within that year. Otherwise, firms are identified as more-constrained. The subset of young firms operating in high-volatility industries with a credit rating contains as few as 12 observations in the early 1990's, which casts doubt on the reliability of the results.

For that reason, we perform another robustness check using Whited and Wu's (2006) index. The index is derived from a GMM estimation of an investment Euler equation, as described in the appendix. It represents the shadow cost of external financing. Whited and Wu (2006) specify it as a function of observable firm

Almeida, Campello, and Weisbach (2004) examine a large sample of manufacturing firms from 1971 to 2000 and find that firms categorized as unconstrained according to the Kaplan and Zingales index are more likely to be small and without a bond or commercial paper rating.

¹⁴Our results remain qualitatively unchanged if we do not exclude the medium-sized firms, as well as if we use alternative cut-off points to define the extreme groups of more-constrained and less-constrained firms – bottom third versus the rest, top and bottom two quintiles, and top and bottom half.

characteristics and estimate its parameters. To mitigate the possible endogeneity between firms' investment decisions and some of the variables used to compute the index, we use lagged values of the index to split firms according to financial constraints. High values of the index are associated with firms more likely to be financially constrained and facing higher costs of external financing. We compute the index for each observation in our sample and rank firms each year by their index values. Similar to the classification using firm size, firms with beginning-of-the-period index values in the bottom half of the distribution are identified as less-constrained, while firms with values in the upper third are identified as more-constrained. Again we exclude observations in the middle of the distribution in order to avoid possible misclassification.

In addition to firm age, industry volatility, and financial constraints, we also account for firm-year observations with negative income. We follow Allayannis and Mozumdar (2004), Bhagat et al. (2005), and Cleary et al. (2004), who document a different investment behavior for firms with negative income. Those firms are isolated from the rest of the sample using a dummy variable for negative operating income before depreciation. In Table XIV, we perform a robustness check using a dummy for negative profits.

The sample consists of all North American COMPUSTAT firms in the annual files that have sufficient data to construct the regression variables and the variables used to classify firms into the different subsets. The regression variables are measured as follows: investment I/K by capital expenditures standardized by capital stock, profits Π/K by the sum of income before extraordinary items and depreciation, standardized by capital stock, and Tobin's Q by macro Q which equals the market values of the long-term debt and equity less inventories, all divided by the replacement value of capital stock. The replacement value of the capital stock is calculated as in Fazzari et al. (1988), Salinger and Summers (1983), and Whited (1992). In a robustness check below (see Table XIV), we use gross property, plant, and equipment to proxy for the replacement value of the capital stock. All flow variables are measured over the course of the year and all stock variables are measured at the beginning of the year.

The sample must meet three additional data requirements. The first requirement applies to the time period. We are interested in the unbalanced panel of firms from 1988 to 2009 with available data in any given year. The sample begins in 1988 to assure a consistent data measurement for capital expenditures and cash flow, as the Statement of Financial Accounting Standards no. 95, issued in November 1987, standardized the reporting of cash flow and capital expenditures.

The second data requirement involves reasonable values. Firms in the sample are required to have positive values for Total Assets (COMPUSTAT mnemonic *at*), Net Sales (*sales*), and Tobin’s Q . As is customary, we also exclude very small firms, by requiring Gross Property, Plant, and Equipment (*ppegt*) of at least three million dollars, and we exclude firms with only one observation. To avoid the impact of influential observations, we winsorize the regression variables (investment I/K , profits Π/K , and Tobin’s Q) at the 2 percent and 98 percent levels.

The final requirement covers the industries. Utilities (SIC code 4000-4999), financial institutions (6000-6799) and public administrations (9000-9999) are excluded from the sample. We end up with a large sample: 10,603 firms. A few belong to agriculture, forestry, and fishing (53), a few more belong to construction (128), some more come from transportation and communication (909), retail and wholesale (1,230), mining (1,147), a larger number originate from the service industry (2,315), and slightly fewer than half in our sample are manufacturing firms (4,821). Table IV summarizes how the various data requirements affect the composition of the sample.

Table V provides descriptive statistics for different subsets of firms. The statistics describe three types of variables. First, regression variables consist of investment I/K , profits Π/K , and the two definitions of Tobin’s Q . Second, the variables used to classify firms into different subsets consist of firm age; industry R&D intensity; Whited and Wu’s (2006) index; total assets; gross property, plant, and equipment; and the replacement value of the capital stock (RVCS). Third, the other variable of interest is the ratio of long-term debt to total assets. The mean of each variable is computed for each firm, and then the median within a subset of firms is reported in Table V.

Regardless of industry volatility and financial constraints, the bottom panel of Table V shows that young firms on average invest more, have higher profit-to-capital ratios, higher Tobin’s average Q , and operate in more R&D intensive industries compared to mature firms. They often have higher WW index values, suggesting more binding constraints than mature firms.

More-constrained young firms tend to operate in high-volatility industries (1,928 observations versus 1,025 observations in low-volatility industries). Less-constrained young firms, in contrast, tend to operate in low-volatility industries (3,004 observations versus 1,366 observations in high-volatility industries). Regardless of firm age and financial constraints, firms in high-volatility industries on average invest more, have higher

profits, higher Tobin's average Q , they are older and use less debt.

Regardless of firm age and industry volatility, more-constrained firms are younger, have higher profit-to-capital ratios, higher Tobin's average Q , operate in more volatile industries, and use less debt compared to less-constrained firms.

5. Results

The specification in Equation (14), along with similar specifications in Equations (15) and (16) estimated above on model-simulated series, are now estimated in the data. In Equations (15) and (16), we include a negative income dummy variable as in Equation (14) because, contrary to the model, there are negative income firms in the data. We obtain our estimates in two steps. First, we obtain estimates for each cross section of our unbalanced panel. Next, we summarize the estimates using the Fama and MacBeth (1973) procedure and report them in the tables below along with their standard errors. At the bottom of each table we also report p -values testing the significance of the difference between the investment-to-profit responses of particular subsets of firms.¹⁵ The p -values are based on one-tailed t -tests of the hypothesis that a particular difference in responses is positive.

In addition to ordinary least squares (OLS) estimates, we also present estimates from Erickson and Whited's (2000) measurement error-consistent GMM models. In our context, as in many others in applied economics, measurement errors are likely to arise in empirical proxies. For example, the theoretical concept of Tobin's marginal q capturing investment opportunities is not directly observable and can be measured only imperfectly. As is standard, we control for such errors using the GMM estimator developed by Erickson and Whited (2000).

There are other techniques for addressing measurement errors. Almeida, Campello, and Galvao (2010) compare the performance of the Erickson and Whited (2000) estimator to instrumental variable estimators such as the Arellano and Bond (1991) dynamic panel estimator. This represents an important area of inquiry as there is an abundant empirical investment-cash flow sensitivity literature which has produced different results, in part, depending on the different estimation techniques where measurement errors may not be

¹⁵We have also verified that the bootstrapping procedure proposed by Cleary (1999) generates similar p -values for the significance of differences.

addressed. The results of Almeida et al. (2010) suggest that the Erickson and Whited (2000) estimator is empirically biased and inefficient, performing poorly compared to more traditional instrumental variables estimators. In a reply, Erickson and Whited (2011) resolve the debate by showing that the conclusions of Almeida et al. (2010) depend on local rather than global minima. The Erickson and Whited (2000) estimator typically performs better than other estimators in terms of bias and dispersion. We are not concerned about situations when it under-performs (with fixed effect or a symmetric distribution for the mismeasured regressor), as we have no fixed effect and Tobin's q is naturally skewed because prices cannot take negative values. In addition, Erickson and Whited (2011) show that misspecifications are easiest to detect with higher-order moment estimators.

Our data provides support for Erickson and Whited's (2000) GMM model. The GMM specification is identified when two assumptions are satisfied. The first assumption requires that the parameter on Tobin's q , β , be different from zero. The second assumption requires that residuals obtained from regressing investment I/K on the perfectly measured vector $\mathbf{z}$ containing a constant, dummy variables, and profit terms be skewed. The first restriction is easily satisfied: the coefficient on Tobin's q in investment–Tobin's q regressions has been documented to be positive and significant in the empirical literature. The second (skewness) restriction may be more difficult to meet. The identification test is applied to each cross-section of firms. Consequently, the test produces 22 statistics corresponding to the 22 years of the sample period from 1988 to 2009. We report 22 p -values of the statistics for the GMM estimator under the three different regression specifications considered in Tables VIII to X. Table VI therefore reports 66 p -values. The model is well identified, as all 66 p -values are under five percent and 63 are below one percent.

GMM estimators using higher than third-order moments offer overidentifying restrictions that can be tested. We examine the p -values from the J -test whether the restrictions are rejected by the data. The test is applied to the data in each cross section for each estimator using moments up to the fourth order and alternatively using moments up to the fifth order. Table VII indicates that, using the specification in Table X recognizing firm age, industry volatility, financial constraints, and negative income, the data reject (at the 5 percent level) the overidentifying restrictions in only one cross section out of 22, while those imposed by the estimator using up to fifth-order moments are rejected in four cross sections. Like Bakke and Whited (2009), we conclude that our data are most consistent with the overidentifying restrictions imposed by the

estimator using up to fourth-order moments. In a robustness check below (see Table XI) we confirm our main results using moments up to third and fifth orders.

5.1. FIRM AGE

In Table VIII, we examine the prediction that investments of young firms learning about their long-run quality should respond more to current profit realizations than investments of mature firms. The profit coefficient of young firms is indeed larger: the OLS coefficients are 0.069 for young firms as compared to 0.048 for mature firms. The reported Fama-MacBeth OLS standard errors indicate that the two investment-to-profit responses are statistically different from zero. The estimate of -0.011 for the subset of negative income firms confirms previous findings of Allayannis and Mozumdar (2004), Cleary et al. (2004), and Bhagat et al. (2005).

With the GMM estimator, the coefficient for young firms is 0.017, while the coefficient for mature firms is -0.024. The p -values at the bottom of the table indicate that the difference in investment-to-profit responses between young and mature firms is statistically significant under both OLS and GMM. Also under both OLS and GMM, dummy variables indicate that young firms invest more and negative income firms invest less on average.

5.2. INDUSTRY VOLATILITY

A young firm cannot immediately learn about its quality by observing profit realizations $\Pi(K_t; \theta_t)$, because of the noise introduced by the productivity process θ_t . To further explore the learning mechanism, we examine whether the informativeness of the shock varies across different economic environments. As we noted above, industries intensively conducting R&D activities face more technical uncertainty.

In Table IX, profit observations are grouped along the dimensions of firm age and industry volatility. Controlling for age, the investments of firms in high-volatility industries respond less to profits than those of firms in low-volatility industries. With a more volatile economic environment, firms have a harder time inferring from profit realizations whether their quality is high or whether they simply received a good shock. For young firms, those facing low volatility have a larger coefficient (e.g., 0.093 for the OLS estimation and 0.040 for GMM) than those facing high volatility (0.055 for OLS and not statistically different from zero for GMM). Similarly for mature firms, those facing low volatility have a larger investment-to-profit coefficient

than firms facing high volatility.

Table IX also reaffirms the result of Table VIII. When controlling for industry volatility, the investments of young firms respond more to profits than those of mature firms.

5.3. FINANCIAL STATUS

Obviously a financially constrained firm may not be able to invest as much as it desires, so we take into account financial constraints when investigating the learning mechanism. This is important because Table V shows that young firms and firms in high-volatility industries are smaller, suggesting that they face more binding financial constraints. The above results on investment-to-profit responses could therefore be influenced by the effect of financial constraints. In Table X, we further separate the firm age and industry volatility subsets by financial constraints.

We investigate the theoretical prediction that less-constrained firms invest more in response to profit realizations than more-constrained firms do. The OLS results provide support for the prediction, regardless of firm age and industry volatility. The measurement-error consistent GMM results, however, do not show any statistically significant differences in investment-profit responses among mature firms or firms in high-volatility industries. For young firms operating in low-volatility industries, GMM results document that less-constrained firms invest more in response to profit realizations than more-constrained firms. The conclusion that financial constraints matter only for young firms is intuitively appealing, indicating that the plight of the financially constrained may be related to learning.

We are not particularly concerned about the financial constraint results per se, only to the extent that we control for constraints when estimating the firm age (and industry volatility) results. Table X confirms the results from the previous tables. As in Tables VIII and IX, young firms invest more in response to profit realizations than mature firms in all subsets. As in Table IX, firms in low-volatility industries invest more in response to profits than firms in high-volatility industries.

5.4. ROBUSTNESS

We examine the robustness of our results on a number of dimensions.

5.4.1. GMM Estimation Using Different Order Moments

In Table XI, we present estimates using Erickson and Whited’s (2000) GMM model with up to third-order moments (GMM3) and up to fifth-order moments (GMM5). For comparison, we reproduce the benchmark estimates with up to fourth-order moments in the middle column. The estimates are very similar in magnitude, and none of the qualitative results change when moments of a different order are considered. The largest responses of investment to profits are still associated with young firms in low-volatility industries. In fact, throughout all the robustness checks below, the firm age and industry volatility predictions receive widespread support, while the financial constraint prediction continues to receive support among the subset of young firms in low-volatility industries.

5.4.2. Different Definitions of Firm Age

In Table XII, we consider variations of our firm age definition. In the first two columns, we identify young firms as those within four years of a large-scale project and alternatively within two years, instead of the benchmark three years. In the last two columns, we identify young firms as those within three years of a large-scale project, but here we perturb the threshold that marks the start of a large project: a 100% change in capital stock and alternatively a change of 50%, instead of the benchmark 75% change.

The results of Table XII confirm those of Table X. The p -values for the difference between investment-to-profit responses of different subsets of firms indicate that young firms (and firms in low-volatility industries) have larger responses than mature firms (and firms in high-volatility industries). Similar to Table X, the p -values for the difference in investment-to-profit responses between less-constrained and more-constrained firms are statistically significant only for the subset of young firms in low-volatility industries.

In Table XIII, we reconsider our definition of firm age. In choosing an instrument for learning that is not related to financial constraint, we identified young firms as those within three years of a major project. In Tables V to XII, we excluded firm-year observations within three years of foundation from the young firm subset for fear that these may also be related to constraints. In the first column of Table XIII, we no longer exclude observations within three years of foundation. Surprisingly, the qualitative results do not change. As it turns out, the exclusion of historically young firms does not affect investment-profit responses.

In the second column, we include in the sample only firms for which we were able to determine the year

of foundation (or incorporation). We exclude all firms for which we would have set the date of foundation to their first year in COMPUSTAT. We are left with 52.9 percent of firms with foundation (or incorporation) dates and 76.2 percent of the firm-year observations. Our firm age and industry volatility results remain unchanged. However, there is no longer any difference in investment-profit responses based on financial constraints. Perhaps the requirement to determine the foundation date excludes too many constrained firms from the sample.

The third and fourth columns also include firms within three years of foundation, but measures foundation using the Field-Ritter data and alternatively the first year a firm enters into the COMPUSTAT data set. The Field-Ritter data represent another source for foundation years, one that is better suited for analysis of stock prices than accounting data, as firms are identified by CRSP permanent identification numbers. The two foundation year procedures are also different when firms merge or are acquired: our procedure records the foundation year of the oldest firm, while the Field-Ritter procedure traces back the origin of the legal name. For example, the Field-Ritter data would identify 1,189 additional firm-year observations as within three years of foundation compared to our foundation data. Likewise relying solely on the first COMPUSTAT year would identify 2,838 additional observations as within their first three years. The different classifications, however, do not have a large impact on the estimated coefficients. Perhaps it is not surprising that the qualitative results remain the same among these two columns as the young firm subset includes a significant number of otherwise mature firms who have gone through major increases in capital stock within the last three years. A major change in capital stock resets firm age.

To investigate further whether we adequately control for financial constraints, in the last column of Table XIII we exclude firms with large-scale projects from the sub-sample of young firms. Young firms are defined only with respect to their foundation year. It is evident that those historically young firms are associated with financial constraints, as there are years when no such young firm is found in the subset of less-constrained firms operating in high-volatility industries. To permit a reasonable number of observations in each subset of firms, we must relax the firm age cut-off to seven years from foundation. With a seven year cut-off, there are at least 14 observations in any given year for the subset of young, less-constrained firms operating in high-volatility industries. While we would not want to conduct our main analysis using only 14 observations for a subset in a given year, we present the evidence here as a robustness check. Relaxing the age cut-off

from three to seven years increases the average age of the “somewhat young” firms and makes it harder to find significant differences with mature firms. The last column of Table XIII presents the results. The firm age and industry volatility results remain essentially the same. Young firms invest more in response to profits than mature firms, regardless of industry volatility and financial constraints. Firms in low-volatility industries invest more in response to profits than those in high-volatility industries, regardless of firm age and financial constraints. As for the financial constraint result, young and less-constrained firms invest more in response to profits than young and more-constrained firms, irrespective of industry volatility. As before, there is no financial constraint difference in investment-profit responses for mature firms.

5.4.3. Different Definitions of Industry Volatility, Financial Status, and other Regression Variables

In Table XIV, we consider alternative measures of industry volatility, financial constraint, negative income, and capital stock. In the first column, industry volatility is measured as the average standard deviation of profits across all firms in an industry. First, the standard deviation of profits for each firm is calculated over all of the available years for each firm in COMPUSTAT. After assigning each firm to one of the 48 industries defined in Fama and French (1997), we average the standard deviations of all firms within an industry to measure the volatility of that industry. Each year, the industries represented in our sample are ranked according to their volatility. Those in the top two quintiles with the highest average standard deviations are considered high-volatility industries, while those in the bottom two quintiles are considered low-volatility.

Results in the first column confirm those of Table X. The p -values for the difference between investment-to-profit responses of different subsets of firms indicate that the investments of young firms are more responsive to profits than those of mature firms, after we control for industry volatility and financial status. They also confirm that the investments of firms in low-volatility industries are more responsive to profits than those of firms in high-volatility industries, once we control for firm age and financial status. Under this definition of industry volatility, the investment of less-constrained firms responds no more to profits than those of more-constrained firms. The financial constraint prediction receives no support, even among subsets of young firms.

In the second column, we report estimates from a specification using the median age of the firms in

an industry to measure industry volatility. New industries arise because of new technologies and products. Using industry age as a measure of volatility induced by the new technologies and products is valid, even though we also control for firm age. Industry age and firm age contain different information: median firms in young industries are already 9.5 years old since inception, which is dramatically different from our three-year cut-off defining young firms. For each of the 48 Fama and French (1997) industries, we calculate each year the median firm age since foundation using the entire COMPUSTAT universe. Each year, the industries represented in our sample are ranked according to their median firm age, and those in the two quintiles with the smallest median firm age since foundation are considered high-volatility industries, while those in the most established two quintiles are considered low-volatility.

Results in the second column confirm the firm age prediction that the investments of young firms are more responsive to profits than those of mature firms, after we control for industry volatility and financial status. As for the industry volatility prediction, only one subset of firms (the young and less-constrained) does not exhibit a significant statistical difference in investment responses. For that subset, firms operating in low-volatility industries do have higher investment-to-profit responses than firms operating in high-volatility industries, but the difference is not statistically significant. As for the financial constraint prediction, only the subset of young firms operating in high-volatility industries provides some support.

In the third column, we report estimates from a specification using the availability of a credit rating to identify less-constrained firms. Young firms invest more in response to profits than mature firms, except for firms with a credit rating operating in high-volatility industries. As discussed in the previous section, this is exactly where lies the low number of observations for the subset of young firms operating in high-volatility industries that have been granted a credit rating. The p -value for the difference in investment-profit responses is over 10 percent (0.14). We note that this is the only exception throughout all robustness checks where there is no statistical significance for the firm age prediction. We also note that, although firms operating in low-volatility industries invest more in response to profits than those in high-volatility industries, the difference is not significant (p -value of 0.287) for the mature subset with a credit rating. It is possible that the relaxed identification of financially constrained firms (requiring only one month of any rating data available) affects our results in these two instances.

In the fourth column, we report estimates from a specification using the Whited and Wu (2006) index

to measure the degree of financial constraint. The results provide support for the firm age and industry volatility predictions, but no support for the financial constraint prediction, even among young firms.

The fifth column uses gross property, plant, and equipment to proxy for the replacement value of capital stock. The results confirm our main findings in Table X concerning the firm age and industry volatility predictions. Again, there is no support for the financial constraint prediction, even among young firms.

Finally, in the sixth column, we confirm the robustness of our results from a specification using profits – specifically the sum of income before extraordinary items and depreciation – to identify firms with negative income.

5.4.4. Summary of Robustness Results

In sum, we find that the firm age prediction is verified in all but one subset of industry volatility and financial status. It is clear that young firms invest more in response to profits than mature firms. This is a new empirical contribution to the literature, and it is consistent with our model describing how young firms learn with time about their quality and become less sensitive to current profits. The industry volatility prediction receives support in all but two subsets of firm age and financial status. Firms operating in low-volatility industries invest more in response to profits than firms in industries where there is a lot of uncertainty. This corollary result represents another new empirical contribution to the literature. Finally, we qualify the importance of financial constraints when controlling for firm age and industry volatility. There is mixed empirical support for the financial constraint prediction, but never among mature firms. More to our point, when controlling for financial constraints, we obtain robust results describing how young firms learn and how that learning is affected by the degree of industry uncertainty.

6. Concluding Remarks

About one in five U.S. businesses is newly founded or restructured from a major increase in capital stock. New businesses influence the macroeconomy through distinct firm dynamics, including higher growth rates and higher volatilities. We investigate these firm dynamics by building on the learning models of Jovanovic (1982) and Alti (2003), who describe how young firms grow their assets over time as they resolve the uncertainty about their long-run prospects.

Because young firms are often constrained financially, we proxy firm age from the time of an important

increase in capital stock. Firms with new, large-scale projects experience much learning but no systematic relationship with financial constraints. We show that investments of these young businesses react more to profit realizations than investments of mature firms. In a robustness check, we confirm that recently founded firms similarly invest more in response to profits. This new empirical finding is consistent with a neoclassical Tobin’s q framework augmented with Bayesian learning. As firms mature, their investment decisions become less influenced by the profit shocks they receive. In volatile economic environments where learning may be more difficult, we find that firms depend less on profits when making their investment decisions. There is more noise and less signal to guide firms in evaluating their investment opportunities.

These new empirical results are robust to controlling for financial constraints. In fact, only among young firms do less-constrained ones invest more in response to profits. There is no financial constraint difference in investment-profit responses for mature firms.

Further research on firm dynamics and financial constraints may prove fruitful, as our results suggest that financial constraints may be endogenously relaxed when firms mature. In another line of inquiry, the strong empirical support for the learning predictions indicates many promising research avenues. Learning may manifest itself in all corporate decisions – real or financial – potentially explaining other interesting firm dynamics. For instance, we would expect decision policies regarding precautionary cash savings and debt maturity to change as firms learn about their economic prospects.

7. Appendix

7.1. NUMERICAL METHOD

The model is solved numerically using finite element methods as described in Coleman’s (1990) algorithm. We approximate K_{t+1} and V_t by piecewise linear interpolation. The policy approximants are written as linear combinations of the state variables K_t , b_{t-1} , z_{t-1} , and z_t . The coefficients are chosen by collocation to satisfy Equation (1) and Equation (11) or (12) at all grid points. The state space grid consists of 81 uniformly spaced points. The lower and upper bounds for the capital stock are 10 percent and 400 percent of the steady state value. The probability that the firm is of a high quality, b , lies between 0 and 1. The lowest unconditional outcome for the variable determining the productivity shock z is set to $\tau^L - \left(\frac{\sigma}{1-\rho}\right)$, and the highest unconditional outcome is set to $\tau^H + \left(\frac{\sigma}{1-\rho}\right)$. We compute expectations using the Gauss-Hermite

quadrature rule. For simplicity, ϵ_t has two quadrature nodes $\{-1,1\}$ with equal 0.5 weights.

7.2. VARIABLE DEFINITIONS

We construct the regression variables following previous work in the investments literature. Investment I/K is measured as capital expenditures (COMPUSTAT mnemonic capx) over the replacement value of the capital stock. Profits Π/K is measured as the sum of income before extraordinary items (ib) and depreciation and amortization (dp), over the replacement value of the capital stock. Tobin's Q is measured as macro Q , which is the market value of equity ($\text{prcc.f} \times \text{csho}$) plus total long-term debt ($\text{dltt} + \text{dlc}$) minus inventories (invt), all divided by the replacement value of the capital stock. We consider two alternative measures for the replacement value of the capital stock. The main results use the procedure outlined by Fazzari et al. (1988), Salinger and Summers (1983), and Whited (1992), while the robustness check follows Bakke and Whited (2010) and proxies the replacement value with gross property, plant, and equipment (ppeg).

Like Fazzari et al. (1988), Salinger and Summers (1983), and Whited (1992), we set the replacement value of the capital stock equal to the book value of gross property, plant, and equipment for the first year a firm appears in COMPUSTAT. Next, we calculate the useful life (L_{it}) of the capital stock of each firm in any year as the sum of the beginning-of-the-year gross property, plant, and equipment and capital expenditures, divided by Depreciation. To find the useful life of capital goods of each firm L_i , we average the annual values L_{it} over the life of each firm. The replacement value of the capital stock is then defined as

$$K_{it} = \left(K_{it-1} \left(\frac{P_t^k}{P_{t-1}^k} \right) + I_{it} \right) \times (1 - 2/L_i), \quad (17)$$

where P_t^k is the level of the *Producer Price Index for Finished Goods: Capital Equipment* for the last month of firm i 's fiscal year t , provided by the Federal Reserve Bank of Saint Louis.

The values for Whited and Wu's (2006) index are obtained from the expression

$$WW_{it} = -0.091 CF_{it} - 0.062 DIVPOS_{it} + 0.021 TLTD_{it} - 0.044 LNTA_{it} + 0.102 ISG_{it} - 0.035 SG_{it}, \quad (18)$$

where CF is the sum of income before extraordinary items (ib) and depreciation and amortization (dp), $DIVPOS$ is an indicator variable equal to one if the firm pays cash dividends (when dvc or dvp is positive), $TLTD$ is the ratio of long-term debt (dltt) to total assets (at), $LNTA$ is the natural logarithm of total assets (at), ISG is the average three-digit-SIC industry sales growth obtained by averaging the sales growth of all

firms in a particular three-digit SIC category in a particular year, and SG is the individual firm sales (sale) growth from year $t - 1$ to year t .

We single out firms with negative income. We follow Bhagat et al. (2005) and isolate firms with negative Operating Income Before Depreciation (oibdp). In a robustness check, we follow Allayannis and Mozumdar (2004) and Cleary et al. (2004) and isolate firms with negative profits, i.e., income before extraordinary items plus depreciation and amortization.

7.3. FOUNDATION DATE

We determine the date of foundation by tracing back to the start of a firm's operations. We assume that firms learn from their inception. Therefore, we determine the start of the learning process within a firm as the start of the oldest segment in a related business. Changes in name or legal incorporations are not treated as a new beginning. We use the incorporation date only if the foundation date is not available.

We hand-collected foundation dates from five sources. Foundation dates were mostly determined from 10-K forms (10-KSB for small businesses or 20-F for non-U.S. firms) filed with the U.S. Securities and Exchange Commission.¹⁶ When the information was not available from the 10-Ks, we referred to *Thomson Gale's Business and Company Resource Center*, then to *Bloomberg Businessweek's Company Insight Center*, and then to *Hoover's Online*.¹⁷ Finally, when no information was available in these four electronic sources, we searched the volumes of Thomson Gale's *International Directory of Company Histories* from St. James Press.

Firm restructurings, changes of ownership, divestitures, and consolidations present complicated situations. We proceed as follows:

- When a firm is the result of the combination of several entities through mergers and acquisitions at different points of time, we take the foundation date of the oldest entity whose business is related to that of the modern firm.

¹⁶Provided by the EDGAR database at <http://www.sec.gov/>

¹⁷At <http://galenet.galegroup.com/> , <http://investing.businessweek.com/research/company/overview/overview.asp> , and <http://premium.hoovers.com/>

- When a firm is the result of a divestiture from another entity, we determine whether the modern firm started operating as a separate segment within the (divesting) entity before it was divested. If so, we take this earlier date as the foundation date.
- When a firm is organized as a holding of many entities, we take the foundation date of the oldest entity.
- When a firm ceased operations for some period before restarting them again, on the same site and in the same line of business, we take the foundation date of the first period of operation.

Table IV provides a detailed account for the number of observations and firms in our sample. For our sample of 10,603 firms and 78,508 firm-year observations, we were able to collect information on the foundation year or the incorporation year for 5,611 firms accounting for 59,825 firm-year observations. We also check that these dates precede the first year in which firms appear in COMPUSTAT. For all 5,611 firms, the foundation year or the incorporation year either precedes or coincides with the first year in which they appear in COMPUSTAT. For the rest of the firms we use the first year in which they appear in COMPUSTAT as their foundation year.

The information contained in our data set is similar to the information available in the Field-Ritter data set.¹⁸ Although the two data sets serve the same general purpose, there are differences between them. First, the unique firm identifiers are different: the Field-Ritter data set uses the CRSP permanent IDs to match them easily with security prices, while our data set uses COMPUSTAT's gvkey for convenience in matching with accounting data. In addition, when a firm is the result of a merger or an acquisition, we always look for the start of operations of the oldest firm and assume that this is the starting date of the currently existing firm, regardless of how the firms changed names throughout the years. Our assumption is that after name changes, mergers, or acquisitions, companies acquire not only the assets, but also knowledge about the quality.

In contrast, the Field-Ritter data records the foundation year of a merged firm as the foundation year of the oldest firm from which the legal name of the company originates. Jay Ritter explains on his website, "For

¹⁸Description and data are available on Jay Ritter's IPO Data web site: <http://bear.warrington.ufl.edu/ritter/FoundingDates.htm>

instance, assume a company started as a partnership with the name of the Field Co. in 1965, incorporated in Florida in 1967, reincorporated in 1974 in Delaware under the name Field Computer Co., merged in 1982 with the Ritter Co. (which had been founded in 1957), and went public in 1983 as the Field Computer Co. We would deem the founding date to be 1965. But if the name had been changed to the Field-Ritter Computing Co. when the merger occurred in 1982, we would deem the founding date to be 1957, the older of the two merged companies.”¹⁹ For our purpose, we would deem the founding year to be 1957 regardless of the current name of the company.

References

- Albuquerque, R. and Hopenhayn, H. (2004) Optimal lending contracts and firm dynamics, *Review of Economic Studies* 71, 285-315.
- Allayannis, G. and Mozumdar, A. (2004) The impact of negative cash flow and influential observations on investment-cash flow sensitivity estimates, *Journal of Banking and Finance* 28, 901-930.
- Almeida, H. and Campello, M. (2007) Financial constraints, asset tangibility, and corporate investment, *Review of Financial Studies* 20, 1429-1460.
- Almeida, H., Campello, M., and Galvao, A. (2010) Measurement Errors in Investment Equations, *Review of Financial Studies* 23, 3279-3382.
- Alti, A. (2003) How sensitive is investment to cash flow when financing is frictionless? *Journal of Finance* 58, 707-722.
- Arellano, M., and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* 58, 277-297.
- Baker, M., Stein, J. and Wurgler, J. (2003) When does the market matter? stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969-1005.
- Bakke, T. and Whited, T. (2010) Which firms follow the market? an analysis of corporate investment decisions, *Review of Financial Studies* 23, 1941-1980.
- Berk, J.B. and Green, R.C. (2004) Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.
- Bhagat, S., Moynihan, N. and Suh, I. (2004) Investment and internal funds of distressed firms, *Journal of Corporate Finance* 11, 449-472.

¹⁹<http://bear.warrington.ufl.edu/ritter/FoundingDates.htm>

- Chen, Q., Goldstein, I. and Jiang, W. (2007) Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619-650.
- Cleary, S. (1999) The relationship between firm investment and financial status, *Journal of Finance* 54, 673-692.
- Cleary, S., Povel, P. and Raith, M. (2007) The U-shaped investment curve: theory and evidence, *Journal of Financial and Quantitative Analysis* 42, 1-39.
- Clementi, G.L. and Hopenhayn, H.A. (2006) A theory of financing constraints and firm dynamics, *Quarterly Journal of Economics* 121, 229-265.
- Cochrane, J.H. (1991) Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209-237.
- Coleman, W.J., II (1990) Solving the stochastic growth model by policy-function iteration, *Journal of Business and Economic Statistics* 8, 27-29.
- Comin, D. and Philippon, T. (2005) The rise in firm-level volatility: causes and consequences, *NBER Macroeconomics Annual* 20, 167-201.
- Cooley, T. and Quadrini, V. (2001) Financial markets and firm dynamics, *American Economic Review* 91, 1286-1310.
- Cooley, T., Marimon, R. and Quadrini, V. (2004) Aggregate consequences of limited contract enforceability, *Journal of Political Economy* 112, 817-847.
- Cooper, R.W. and Haltiwanger, J.C. (2006) On the nature of capital adjustment costs, *Review of Economic Studies* 73, 611-633.
- Croce, M.M., Lettau, M. and Ludvigson, S.C. (2009) Investor information, long-run risk, and the duration of risky cash flows, Working paper.
- Dangl, T., Wu, Y. and Zechner, J. (2008) Market discipline and internal governance in the mutual fund industry, *Review of Financial Studies* 21, 2307-2343.
- DeMarzo, P.M. and Fishman, M.J. (2007) Optimal long-term financial contracting, *Review of Financial Studies* 20, 2079-2128.
- Dow, J. and Gorton, G. (1997) Stock market efficiency and economic efficiency: is there a connection? *Journal of Finance* 52, 1087-1129.
- Eberly, J., Rebelo, S. and Vincent, N. (2009) Investment and value: a neoclassical benchmark, Working paper.
- Erickson, T. and Whited, T.M. (2000) Measurement error and the relationship between investment and q , *Journal of Political Economy* 108, 1027-1057.

- Erickson, T. and Whited, T.M. (2011) Treating Measurement Error in Tobins q , *Review of Financial Studies* forthcoming.
- Evans, D.S. (1987) Tests of alternative theories of firm growth, *Journal of Political Economy* 95, 657-674.
- Fama, E.F. and French, K. (1997) Industry costs of equity, *Journal of Financial Economics* 43, 153-193.
- Fazzari, S.M., Hubbard, R.G. and Petersen, B.C. (1988) Financing constraints and corporate investment, *Brookings Paper on Economic Activity* 1, 141-195.
- Gomes, J. (2001) Financing investment, *American Economic Review* 91, 1263-1285.
- Hall, B.H. (1987) The relationship between firm size and firm growth in the U.S. manufacturing sector, *Journal of Industrial Economics* 35, 583-606.
- Hayashi, F. (1982) Tobin's marginal and average q : A neoclassical interpretation, *Econometrica* 50, 213-224.
- Hennessy, C. and Whited, T. (2007) How costly is external financing? evidence from a structural estimation, *Journal of Finance* 62, 1705-1745.
- Hochberg, Y., Ljungqvist, A. and Vissing-Jorgensen, A. (2009) Informational hold-up and performance persistence in venture capital, Working paper.
- Hopenhayn, H. (1992) Entry, exit, and firm dynamics in long run equilibrium, *Econometrica* 60, 1127-1150.
- Johnson, T.C. (2004) Forecast dispersion and the cross section of expected returns, *Journal of Finance* 59, 1957-1978.
- Johnson, T.C. (2007) Optimal learning and new technology bubbles, *Journal of Monetary Economics* 54, 2486-2511.
- Jovanovic, B. (1982) Selection and the evolution of industry, *Econometrica* 50, 649-670.
- Lewellen, J. and Shanken, J. (2002) Learning, asset-pricing tests, and market efficiency, *Journal of Finance* 57, 1113-1145.
- Linnainmaa, J. (2011) Why do (some) households trade so much? *Review of Financial Studies* 24, 1630-1666.
- Luo, Y. (2005) Do insiders learn from outsiders? Evidence from mergers and acquisitions, *Journal of Finance* 60, 1951-1982.
- Marcet, A. and Marimon, R. (1992) Communication, commitment, and growth, *Journal of Economic Theory* 58, 219-249.
- Oliner, S.D. and Rudebusch, G.D. (1992) Sources of the financing hierarchy for business investment, *Review of Economics and Statistics* 74, 643-654.
- Pástor, L. and Veronesi, P. (2003) Stock valuation and learning about profitability, *Journal of Finance* 58, 1749-1789.

- Pástor, L. and Veronesi, P. (2009a) Learning in financial markets, *Annual Review of Financial Economics* 1, 361-381.
- Pástor, L. and Veronesi, P. (2009b) Technological revolutions and stock prices, *American Economic Review* 99, 1451-1483.
- Petersen, M.A. (2009) Estimating standard errors in finance panel data sets: comparing approaches, *Review of Financial Studies* 22, 435-480.
- Quadrini, V. (2003) Investment and liquidation in renegotiation-proof contracts with moral hazard, *Journal of Monetary Economics* 51, 713-751.
- Riddick, L. and Whited, T. (2009) The corporate propensity to save, *Journal of Finance* 64, 1729-1766.
- Salinger, M. and Summers, L. (1984) Tax reform and corporate investment: a microeconomic simulation study, NBER Working Paper No. 0757.
- Schiantarelli, F. (1996) Financial constraints and investment: a critical review of methodological issues and international evidence, *Oxford Review of Economic Policy* 12, 70-89.
- Sorensen, M. (2008) Learning by investing: evidence from venture capital, Working paper.
- Subrahmanyam, A. and Titman, S. (1999) The going-public decision and the development of financial markets, *Journal of Finance* 54, 1045-1082.
- Taylor, L.A. (2010) Why are CEOs rarely fired? Evidence from a structural estimation, *Journal of Finance* 65, 2051-2087.
- Veronesi, P. (1999) Stock market overreaction to bad news in good times: a rational expectations equilibrium model, *Review of Financial Studies* 12, 975-1007.
- Whited, T. (1992) Debt, liquidity constraints, and corporate investment: evidence from panel data, *Journal of Finance* 47, 1425-1460.
- Whited, T.M. and Wu, G. (2006) Financial constraints risk, *Review of Financial Studies* 19, 531-559.

Table I. Firm age regression results from simulated data

The table presents estimates from a panel regression on data simulated from the model. The regression is specified as in equation (15), where the dependent variable is investment (I/K) and the explanatory variables are two profit (Π/K) terms interacted with dummy variables for *young* and *mature* firms, Tobin's average Q , a dummy variable identifying *young* firms, and a constant. Panel-corrected standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	Interactions with Π/K
<i>Young</i> $\times (\Pi/K)$	0.224*** (0.003)
<i>Mature</i> $\times (\Pi/K)$	0.144*** (0.002)
Tobin's Q	0.351E-3 (0.472E-3)
<i>Young</i>	-0.113*** (0.003)
Intercept	0.010*** (0.004)
Difference in Π/K responses: p -value	
<i>Young</i> vs. <i>mature</i> firms	<0.001***
R^2	0.456

Table II. Firm age and industry volatility regression results from simulated data

The table presents estimates from a panel regression on data simulated from the model. The regression is specified as in equation (16), where the dependent variable is investment (I/K) and the explanatory variables are four profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, and in *high-volatility* industries, Tobin's average Q , two dummy variables identifying *young* firms and firms in *low-volatility* industries, and a constant. Panel-corrected standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	Interactions with Π/K
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times (\Pi/K)$	0.429*** (0.004)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times (\Pi/K)$	0.268*** (0.003)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times (\Pi/K)$	0.361*** (0.004)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times (\Pi/K)$	0.189*** (0.003)
Tobin's Q	-0.005*** (0.495E-3)
<i>Young</i>	-0.088*** (0.002)
In <i>low-volatility</i> industries	-0.212*** (0.002)
Intercept	0.056*** (0.004)
Differences in Π/K responses: p -values	
<i>Young</i> vs. <i>mature</i> firms	
In <i>low-volatility</i> industries	<0.001***
In <i>high-volatility</i> industries	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries	
<i>Young</i>	<0.001***
<i>Mature</i>	<0.001***
R^2	0.681

Table III. Firm age, industry volatility, and financial status regression results from simulated data

The table presents estimates from a panel regression on data simulated from the model. The regression is specified as in equation (12), where the dependent variable is investment (I/K) and the explanatory variables are eight profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, in *high-volatility* industries, *unconstrained*, and *constrained* firms, Tobin's average Q , three dummy variables identifying *young* firms, firms in *low-volatility* industries, and *unconstrained* firms, and a constant. Panel-corrected standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	Interactions with Π/K
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>unconstrained</i> $\times$ (Π/K)	0.524*** (0.004)
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>constrained</i> $\times$ (Π/K)	0.243*** (0.006)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>unconstrained</i> $\times$ (Π/K)	0.335*** (0.003)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>constrained</i> $\times$ (Π/K)	0.229*** (0.004)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>unconstrained</i> $\times$ (Π/K)	0.400*** (0.003)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>constrained</i> $\times$ (Π/K)	0.209*** (0.004)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>unconstrained</i> $\times$ (Π/K)	0.240*** (0.003)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>constrained</i> $\times$ (Π/K)	0.114*** (0.003)
Tobin's Q	0.009*** (0.673E-3)
<i>Young</i>	-0.064*** (0.003)
In <i>low-volatility</i> industries	-0.168*** (0.003)
<i>Unconstrained</i>	-0.175*** (0.003)
Intercept	0.014*** (0.005)
Differences in Π/K responses: p -values	
<i>Young</i> vs. <i>mature</i> firms	
In <i>low-volatility</i> industries, <i>unconstrained</i>	<0.001***
In <i>high-volatility</i> industries, <i>unconstrained</i>	<0.001***
In <i>low-volatility</i> industries, <i>constrained</i>	<0.001***
In <i>high-volatility</i> industry, <i>constrained</i>	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries	
<i>Young</i> , <i>unconstrained</i>	<0.001***
<i>Mature</i> , <i>unconstrained</i>	<0.001***
<i>Young</i> , <i>constrained</i>	<0.001***
<i>Mature</i> , <i>constrained</i>	<0.001***
<i>Unconstrained</i> vs. <i>constrained</i> firms	
<i>Young</i> , in <i>low-volatility</i> industries	<0.001***
<i>Mature</i> , in <i>low-volatility</i> industries	<0.001***
<i>Young</i> , in <i>high-volatility</i> industries	<0.001***
<i>Mature</i> , in <i>high-volatility</i> industries	<0.001***
R^2	0.797

Table IV. Composition of sample

The table contains observation and firm counts for each step of the construction of the sample. We count firms using the Compustat identifier *gvkey*.

	observations	firms
Number of records in the 2010 Compustat Industrial Annual file	411,765	31,533
–		
Number of records with missing fiscal year, or duplicates	24	0
=		
Number of unique records in the 2010 Compustat Industrial Annual file with non-missing fiscal year	411,741	31,533
–		
Number of records outside the period 1988-2009	165,245	5,880
=		
Number of records for the period 1988-2009	246,496	25,653
–		
Number of records with negative Total Assets, negative Net Sales, negative Tobin's Q	141,486	11,131
=		
Number of records with non-negative Total Assets, Net Sales, and Tobin's Q	105,010	14,522
–		
Number of records in regulated, financial, or quasi-public industries	10,094	1,563
=		
Number of records outside of the regulated, financial, or quasi-public industries	94,916	12,959
–		
Number of records with gross property, plant, and equipment of less than \$3 mil.	12,283	1,726
=		
Number of records with gross property, plant, and equipment of at least \$3 mil.	82,633	11,233
–		
Number of records with missing data for the construction of at least one regression variable	494	105
=		
Number of records with data for the construction of all regression variables	82,139	11,128
–		
Number of records with historical age of 3 years or less	3,631	525
=		
Number of records with historical age of more than 3 years and data for the construction of all regression variables	78,508	10,603
Number of records with data collected on their foundation date	59,825	5,611
Number of records for which the first year in Compustat is used as their foundation date	18,683	4,992

Table V. Descriptive statistics for different subsets of firms

Descriptive statistics are presented for investment (I/K), profit (Π/K), two Tobin's average Q measures – one using the replacement value of capital stock (RVCS) as denominator and the other using gross property, plant, and equipment (Gross PPE) – firm age, the industry median research and development expenses scaled by the beginning-of-the-period total assets, where industries are defined as in Fama and French (1997), firm size using total assets, gross property, plant and equipment (Gross PPE), and the replacement value of capital stock (RVCS), computed as in Salinger and Summers (1983), financial status using Whited and Wu's (2006) (WW) index, and the long term debt-to-total assets ratio.

	entire sample	low volatility				high volatility				more constrained			
		young	mature	low volatility	high volatility	less constrained	more constrained	distressed		less constrained	more constrained	distressed	
Investment (I/K)	0.297	0.524	0.219	0.255	0.357	0.251	0.309	0.236					
Profit (Π/K)	0.163	0.461	0.303	0.245	0.564	0.278	0.504	-0.851					
Tobin's Q (RVCS)	5.379	7.954	3.561	2.562	9.512	3.102	7.158	6.945					
Tobin's Q (Gross PPE)	2.814	3.534	1.870	1.544	4.463	1.730	3.294	3.494					
Age	5.500	1.500	8.000	6.000	6.000	7.400	5.000	4.000					
Ind. R&D intensity	0.045	0.043	0.027	0.000	0.090	0.013	0.069	0.104					
Total assets (\$MM)	122.304	147.441	180.629	243.612	116.266	813.839	29.568	45.936					
Gross PPE (\$MM)	48.450	49.748	81.885	142.118	34.990	444.734	9.807	16.470					
RVCS (\$MM)	23.600	21.741	42.317	81.049	14.490	236.762	4.509	8.558					
WW index	-0.136	-0.140	-0.165	-0.181	-0.114	-0.257	-0.064	-0.064					
LT Debt/TA ratio	0.138	0.152	0.151	0.208	0.080	0.232	0.057	0.064					
No. of observations	78,508	14,889	49,170	26,680	21,661	32,325	11,836	14,449					

	low volatility				high volatility			
	young	mature	low volatility	high volatility	young	mature	low volatility	high volatility
Investment (I/K)	0.489	0.192	0.602	0.273				
Profit (Π/K)	0.325	0.221	0.795	0.495				
Tobin's Q (RVCS)	4.154	2.150	17.070	6.987				
Tobin's Q (Gross PPE)	2.057	1.333	7.005	3.321				
Age	1.500	8.000	1.500	8.000				
Ind. R&D intensity	0.000	0.000	0.102	0.084				
Total assets (\$MM)	201.833	260.080	106.026	117.748				
Gross PPE (\$MM)	106.158	152.955	27.064	41.724				
RVCS (\$MM)	56.375	89.286	10.219	17.075				
WW index	-0.153	-0.188	-0.094	-0.120				
LT Debt/TA ratio	0.222	0.203	0.065	0.082				
No. of observations	6,472	20,208	5,758	15,903				

	less constrained				more constrained			
	young	mature	low volatility	high volatility	young	mature	low volatility	high volatility
Investment (I/K)	0.426	0.195	0.619	0.255	0.510	0.188	0.518	0.246
Profit (Π/K)	0.301	0.222	0.642	0.408	0.490	0.297	0.724	0.536
Tobin's Q (RVCS)	3.326	2.153	10.998	4.873	7.362	3.011	14.029	7.743
Tobin's Q (Gross PPE)	1.701	1.316	5.116	2.482	3.048	1.477	6.135	3.233
Age	1.500	9.000	1.500	11.167	1.333	7.500	1.500	8.000
Ind. R&D intensity	0.000	0.000	0.080	0.058	0.000	0.000	0.108	0.103
Total assets (\$MM)	757.693	840.387	709.306	974.201	28.518	23.016	32.575	31.605
Gross PPE (\$MM)	516.818	542.478	242.583	423.853	9.757	10.867	8.452	9.933
RVCS (\$MM)	258.551	323.637	105.032	201.766	4.562	5.821	3.492	4.014
WW index	-0.219	-0.260	-0.224	-0.251	-0.077	-0.076	-0.003	-0.013
LT Debt/TA ratio	0.290	0.245	0.176	0.159	0.099	0.099	0.035	0.028
No. of observations	3,004	12,271	1,366	6,259	1,025	2,231	1,928	4,542

Table VII. p -values of J -tests of overidentifying restrictions of various model specifications

The J -test of overidentifying restrictions is applied to each cross-section of firms for each of the GMM estimators utilizing moments of fourth and higher order. Consequently, the test produces twenty-two statistics corresponding to the twenty-two years of the sample period from 1988 to 2009. The table reports twenty-two p -values for each of the GMM estimators using moments of fourth (and fifth) order, for each of the specifications presented in Tables VIII to XI.

Year	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Table VIII. Firm age regression results																						
GMM(4)	0.041	0.319	0.755	0.326	0.982	0.001	0.002	0.491	0.028	<0.001	0.022	0.066	0.255	0.202	0.818	0.018	0.343	0.565	0.021	0.156	0.014	0.014
Table IX. Firm age and industry volatility regression results																						
GMM(4)	0.255	0.180	0.238	0.372	0.814	0.002	0.002	0.313	0.167	0.006	0.017	0.015	0.046	0.935	0.629	0.017	0.017	0.379	0.749	0.049	0.372	0.035
Table X. Firm age, industry volatility, and financial status regression results (and GMM5 from Table XI)																						
GMM(4)	0.353	0.417	0.533	0.125	0.897	0.019	0.054	0.592	0.521	0.077	0.439	0.558	0.136	0.707	0.518	0.519	0.466	0.193	0.831	0.256	0.960	0.353
GMM5	0.135	0.330	0.305	0.206	0.255	0.034	0.054	0.040	0.124	0.010	0.299	0.151	0.003	0.271	0.681	0.236	0.357	0.510	0.955	0.186	0.973	0.362

Table VIII. Firm age regression results

The table presents OLS and GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. The regressions are specified as in equation (15) augmented with a dummy variable for firms with *negative income* as in equation (14). The dependent variable is investment (I/K) and the explanatory variables are two profit terms (Π/K) interacted with dummy variables for *young*, and *mature* firms, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, two dummy variables identifying *young* firms and firms with *negative income*, as well as a constant. Firms within three years of a major change (at least 75%) in capital stock are considered *young*, while the rest of the firms are considered *mature* (except for firms within three years of foundation which are excluded from the sample). Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth (1973) standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	OLS	GMM
Interactions with Π/K		
<i>Young</i> $\times (\Pi/K)$	0.069*** (0.008)	0.017** (0.007)
<i>Mature</i> $\times (\Pi/K)$	0.048*** (0.005)	-0.024*** (0.007)
<i>Negative income</i> $\times (\Pi/K)$	-0.011*** (0.003)	0.026*** (0.003)
Tobin's Q	0.011*** (4.0E-4)	0.021*** (0.001)
<i>Young</i>	0.231*** (0.014)	0.177*** (0.013)
<i>Negative income</i>	-0.080*** (0.004)	-0.091*** (0.006)
Intercept	0.162*** (0.004)	0.125*** (0.005)
No. of observations	78,508	78,508
Difference in Π/K responses: p -values		
<i>Young</i> vs. <i>mature</i> firms	0.001***	<0.001***

Table IX. Firm age and industry volatility regression results

The table presents OLS and GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. The regressions are specified as in equation (16) augmented with a dummy variable for firms with *negative income* as in equation (14). The dependent variable is investment (I/K) and the explanatory variables are four profit terms (Π/K) interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, and in *high-volatility* industries, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, three dummy variables identifying *young* firms, firms in *low-volatility* industries, and firms with *negative income*, as well as a constant. Firms within three years of a major change (at least 75%) in capital stock are considered *young*, while the rest of the firms are considered *mature* (except for firms within three years of foundation which are excluded from the sample). Industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest median R&D intensity are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	OLS	GMM
	Interactions with Π/K	
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ (Π/K)	0.093*** (0.010)	0.040*** (0.008)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ (Π/K)	0.055*** (0.009)	-0.007 (0.005)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ (Π/K)	0.061*** (0.007)	-0.013 (0.009)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ (Π/K)	0.040*** (0.007)	-0.043*** (0.007)
<i>Negative income</i> $\times$ (Π/K)	-0.012*** (0.004)	0.029*** (0.004)
Tobin's Q	0.011*** (4.0E-4)	0.023*** (0.001)
<i>Young</i>	0.227*** (0.014)	0.162*** (0.012)
In <i>low-volatility</i> industries	0.017* (0.009)	0.092*** (0.016)
<i>Negative income</i>	-0.087*** (0.005)	-0.082*** (0.008)
Intercept	0.161*** (0.004)	0.065*** (0.014)
No. of observations	60,803	60,803
Differences in Π/K responses: p -values		
<i>Young</i> vs. <i>mature</i> firms		
In <i>low-volatility</i> industries	0.003***	<0.001***
In <i>high-volatility</i> industries	0.007***	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries		
<i>Young</i>	<0.001***	<0.001***
<i>Mature</i>	0.002***	0.001***

Table X. Firm age, industry volatility, and financial status regression results

The table presents OLS and GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. The regressions are specified as in equation (14), where the dependent variable is investment (I/K) and the explanatory variables are eight profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, in *high-volatility* industries, *less-constrained*, and *more-constrained* firms, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, four dummy variables identifying *young* firms, firms in *low-volatility* industries, *less-constrained* firms, and firms with *negative income*, as well as a constant. Firms within three years of a major change (at least 75%) in capital stock are considered *young*, while the rest of the firms are considered *mature* (except for firms within three years of foundation which are excluded from the sample). Industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest median R&D intensity are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firms in the lower one third of each year's distribution of total assets and each year's distribution of capital stock are considered *more-constrained*, while firms in the higher half of each year's distribution of total assets and each year's distribution of capital stock are considered *less-constrained*. Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	OLS	GMM
	Interactions with Π/K	
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	0.151*** (0.019)	0.085*** (0.016)
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.120*** (0.014)	0.050*** (0.014)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	0.117*** (0.020)	-0.006 (0.023)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.072*** (0.011)	0.006 (0.008)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	0.101*** (0.013)	-0.033** (0.014)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.074*** (0.009)	0.011 (0.010)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	0.067*** (0.015)	-0.095*** (0.021)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.046*** (0.008)	-0.037*** (0.008)
<i>Negative income</i> $\times$ (Π/K)	-0.012*** (0.005)	0.040*** (0.007)
Tobin's Q	0.010*** (4.0E-4)	0.026*** (0.001)
<i>Young</i>	0.208*** (0.014)	0.140*** (0.013)
In <i>low-volatility</i> industries	0.011 (0.008)	0.071*** (0.013)
<i>Less-constrained</i>	0.020*** (0.005)	0.069*** (0.010)
<i>Negative income</i>	-0.067*** (0.005)	-0.063*** (0.010)
Intercept	0.139*** (0.005)	0.023 (0.016)
No. of observations	41,052	41,052
Differences in Π/K responses: p -values		
<i>Young</i> vs. <i>mature</i> firms		
In <i>low-volatility</i> industries, <i>less-constrained</i>	0.006***	<0.001***
In <i>low-volatility</i> industries, <i>more-constrained</i>	0.002***	0.009***
In <i>high-volatility</i> industries, <i>less-constrained</i>	0.001***	<0.001***
In <i>high-volatility</i> industries, <i>more-constrained</i>	0.014**	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries		
<i>Young</i> , <i>less-constrained</i>	0.077*	0.001***
<i>Young</i> , <i>more-constrained</i>	0.001***	0.006***
<i>Mature</i> , <i>less-constrained</i>	0.003***	<0.001***
<i>Mature</i> , <i>more-constrained</i>	0.005***	<0.001***
<i>Less-constrained</i> vs. <i>more-constrained</i> firms		
<i>Young</i> , in <i>low-volatility</i> industries	0.100*	0.059*
<i>Young</i> , in <i>high-volatility</i> industries	0.009***	0.716
<i>Mature</i> , in <i>low-volatility</i> industries	0.020**	0.994
<i>Mature</i> , in <i>high-volatility</i> industries	0.059*	0.997

Table XI. Robustness results using alternative measurement error-consistent estimators with up to third, fourth, and fifth order moments

The table presents GMM estimates, using the Erickson and Whited (2000) model with up to third, fourth, and fifth order moments. The regressions are specified as in equation (14), where the dependent variable is investment (I/K) and the explanatory variables are eight profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, in *high-volatility* industries, *less-constrained*, and *more-constrained* firms, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, four dummy variables identifying *young* firms, firms in *low-volatility* industries, *less-constrained* firms, and firms with *negative income*, as well as a constant. Firms within three years of a major change (at least 75%) in capital stock are considered *young*, while the rest of the firms are considered *mature* (except for firms within three years of foundation which are excluded from the sample). Industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest median R&D intensity are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firms in the lower one third of each year's distribution of total assets and each year's distribution of capital stock are considered *more-constrained*, while firms in the higher half of each year's distribution of total assets and each year's distribution of capital stock are considered *less-constrained*. Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

	GMM3	GMM4	GMM5
Interactions with Π/K			
<i>Young</i> × in <i>low-volatility</i> industries × <i>less-constrained</i> × (Π/K)	0.092*** (0.017)	0.085*** (0.016)	0.080*** (0.016)
<i>Young</i> × in <i>low-volatility</i> industries × <i>more-constrained</i> × (Π/K)	0.060*** (0.013)	0.050*** (0.014)	0.049*** (0.013)
<i>Young</i> × in <i>high-volatility</i> industries × <i>less-constrained</i> × (Π/K)	0.005 (0.025)	-0.006 (0.023)	-0.013 (0.020)
<i>Young</i> × in <i>high-volatility</i> industries × <i>more-constrained</i> × (Π/K)	0.014 (0.009)	0.006 (0.008)	0.001 (0.007)
<i>Mature</i> × in <i>low-volatility</i> industries × <i>less-constrained</i> × (Π/K)	-0.020 (0.017)	-0.033** (0.014)	-0.039*** (0.011)
<i>Mature</i> × in <i>low-volatility</i> industries × <i>more-constrained</i> × (Π/K)	0.019* (0.010)	0.011 (0.010)	0.006 (0.011)
<i>Mature</i> × in <i>high-volatility</i> industries × <i>less-constrained</i> × (Π/K)	-0.078*** (0.024)	-0.095*** (0.021)	-0.102*** (0.017)
<i>Mature</i> × in <i>high-volatility</i> industries × <i>more-constrained</i> × (Π/K)	-0.028*** (0.009)	-0.037*** (0.008)	-0.044*** (0.008)
<i>Negative income</i> × (Π/K)	0.034*** (0.007)	0.040*** (0.007)	0.043*** (0.006)
Tobin's Q	0.024*** (0.001)	0.026*** (0.001)	0.027*** (0.001)
<i>Young</i>	0.147*** (0.014)	0.140*** (0.013)	0.137*** (0.013)
In <i>low-volatility</i> industries	0.068*** (0.014)	0.071*** (0.013)	0.071*** (0.013)
<i>Less-constrained</i>	0.064*** (0.010)	0.069*** (0.010)	0.071*** (0.009)
<i>Negative income</i>	-0.061*** (0.009)	-0.063*** (0.010)	-0.064*** (0.009)
Intercept	0.031* (0.016)	0.023 (0.016)	0.021 (0.015)
No. of observations	41,052	41,052	41,052
Differences in Π/K responses: p -values			
<i>Young</i> vs. <i>mature</i> firms			
In <i>low-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***
In <i>low-volatility</i> industries, <i>more-constrained</i>	0.006***	0.009***	0.006***
In <i>high-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***
In <i>high-volatility</i> industries, <i>more-constrained</i>	<0.001***	<0.001***	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries			
<i>Young</i> , <i>less-constrained</i>	0.001***	0.001***	<0.001***
<i>Young</i> , <i>more-constrained</i>	0.004***	0.006***	0.003***
<i>Mature</i> , <i>less-constrained</i>	<0.001***	<0.001***	<0.001***
<i>Mature</i> , <i>more-constrained</i>	0.001***	<0.001***	<0.001***
<i>Less-constrained</i> vs. <i>more-constrained</i> firms			
<i>Young</i> , in <i>low-volatility</i> industries	0.074*	0.059*	0.079*
<i>Young</i> , in <i>high-volatility</i> industries	0.660	0.716	0.759
<i>Mature</i> , in <i>low-volatility</i> industries	0.982	0.994	0.995
<i>Mature</i> , in <i>high-volatility</i> industries	0.991	0.997	0.998

Table XII. Robustness results using alternative measures of firm age

The table presents GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. The regressions are specified as in equation (14), where the dependent variable is investment (I/K) and the explanatory variables are eight profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, in *high-volatility* industries, *less-constrained*, and *more-constrained* firms, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, four dummy variables identifying *young* firms, firms in *low-volatility* industries, *less-constrained* firms, and firms with *negative income*, as well as a constant. Firms within three (or four, or two) years of a major change (at least 75%, or 100%, or 50%) in capital stock are considered *young*, while the rest of the firms are considered *mature* (except for firms within three or four or two years of foundation which are excluded from the sample). Industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest median R&D intensity are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firms in the lower one third of each year's distribution of total assets and each year's distribution of capital stock are considered *more-constrained*, while firms in the higher half of each year's distribution of total assets and each year's distribution of capital stock are considered *less-constrained*. Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

Identified as <i>young</i> if age is:	≤ 4 years	≤ 2 years	≤ 3 years	≤ 3 years
Firm age from:	$\frac{\Delta K}{K} > 0.75$	$\frac{\Delta K}{K} > 0.75$	$\frac{\Delta K}{K} > 1$	$\frac{\Delta K}{K} > 0.5$
Interactions with Π/K				
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	0.085*** (0.021)	0.091*** (0.015)	0.114*** (0.021)	0.070*** (0.013)
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.056*** (0.015)	0.054*** (0.014)	0.051*** (0.015)	0.040*** (0.013)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	-0.022 (0.022)	-0.001 (0.023)	0.005 (0.024)	-0.037* (0.022)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	-3.0E-4 (0.009)	0.006 (0.011)	0.017 (0.011)	-0.004 (0.005)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	-0.051*** (0.014)	-0.024* (0.013)	-0.027* (0.014)	-0.052*** (0.015)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	0.005 (0.013)	0.019* (0.010)	0.018* (0.011)	0.012 (0.012)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constrained</i> $\times$ (Π/K)	-0.112*** (0.022)	-0.081*** (0.021)	-0.084*** (0.021)	-0.099*** (0.021)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constrained</i> $\times$ (Π/K)	-0.045*** (0.009)	-0.027*** (0.007)	-0.034*** (0.008)	-0.045*** (0.008)
<i>Negative income</i> $\times$ (Π/K)	0.044*** (0.006)	0.037*** (0.005)	0.039*** (0.006)	0.041*** (0.007)
Tobin's Q	0.026*** (0.002)	0.025*** (0.001)	0.025*** (0.001)	0.026*** (0.001)
<i>Young</i>	0.107*** (0.012)	0.198*** (0.015)	0.152*** (0.014)	0.125*** (0.011)
In <i>low-volatility</i> industries	0.069*** (0.013)	0.073*** (0.013)	0.071*** (0.014)	0.073*** (0.013)
<i>Less-constrained</i>	0.072*** (0.009)	0.069*** (0.010)	0.069*** (0.010)	0.070*** (0.010)
<i>Negative income</i>	-0.066*** (0.009)	-0.055*** (0.008)	-0.061*** (0.010)	-0.060*** (0.010)
Intercept	0.023 (0.015)	0.022 (0.016)	0.029* (0.016)	0.009 (0.015)
No. of observations	39,761	42,014	41,052	41,052
Differences in Π/K responses: p -values				
<i>Young</i> vs. <i>mature</i> firms				
In <i>low-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***
In <i>low-volatility</i> industries, <i>more-constrained</i>	0.003***	0.009***	0.035**	0.047**
In <i>high-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***
In <i>high-volatility</i> industries, <i>more-constrained</i>	0.001***	0.004***	0.001***	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries				
<i>Young</i> , <i>less-constrained</i>	<0.001***	<0.001***	0.001***	<0.001***
<i>Young</i> , <i>more-constrained</i>	0.003***	0.008***	0.043**	0.002***
<i>Mature</i> , <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	0.001***
<i>Mature</i> , <i>more-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***
<i>Less-constrained</i> vs. <i>more-constrained</i> firms				
<i>Young</i> , in <i>low-volatility</i> industries	0.091*	0.058*	0.010*	0.066*
<i>Young</i> , in <i>high-volatility</i> industries	0.860	0.611	0.708	0.949
<i>Mature</i> , in <i>low-volatility</i> industries	0.999	0.997	0.995	0.998
<i>Mature</i> , in <i>high-volatility</i> industries	0.999	0.996	0.992	0.996

Table XIII. Robustness results using alternative criteria to identify *young* firms

The table presents GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. The regressions are specified as in equation (14), where the dependent variable is investment (I/K) and the explanatory variables are eight profit (Π/K) terms interacted with dummy variables for *young*, *mature*, in *low-volatility* industries, in *high-volatility* industries, *less-constrained*, and *more-constrained* firms, a profit (Π/K) term interacted with a dummy variable for firms with *negative income*, Tobin's average Q , measured as the market value of equity plus total long-term debt minus inventories all divided by the replacement value of capital stock, four dummy variables identifying *young* firms, firms in *low-volatility* industries, *less-constrained* firms, and firms with *negative income*, as well as a constant. In the first column, we augment the definition of *young* firms to include not only those within three years of a major change (at least 75%) in capital stock, but also those within three years of their foundation. In the second column, we consider only the firms for which we were able to find the year of foundation. In the third and fourth columns we alternatively use the Field-Ritter foundation year data and the first year in Compustat to proxy for the foundation years of the firms. In the fifth column, we define *young* firms as those within seven years of their foundation and exclude all firms within seven years of a major change (at least 75%) in capital stock. Across all columns, industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest median R&D intensity are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firms in the lower one third of each year's distribution of total assets and each year's distribution of capital stock are considered *more-constrained*, while firms in the higher half of each year's distribution of total assets and each year's distribution of capital stock are considered *less-constrained*. Firm-year observations with negative operating income before depreciation are considered *negative income*. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

Firm age based on:	≤ 3 years from foundation or major project	Foundation date known	Foundation as Field-Ritter	Foundation as 1 st year in Compustat	≤ 7 years from foundation
Interactions with Π/K					
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constr.</i> $\times (\Pi/K)$	0.091*** (0.015)	0.083*** (0.021)	0.091*** (0.016)	0.092*** (0.015)	0.171*** (0.033)
<i>Young</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constr.</i> $\times (\Pi/K)$	0.060*** (0.014)	0.061*** (0.016)	0.062*** (0.014)	0.059*** (0.013)	0.030** (0.015)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constr.</i> $\times (\Pi/K)$	-0.005 (0.024)	-0.007 (0.021)	-0.005 (0.024)	-0.008 (0.023)	0.082 (0.056)
<i>Young</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constr.</i> $\times (\Pi/K)$	0.009 (0.009)	0.022** (0.010)	0.010 (0.009)	0.003 (0.008)	-0.036** (0.014)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>less-constr.</i> $\times (\Pi/K)$	-0.040** (0.016)	-0.038*** (0.011)	-0.038** (0.016)	-0.043*** (0.016)	-0.035 (0.026)
<i>Mature</i> $\times$ in <i>low-volatility</i> industries $\times$ <i>more-constr.</i> $\times (\Pi/K)$	0.006 (0.011)	0.001 (0.012)	0.005 (0.011)	0.012 (0.012)	-0.022 (0.013)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>less-constr.</i> $\times (\Pi/K)$	-0.094*** (0.022)	-0.103*** (0.018)	-0.095*** (0.022)	-0.093*** (0.023)	-0.107*** (0.029)
<i>Mature</i> $\times$ in <i>high-volatility</i> industries $\times$ <i>more-constr.</i> $\times (\Pi/K)$	-0.035*** (0.007)	-0.040*** (0.008)	-0.037*** (0.007)	-0.031*** (0.008)	-0.056*** (0.011)
<i>Negative income</i> $\times (\Pi/K)$	0.034*** (0.006)	0.050*** (0.009)	0.034*** (0.006)	0.034*** (0.006)	0.038*** (0.007)
Tobin's Q	0.026*** (0.001)	0.025*** (0.001)	0.026*** (0.001)	0.026*** (0.001)	0.027*** (0.001)
<i>Young</i>	0.140*** (0.013)	0.125*** (0.012)	0.129*** (0.012)	0.118*** (0.012)	0.084*** (0.012)
In <i>low-volatility</i> industries	0.081*** (0.014)	0.059*** (0.011)	0.081*** (0.014)	0.084*** (0.014)	0.083*** (0.015)
<i>Less-constrained</i>	0.071*** (0.011)	0.062*** (0.007)	0.071*** (0.011)	0.070*** (0.011)	0.041*** (0.011)
<i>Negative income</i>	-0.058*** (0.009)	-0.069*** (0.010)	-0.057*** (0.009)	-0.055*** (0.009)	-0.051*** (0.011)
Intercept	0.015 (0.016)	0.037*** (0.011)	0.014 (0.017)	0.012 (0.016)	0.031** (0.015)
No. of observations	42,378	31,789	42,378	42,378	29,322
Differences in Π/K responses: p -values					
<i>Young</i> vs. <i>mature</i> firms					
In <i>low-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
In <i>low-volatility</i> industries, <i>more-constrained</i>	0.001***	<0.001***	0.001***	0.002***	0.011**
In <i>high-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
In <i>high-volatility</i> industries, <i>more-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***	0.068*
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries					
<i>Young</i> , <i>less-constrained</i>	0.001***	0.002***	0.001***	<0.001***	0.047**
<i>Young</i> , <i>more-constrained</i>	0.003***	0.029**	0.003***	0.001***	0.001***
<i>Mature</i> , <i>less-constrained</i>	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
<i>Mature</i> , <i>more-constrained</i>	0.001***	0.002***	0.002***	0.001***	0.017**
<i>Less-constrained</i> vs. <i>more-constrained</i> firms					
<i>Young</i> , in <i>low-volatility</i> industries	0.077*	0.211	0.097*	0.059*	0.001***
<i>Young</i> , in <i>high-volatility</i> industries	0.738	0.915	0.747	0.700	0.021**
<i>Mature</i> , in <i>low-volatility</i> industries	0.994	0.990	0.989	0.999	0.682
<i>Mature</i> , in <i>high-volatility</i> industries	0.997	0.999	0.996	0.997	0.960

Table XIV. Robustness results using alternative measures of industry volatility, financial status, capital stock, and negative income

The table presents GMM estimates, using the Erickson and Whited (2000) model with up to fourth order moments. Industries in the top two quintiles out of the 48 industries, defined in Fama and French (1997), with the highest standard deviation of profits, in the first column, with the smallest median industry age, in the second column, and with the highest median R&D intensity, in columns three through six, are considered *high-volatility* industries, while industries in the bottom two quintiles are considered *low-volatility* industries. Firms with credit rating in a given year, in the third column, and firms in the bottom one half of each year's distribution of Whited and Wu's (2006) index, in the fourth column, are considered *less-constrained*, while firms without credit rating, in the third column, and firms in the top one third of each year's distribution of Whited and Wu's (2006) index, in the fourth column, are considered *more-constrained*. In the first, second, fifth, and sixth columns, firms in the top half of each year's distribution of total assets and each year's distribution of capital stock are considered *less-constrained*, while firms in the bottom one third of each year's distribution of total assets and each year's distribution of capital stock, are considered *more-constrained*. In the fifth column, the replacement value of capital stock is measured as in Bakke and Whited (2010), by the gross property, plant, and equipment, while in the rest of the columns it is measured as in Salinger and Summers (1983). Firm-year observations with negative operating income before depreciation (*OI*) are considered *negative income* in the first through the fifth columns, while firm-year observations with negative profits are considered *negative income* in the sixth column. Fama-MacBeth standard errors are in parenthesis. ***, **, and * indicate significance at the one, five, and ten percent levels.

Industry volatility measured using:	$\sigma(\Pi/K)$	industry age	ind. R&D	int. ind. R&D	int. ind. R&D	int. ind. R&D
Financial status measured by:	firm size	firm size	credit rating	WW index	firm size	firm size
Capital stock measured by:	<i>RVCS</i>	<i>RVCS</i>	<i>RVCS</i>	<i>RVCS</i>	Gross <i>PPE</i>	<i>RVCS</i>
Negative income status measure by:	<i>OI</i> < 0	<i>OI</i> < 0	<i>OI</i> < 0	<i>OI</i> < 0	<i>OI</i> < 0	Π/K < 0
Interactions with Π/K						
<i>Young</i> × in <i>low-volatility</i> ind. × <i>less-constr.</i> × (Π/K)	0.082*** (0.018)	0.002 (0.022)	0.053*** (0.019)	0.016 (0.014)	0.084*** (0.016)	0.058*** (0.019)
<i>Young</i> × in <i>low-volatility</i> ind. × <i>more-constr.</i> × (Π/K)	0.070*** (0.023)	0.075*** (0.017)	0.020 (0.013)	0.076*** (0.019)	0.060*** (0.027)	0.030 (0.021)
<i>Young</i> × in <i>high-volatility</i> ind. × <i>less-constr.</i> × (Π/K)	-0.021 (0.021)	-0.001 (0.021)	-0.022* (0.013)	-0.014 (0.012)	-0.007 (0.022)	-0.049* (0.026)
<i>Young</i> × in <i>high-volatility</i> ind. × <i>more-constr.</i> × (Π/K)	0.003 (0.008)	-0.002 (0.009)	-0.020*** (0.007)	-0.022*** (0.007)	-0.005 (0.015)	-0.023* (0.012)
<i>Mature</i> × in <i>low-volatility</i> ind. × <i>less-constr.</i> × (Π/K)	-0.029*** (0.010)	-0.056*** (0.015)	-0.031*** (0.011)	-0.031*** (0.009)	-0.016 (0.016)	-0.081*** (0.017)
<i>Mature</i> × in <i>low-volatility</i> ind. × <i>more-constr.</i> × (Π/K)	0.011 (0.020)	-0.001 (0.018)	-0.020* (0.010)	0.007 (0.014)	-0.018 (0.017)	-0.015 (0.013)
<i>Mature</i> × in <i>high-volatility</i> ind. × <i>less-constr.</i> × (Π/K)	-0.100** (0.019)	-0.105*** (0.019)	-0.041*** (0.014)	-0.063*** (0.009)	-0.071*** (0.018)	-0.141*** (0.023)
<i>Mature</i> × in <i>high-volatility</i> ind. × <i>more-constr.</i> × (Π/K)	-0.034*** (0.009)	-0.043* (0.011)	-0.056*** (0.008)	-0.045** (0.007)	-0.055*** (0.017)	-0.075*** (0.014)
<i>Negative income</i> × (Π/K)	0.044*** (0.007)	0.052*** (0.009)	0.034*** (0.005)	0.035*** (0.004)	0.036*** (0.007)	0.046*** (0.006)
Tobin's <i>Q</i>	0.026*** (0.001)	0.027*** (0.002)	0.024*** (0.001)	0.023*** (0.001)	0.020*** (0.001)	0.027*** (0.001)
<i>Young</i>	0.141*** (0.014)	0.151*** (0.015)	0.138*** (0.013)	0.155*** (0.013)	0.083*** (0.008)	0.135*** (0.012)
In <i>low-volatility</i> industries	0.053*** (0.012)	-0.004 (0.006)	0.089*** (0.0018)	0.084*** (0.014)	0.046*** (0.007)	0.059*** (0.011)
<i>Less-constrained</i>	0.073*** (0.010)	0.090*** (0.011)	-0.007 (0.006)	0.023*** (0.006)	0.022*** (0.003)	0.075*** (0.009)
<i>Negative income</i>	-0.064*** (0.010)	-0.056*** (0.008)	-0.081*** (0.008)	-0.086*** (0.007)	-0.022*** (0.006)	-0.081*** (0.006)
Intercept	0.019 (0.016)	0.043*** (0.011)	0.065*** (0.015)	0.053*** (0.012)	0.033*** (0.007)	0.047*** (0.011)
No. of observations	41,434	42,039	51,298	49,243	51,442	41,053
Differences in Π/K responses: <i>p</i> -values						
<i>Young</i> vs. <i>mature</i> firms						
In <i>low-volatility</i> industries, <i>less-constrained</i>	<0.001***	0.003***	0.002***	0.002***	<0.001***	<0.001***
In <i>low-volatility</i> industries, <i>more-constrained</i>	0.025**	<0.001***	0.008***	0.006***	0.006***	0.010**
In <i>high-volatility</i> industries, <i>less-constrained</i>	<0.001***	<0.001***	0.140	<0.001***	<0.001***	<0.001***
In <i>high-volatility</i> industries, <i>more-constrained</i>	0.001***	0.003***	<0.001***	0.003***	0.001***	<0.001***
Firms in <i>low-volatility</i> vs. <i>high-volatility</i> industries						
<i>Young</i> , <i>less-constrained</i>	<0.001***	0.459	<0.001***	0.011**	<0.001***	<0.001***
<i>Young</i> , <i>more-constrained</i>	0.004***	<0.001***	<0.001***	<0.001***	0.006***	0.005***
<i>Mature</i> , <i>less-constrained</i>	<0.001***	<0.001***	0.287	0.009***	<0.001***	<0.001***
<i>Mature</i> , <i>more-constrained</i>	0.019**	0.017**	<0.001***	<0.001***	0.022**	<0.001***
<i>Less-constrained</i> vs. <i>more-constrained</i> firms						
<i>Young</i> , in <i>low-volatility</i> industries	0.320	0.993	0.059*	0.988	0.203	0.157
<i>Young</i> , in <i>high-volatility</i> industries	0.904	0.479	0.578	0.310	0.557	0.858
<i>Mature</i> , in <i>low-volatility</i> industries	0.936	0.986	0.773	0.996	0.447	0.999
<i>Mature</i> , in <i>high-volatility</i> industries	0.999	0.999	0.183	0.992	0.827	0.999