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Research and development, profits, and firm value: A structural estimation

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This study presents a model in which firms invest in research and development (R&D) to generate innovations that increase their underlying profitability and invest in physical capital to produce output. Estimating the model using a method of moments approach reveals that R&D expenditures contribute significantly to profits and firm value. The model also captures variation in R&D intensity, profits, and firm value across R&D-intensive industries. Counterfactual experiments suggest that changes in the distribution of firms in the economy may, over the long run, mitigate tax policy changes designed to encourage R&D expenditures.

Keywords. Research and development, structural estimation, firm dynamics, policy evaluation.

JEL classification. D22, O3.

1. Introduction

Following the seminal article by Griliches (1979), the empirical research and development (R&D) literature has yielded many insights about the importance of R&D expenditures in understanding both firm behavior and overall economic growth. Although the literature acknowledges limitations of production-function-based regressions (see Hall and Mairesse (1995) and Griliches (2000)), it remains the main approach used in empirical R&D studies. Recently, a burgeoning literature has developed that examines the role of R&D using new models (for examples, see Xu (2008), Aw, Roberts, and Xu (2011), Bloom, Schankerman, and van Reenen (2013), and Doraszelski and Jaumandreu (2013)). This paper adds to the literature by estimating a model where firms invest in R&D so as to generate innovations that increase profitability and invest in physical capital to produce output. The estimated model is used to evaluate the response of firms to an increase in the R&D tax credit, both in the short run and across steady states.

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The underlying model used in the estimation in this paper builds on the endogenous growth literature, which emphasizes the role of R&D in generating innovations and economic growth.[1] Firms invest in R&D to increase the probability of innovations, which lead to increases in the underlying profitability process that fade over time. Firms produce output using capital and labor, and, as such, respond to successful innovations with new physical investment. Thus, the model takes into account both the impact of R&D expenditures on profitability as well as the interaction between R&D expenditures and physical investment (see Lach and Schankerman (1989)). One additional feature of the model is that the innovation probability is a function of the accumulated R&D stock, implying that current R&D expenditures influence the probability of innovations in future years.

The model is estimated using the simulated method of moments (see Gourieroux, Monfort, and Renault (1993)). This approach involves matching means, variances, and autocorrelations of and correlations between variables of interest from the data with the corresponding model counterparts. The approach sidesteps difficulties caused by the fact that the model's first-order conditions are not expressed in terms of observable variables. One benefit of this approach is that it yields a joint estimate of all the model parameters of interest.

The data set used in the estimation is derived from the Compustat data base. The sample is restricted to nonfinancial firms that consistently report R&D expenses. The main variables of interest in the estimation are R&D intensity, measured as R&D expenses divided by sales, Tobin's q, measured as the market value of the firm divided by the replacement cost of capital, and profitability, measured as operating income divided by capital. An examination of the data indicates that firms in the sample have, on average, high R&D intensities. These firms also have high Tobin's q values that cannot be justified solely based on investment frictions, suggesting that R&D investment plays an important role in understanding their profits and firm values.

The estimates reveal that R&D expenditures have an economically and statistically significant impact on profits and firm value. The findings imply that firms obtain jumps in profitability from successful innovations in most periods. On average, firms expect their R&D expenditures to generate about an 18.5% increase in the underlying profitability process. These profitability increases are also quite persistent. The large persistent expected profitability increases arising from R&D expenditures enable the model to match the high levels of R&D expenditures observed in the data as well as the high Tobin's q levels. In addition, the model captures the low correlation between Tobin's q and investment observed in the data. Also, the estimation yields an obsolescence rate for R&D stocks of about 32%, somewhat higher than the value of 15% typically used in the literature (see Griliches and Mairesse (1984)). An extension of the model that allows for R&D expenditures to influence both the success rate of innovations and the increase in profitability arising from an innovation generates broadly similar findings. Firms expect innovations to lead to about a 20% increase in profitability, and the estimated obsolescence rate of R&D equals 23%.

[1] See Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992).

Estimating the model on selected R&D-intensive industries—chosen based on four-digit standard industrial classification (SIC) codes—demonstrates that the model successfully captures variations in R&D intensity, profitability, and firm value across these industries. The results from each of these industries reveal that while firms face uncertainty in the outcomes from their R&D expenditures, they can realize economically meaningful increases in profits from innovations. This estimation also highlights the importance of the non-R&D-related parameters, with both the curvature of the profit function and the persistence of shocks to the profitability process influencing firms' R&D expenditures.

The study carries out a number of related analyses to address identification concerns regarding the R&D-related parameters. An examination of the generalized method of moments (GMM) objective function minimized in the estimation reveals that the function is steeply sloped at the estimated parameter values, enabling identification. This steep slope arises from the fact that the moments chosen in the study are sensitive to changes in the underlying parameters. Finally, the estimation method is able to recover the underlying parameter values when applied to data obtained from simulating the model.

The structural estimation approach enables a counterfactual experiment on an increase in the tax subsidy provided to R&D expenditures. This experiment is motivated by recent policy discussions on providing further support to R&D expenditures. The model enables this analysis to be carried out both in the short run and across steady states. In comparison, a regression-based approach typically only identifies the short-run effect of a tax policy change. The counterfactual increase in the R&D tax subsidy leads to an overall increase in R&D expenditures and a small increase in the success rate of innovations. The estimated elasticities imply that a \$1 tax subsidy to R&D expenses generates about \$1 more of R&D expenses, similar to the estimates reported by Hall and van Reenen (2000) and Bloom, Griffith, and van Reenen (2002). The analysis also reveals that the beneficial effect of the increased R&D tax subsidy over the long run may be somewhat smaller than the immediate short-run effect, as the increased R&D expenditures changes the profitability distribution, and therefore R&D expenditures, of firms in the economy.

This study is organized as follows. Section 2 details the model and derives the optimal policy function for R&D. Section 3 discusses the data and the estimation approach. Section 4 presents the results from the various estimations. Section 5 addresses model identification concerns. Section 6 evaluates the policy experiment within the context of the model, and Section 7 concludes. Additional material is available in a supplementary file on the journal website, http://qeconomics.org/supp/282/code_and_data.zip.

2. Model

The model economy consists of a large number of heterogeneous firms. The firms can invest in a physical capital stock, K, and an R&D stock, S. The firms face exogenous profitability shocks as well as endogenous jumps in profitability that arise from their R&D investment. Firms return any cash remaining after investment costs to shareholders as dividends. The objective of each firm is to maximize the present value of dividends.

2.1 *Physical investment and profits*

The output of the ith firm follows a constant returns to scale Cobb–Douglas specification with

$$Y(K_i, x_i) = x_i K_i^{\alpha} L_i^{1-\alpha},$$

where x_i denotes the firm's output productivity level and α denotes the elasticity of output with respect to capital (time subscripts omitted). The firm faces a downward-sloping demand curve with price per unit of output

$$P_i = d_i Y_i^{-\nu},$$

where d_i denotes a demand shift parameter and ν equals the inverse price elasticity of demand. Thus, sales are given by

$$P_i Y_i = d_i Y_i^{1-\nu}.$$

These assumptions correspond to a monopolistic competition setting where each firm possesses a degree of pricing power. Assume flexible labor markets, a deterministic wage process, and a per-period fixed cost of operations, fc. After substituting in the optimal labor input, the profits of the firm can be written as

$$\Pi(K_i, z_i) = z_i K_i^{\theta} - \text{fc}, \tag{1}$$

where the composite profitability level z_i inherits the properties of x_i and d_i. The curvature of the profit function is given by

$$\theta = \frac{\alpha(1-\nu)}{\nu + \alpha(1-\nu)}. \tag{2}$$

The subsequent analysis employs the above profit function. The firm spends its profits on physical investment and R&D expenditures, and returns any cash left as a dividend to shareholders, with negative dividends indicating a share issuance.

Investment or disinvestment of physical capital incurs a quadratic adjustment cost, $b\frac{I_i^2}{2K_i}$, and firms can disinvest.[2] Recent studies such as Cooper and Haltiwanger (2006) emphasize the role of nonconvex adjustment costs in investment; however, this evidence comes from plant-level data. In contrast, Eberly, Rebelo, and Vincent (2008) demonstrate that the quadratic adjustment cost specification fits investment data quite well at the firm level, as the data show little evidence of nonconvex adjustment costs when investment is aggregated to the firm level. The capital stock of the firm in the next period is given by

$$K_i' = K_i(1-\delta) + I_i,$$

where δ denotes the depreciation rate and I_i equals investment.

[2]The model does not include any irreversibility of selling physical capital as in Abel and Eberly (1994) or any costs of external finance as in Gomes (2001) and Brown, Fazzari, and Petersen (2009).

2.2 *R&D investment*

In addition to physical investment, firms also invest in R&D. The R&D stock of the firm does not directly impact the production function as in Griliches (1979) and others. Instead, the R&D stock stochastically affects the transition of profitability across periods. The model views R&D stocks as measuring the potential for future innovations rather than measuring the stock of ideas applicable for production. When a firm's R&D activity is successful, the firm realizes a profitability jump in the next period.[3] If it was unsuccessful, the firm will not realize a jump in profitability. Thus, innovations reflect discoveries by firms that lead to an increased profitability of the firm's capital stock.[4] A fraction of the R&D stock becomes obsolete each period, reflecting the conclusion or abandonment of R&D projects. The model attempts to capture the inherently uncertain nature of the innovation process through this mechanism, as a firm would realize a negative return from its R&D investment in a period in which it failed to innovate.

Denote the accumulated R&D stock of the firm at the end of each period by S_i'. Let R_i equal the investment in R&D activity. The law of motion for S_i is given by

$$S_i' = S_i(1-\gamma) + R_i, \tag{3}$$

where γ denotes the rate at which R&D stocks become obsolete. There are no additional costs of R&D investment, and the only constraint on it is that the R&D stock, S_i', remains nonnegative. This specification assumes that firms can sell their R&D stock for its residual value if necessary. The reversibility assumption is supported by anecdotal evidence of firms selling partially developed products to other firms, particularly in the pharmaceutical sector. Although the assumption of no adjustment costs of R&D investment is debatable, the literature typically does not assume additional adjustment costs for R&D investment (see Doraszelski and Jaumandreu (2013)).

One feature of the modeling framework is that R&D stocks determine the probability of innovation instead of R&D expenditure flows, as in Akcigit (2009), Aw, Roberts, and Xu (2011), and Doraszelski and Jaumandreu (2013). The R&D stock-based approach employed in the model generalizes the flow-based approach, as it allows for R&D expenditures to impact the probability of profit increases not only in the next period, but also in future periods. Put differently, the above specification nests one based solely on R&D flows, as $S_i' = R_i$ when $\gamma = 1$. Generalizing the model to allow for R&D stocks to influence innovation does come at the cost of introducing an additional parameter, γ, that needs to be estimated.

Let j_i denote a binary variable that equals 1 if the firm successfully innovates and 0 otherwise. The probability of a successful innovation is given by a Bernoulli distribution with success probability

$$p(j_i = 1) = 1 - \exp\left(-a\frac{S_i'}{K_i^{\theta}}\right), \tag{4}$$

[3]Other papers that provide a similar treatment of the innovation process include Thompson (2001), Klette and Kortum (2004), and Aghion, Bloom, Blundell, Griffith, and Howitt (2005).

[4]The vintage capital models of Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) emphasize macro level technological revolutions that have different impacts on the value of current and future capital.

where a is a parameter that influences the success rate of innovations and K_i^θ reflects the scaling of revenues with the firm's capital stock.[5] Higher R&D stocks lead to a greater probability of a successful innovation. This parsimonious parametrization implies that success probabilities are concave in S_i', consistent with economic reasoning. In the event of success, log profitability, z, jumps by a constant, λ, which measures the improvement in the firm's profitability from a successful innovation. In related work, Pakes and McGuire (1994) analyze a framework where firms realize a constant jump in profitability with endogenous probability that is a decreasing function of product development expenditures.[6]

The success probability decreases as firm size increases. The scaling by K_i^θ can be thought of as capturing an increase in R&D project size with average revenues. As such, larger firms with greater average revenues require a greater level of R&D investment to generate the same probability of success as a small firm. This is similar to the approach in Klette and Kortum (2004), where the firm's innovation intensity is proportional to its R&D investments scaled by revenues.[7] An alternative specification would be to scale by per-period sales instead of the capital stock to the power θ. However, scaling by per-period sales would have the unappealing property that, ceteris paribus, a firm that received a negative profitability shock, and therefore had lower sales, would have a higher probability of realizing an innovation.

The transition equation for profitability includes a standard autoregression (AR(1)) component plus jumps from innovations:

$$\begin{aligned} &\log\left(z_i'\right) = \mu + \rho \log(z_i) + \lambda j_i + \varepsilon_i, \\ &j_i \propto \mathsf{B}\left(p\left(\frac{S_i'}{K_i^\theta}\right)\right), \\ &\varepsilon_i \propto \mathsf{N}\left(0, \sigma^2\right). \end{aligned} \tag{5}$$

The distribution for j_i is independent of the distribution for ε_i. In this setup, the jump intensity varies endogenously with R&D stocks. Further, firms base their decisions on realizations of z_i' and do not distinguish between changes in profitability due to exogenous shocks or innovations. Therefore, the impact of an innovation will decay at the same rate ρ as the impact of exogenous shocks. These assumptions yield the simplification that only the current level of profitability enters into the firm's policy functions.

The model is agnostic on the source of the jump in profitability from a successful innovation. This innovation may arise from either improvements in the current products of the firm, the introduction of entirely new products, or productivity increases. More

[5] In the monopolistically competitive framework development in Section 2.1, profits and revenues exhibit the same curvature with respect to the capital stock.

[6] Kortum (1997) employs a search theoretic approach in which the rate of arrival of ideas is exogenous and the efficiency of the improvement depends on the R&D stock.

[7] The endogenous growth theory model of Romer (1990) implies that innovation increases with the level of R&D. Subsequent work by Jones (1995b) demonstrates that this relationship does not hold in the data. Jones (1995a), Young (1998), and Segerstrom (1998) introduce endogenous growth models without scale effects.

formally, a successful innovation may result in an increase in the productivity parameter x_i or the demand shifter d_i. This is similar to the approach taken in the production-function-based literature, where the impact of R&D on value added could be due to all of the above factors. The model also does not take a stand on whether patent protection is necessary for generating an increase in profitability (see Boldrin and Levine (2008)). The above approach allows R&D investment to have a broad impact on the firm. Correspondingly, the endogenous growth literature highlights both quality improvements and new product introductions as the outcome of innovations.

The timing of the firm's decisions and the notation for R&D and capital stocks warrant clarification. Firms enter each period with an R&D stock, a capital stock, and a profitability level. The firms invest in R&D and capital during the period. Denote the R&D and capital stocks at the end of the period by S' and K', respectively. At the end of the period, each firm discovers whether it successfully innovated or not. The innovation probability depends on the ratio of the R&D stock at the end of the period (S') to the average revenues a firm of that size would have earned over the period (K^θ). If a firm succeeds, its next period profitability will be higher than if it did not. The accumulated R&D stock carries over to the next period, and a fraction of it becomes obsolete after the realization of the innovation outcome. The capital stock, adjusted for investment and depreciation, carries over to the next period and is used to generate output. This timing structure captures the idea that R&D investment in the current period—which determines R&D stocks at the end of the period—impacts the transition function for the firm's profitability from this period to the next.

2.3 *Tax subsidy on R&D investment*

The Research and Experimentation Tax Credit was established by the Economic Recovery Tax Act of 1981 to encourage R&D investment by U.S. firms. However, only some R&D expenses are eligible for the tax credit, and the set of qualifying expenses has evolved over time. The tax credit is calculated as a percentage of qualifying expenses that exceed a base amount that varies either with the company's past qualifying expenses or sales. In addition, an alternative tax credit, established in 1996, benefits companies with smaller increases in R&D expenses. Since inception, the Research and Experimentation Tax Credit has existed as a temporary tax benefit that has been repeatedly extended over time.

The complexities of the Research and Experimentation Tax Credit and the uncertainty over its permanence make it very challenging to accurately capture the details of the tax credit in the model. As such, this study takes a simplified approach that incorporates the Research and Experimentation Tax Credit as a linear tax subsidy, τ_{rd}, of all R&D expenses. The subsidy rate is calibrated at 2.5%, based on the findings of Moris (2005), who reports that the tax credit as a percentage of all corporate R&D expenses ranges from about 1.5% to 3.5%.

2.4 *Firm value*

The dividends paid by the firm in each period are given by

$$\big(\Pi(K_i, z_i) - R_i\big)(1-\tau) + \delta K_t \tau + R_i \tau_{\text{rd}} - I_i - b\frac{I_i^2}{2K_i},$$

where τ denotes a linear tax rate. As in the tax code, R&D expenses are treated as tax deductible. The $\delta K_t \tau$ term captures the tax deductibility of depreciation, and the $R_i \tau_{\text{rd}}$ term captures the R&D tax credit. The tax rate parameter, τ, is calibrated using data on aggregate taxes and profits. The model thus incorporates other factors that affect taxes payable by firms, such as debt financing, in a parsimonious manner.

Denote the value of the firm after the realization of z_i but prior to the obsolescence of the R&D stock as $V(K_i, S_i, z_i)$.[8] For notational convenience, define

$$D(K_i, z_i) = \Pi(K_i, z_i)(1-\tau) + \delta K_t \tau - I_i - b\frac{I_i^2}{2K_i}. \tag{6}$$

The value of the firm can be expressed as a solution to the Bellman equation

$$\begin{aligned}
&V(K_i, S_i, z_i) = \max_{I_i, K_i', R_i, S_i'} D(K_i, z_i) - R_i(1 - \tau_{\text{rd}} - \tau) + \beta E_z\big[V_c\big(K_i', S_i', z_i'\big)\big],\\
&K_i' = K_i(1-\delta) + I_i,\\
&S_i' = S_i(1-\gamma) + R_i,\\
&S_i' \geq 0,
\end{aligned} \tag{7}$$

where the continuation value of the firm, $V_c(K_i', S_i', z_i')$, takes into account the possibility that the firm may exit next period and $E_z[\cdot]$ denotes expectation conditional on the current profitability level, z_i. The expectation in the Bellman equation is taken over the joint distribution for j_i, ε_i. The results in Bertsekas (2000, Chapter 7) yield the existence and uniqueness of the solution to the above problem.

The above value function can be simplified by noting that the absence of any frictions on adjusting R&D imply that the value function is separable in S_i. This simplification helps with the estimation as it reduces the number of state variables in the firm's optimization problem and enables a derivation of the optimal R&D stock as a function of the capital stock and profitability stock. The simplification follows from substituting the expression for R_i into the maximization problem, which yields

$$\begin{aligned}
V(K_i, S_i, z_i) = \max_{I_i, K_i', S_i'}\ & D(K_i, z_i) + S_i(1-\gamma)(1 - \tau_{\text{rd}} - \tau)\\
&- S_i'(1 - \tau_{\text{rd}} - \tau) + \beta E_z\big[V_c\big(K_i', S_i', z_i'\big)\big],\\
K_i' = K_i(1-\delta) + I_i,&\\
S_i' \geq 0.&
\end{aligned}$$

[8] Defining the value function at this point ensures notational symmetry between capital and R&D stocks.

The stock variable S_i does not impact the optimization problem for either K_i' or S_i'. This motivates the conjecture that the value of the firm can be simplified as

$$V(K_i, S_i, z_i) = G(K_i, z_i) + S_i(1-\gamma)(1-\tau_{\mathrm{rd}}-\tau). \tag{8}$$

The value of the R&D stock equals $S_i(1-\gamma)(1-\tau_{\mathrm{rd}}-\tau)$ due to the model's timing convention. The effective value of S_i equals its value after obsolescence, which is modified by the tax benefits of R&D expenses. Substituting the above expression into the Bellman equation, one obtains

$$\begin{aligned} G(K_i, z_i) = &\max_{I_i, K_i', S_i'} D(K_i, z_i) - S_i'(1-\tau_{\mathrm{rd}}-\tau) \\ &+ \beta S_i'(1-\gamma)(1-\tau_{\mathrm{rd}}-\tau) + \beta E_z\big[G_c\big(K_i', z_i'\big)\big], \\ K_i' = &K_i(1-\delta) + I_i, \\ S_i' \geq &0. \end{aligned} \tag{9}$$

The expected value of $E_z[G_c(K_i', z_i')]$ takes into account both the realization of profitability jumps from innovations and the exogeneous shocks. Using the law of iterated expectations, it can be written as

$$\begin{aligned} E_z\big[G_c\big(K_i', z_i'\big)\big] = &E_z\big[G_c\big(K_i', z_i'\big)|j_i = 1\big]p(j_i = 1) \\ &+ E_z\big[G_c\big(K_i', z_i'\big)|j_i = 0\big]p(j_i = 0), \end{aligned} \tag{10}$$

where the probability of a successful innovation depends on the optimal R&D stock S' and is given by equation (4). The continuation value, $G_c(K_i', z_i')$, is given by

$$G_c\big(K_i', z_i'\big) = \max\big\{G\big(K_i', z_i'\big), 0\big\}. \tag{11}$$

This analysis establishes our conjecture and demonstrates that the value function is separable in the R&D stock. Note that this is not a general result; it arises from the assumption that the R&D stocks can be adjusted without any friction. Put differently, the above result states that, because of the lack of adjustment costs, the optimal R&D stock does not depend on the lagged R&D stock. The separability of the value function also has the additional implication that firms realize a negative return to R&D investment in periods where they fail to innovate.

While the R&D stock, S_i, is not a state variable per se in the model, it does influence the optimal R&D expenditure flows, R_i, which equal the optimal next-period R&D stock minus the current period R&D stock adjusted for obsolescence.[9] In addition, firm value is given by equation (8), which incorporates the residual value of the existing R&D

[9]One could draw an analogy with investment policy in (S, s) models, such as Caballero and Engel (1999), where, conditional on adjustment, the next-period capital stock does not depend on the current capital stock. However, conditional on adjustment, the optimal investment policy in these models does depend on the current capital stock, as it equals the next-period capital stock minus the current capital stock adjusted for depreciation.

stock. As such, the formulation of the model in terms of R&D stocks—a more general formulation than using only R&D expenditures—has a meaningful effect on the model implications.

2.5 *R&D policy*

The above analysis enables the derivation of the optimal R&D policy. The optimal choice of S_i' affects the current period dividend payment, the level of the R&D stock carried over to the next period, and the transition function for profitability z. The first two terms are linear in S_i'. Let $\tilde{S}_i'$ be the optimal policy in the interior region where the $S_i' \geq 0$ constraint does not bind. The following proposition characterizes the optimal R&D stock.

PROPOSITION 1. *The optimal R&D stock of the firm when $S_i' > 0$ is given by*

$$\frac{\tilde{S}_i'}{K_i^\theta} = \frac{1}{a}\Bigg[\log(a) - \log\big((1-\tau_{\text{rd}}-\tau)\big(1-\beta(1-\gamma)\big)\big) + \log\left(\frac{\beta(E_z[G_c(K_i', z_i')|j_i=1] - E_z[G_c(K_i', z_i')|j_i=0])}{K_i^\theta}\right)\Bigg].$$

See Appendix A for the proof.

Therefore, the optimal policy function for R&D stocks is given by

$$\frac{S_i'}{K_i^\theta} = \max\left(\frac{\tilde{S}_i'}{K_i^\theta}, 0\right).$$

The optimal R&D stock increases with the expected increase in firm value per unit of average sales from an innovation, which is a function of the profitability jump parameter, λ. In addition, the optimal R&D stock depends on the discount rate, the tax subsidy to R&D, and the obsolence rate, γ. The exponential function for the success rate implies that the above terms affect the optimal R&D stock logarithmically. Finally, the success rate parameter a also enters into the optimal R&D policy function. The above expression indicates that the three R&D related parameters, a, λ, and γ in the model all influence the optimal R&D stock (and therefore R&D expenditures) in a distinct manner.

The above expression indicates that one can decompose the total return from R&D investment into an increase in the residual R&D stock and an expected increase in firm value from an innovation. The increase in firm value from an innovation incorporates both increases in profitability in the next period and beyond and the optimal rebalancing of the capital stock following an innovation. This decomposition highlights the dynamic benefits to R&D in the model, where firms follow a successful innovation with investment in physical capital, amplifying the benefit of the initial profit increase. While the above approach enables one to examine R&D expenditures and investment together, one disadvantage is that it ignores the impact of industry structure on firms' R&D expenditures, as emphasized by Aghion, Harris, Howitt, and Vickers (2001) and Aghion, Blundell, Griffith, Howitt, and Prantl (2009).

3. Data and estimation

This study estimates the above model using simulated methods of moments estimation (see Gourieroux, Monfort, and Renault (1993) for details).[10] This method involves comparing a selected set of data moments with the same moments from an artificial data set obtained by simulating the model for a given set of parameters. The parameter estimates are obtained by minimizing a quadratic form of the difference between the data and simulated moments. Appendices B and C discuss the estimation in more detail.

The simulated method of moments is employed since the model's policy function for R&D is expressed in terms of jumps in firm value arising from innovations, an unobservable variable. Further, using this method enables one to simultaneously estimate all the parameters of interest, which enables policy experiments on changing the R&D tax credit.

3.1 *Data*

The data for the estimation are obtained from the Compustat annual data set.[11] The data set includes information on profits, research and development expenses, capital expenditures, and balance sheet items for listed U.S. corporations. The market value of equity is obtained from the linked Center for Research in Security Prices (CRSP) data set. The sample period extends from 1985 to 2006 and excludes financial firms and regulated utilities. The sample is an unbalanced panel, as firms enter and exit the data. This corresponds to the model where a firm may exit if its continuation value net of the value of the R&D stock, $G(K, z)$, becomes negative.

More than half of the firm–year observations report data on research and development expenditures (Compustat annual data item 46). This series measures company-funded R&D and excludes those funded by the government. Many companies do not report this series for any years. Among the firms that do report, more than 75% report R&D expenses for all years. This indicates that one can fairly clearly identify a subset of firms that engage in R&D. Those that do not engage in R&D are considered to do so for exogenous reasons and are excluded from the estimation. The sample of firms that report R&D expenditures in each year are included in the sample, and these comprise the bulk of it. For firms that report R&D expenditures in some, but not all years, the study includes those with R&D values in at least half their years in the sample.[12] This implies that a few observations in the sample have zero R&D expenditures; the inclusion of these few observations is not inconsistent with data obtained from simulating the model, as a very small fraction of simulated firm–year observations have such steep declines in R&D stocks that their R&D expenditures are slightly negative.

[10] Other papers that use this method include Cooper and Ejarque (2003), Hennessy and Whited (2005, 2007), Cooper and Haltiwanger (2006), Lentz and Mortensen (2008), Eberly, Rebelo, and Vincent (2008), Xu (2008), Akcigit (2009), Bloom (2009), and Kaplan (2012).

[11] Griliches (1994) discusses the various data sources employed in the empirical R&D literature.

[12] The matched moments used in the estimation are not particularly sensitive to changes in this threshold.

One concern is whether the firms are accurately reporting their R&D expenses. Accounting rules provide some comfort in this regard, as they clearly specify the classification and reporting of R&D expenditures. In addition, the Research and Experimentation Tax Credit has indirectly increased the attention firms give to accounting for R&D expenses. Last, a cross-industry examination shows that industries that one might ex ante expect to be R&D intensive have much higher fractions of firms that report R&D expenses.

The study measures sales as net sales (data item 12), profits as operating income before depreciation (data item 13), and investment as capital expenditures (data item 30) net of retirement of fixed assets (data item 184). The replacement value of the capital stock is derived using the perpetual inventory method employed by Summers and Salinger (1983), where the mean life of the capital stock is calculated using the double declining balance method. Profitability equals operating income before depreciation scaled by the replacement value of the capital stock. Tobin's q equals the market value of equity plus the book value of debt minus the book values of inventories and cash divided by the replacement value of capital. This follows the method employed by Whited (1992) and Gomes (2001), with the modification that cash holdings are also subtracted from the numerator.

Panel A of Table 1 reports the summary statistics for the sample of firms used in the study. The statistics reveal that these firms exhibit a high R&D intensity. At the same time, these firms also have high Tobin's q values that would be difficult to reconcile with standard models based on investment frictions such as Hayashi (1982). This suggests that R&D expenditures play a key role in understanding the valuation of these firms, as emphasized in the above model.

3.2 *Industry classification*

In addition to estimating the model on the sample described above, this study also estimates the model for firms in selected R&D-intensive industries. Estimating the model on these industries helps answer the question of whether the model can successfully capture firms' behavior in these industries. In addition, it sheds light on how the model parameters vary across these industries.

The industry groups mostly follow the 49 industry groups constructed by Kenneth French using four-digit SIC code data.[13] The one exception being the medical equipment industry, which combines the medical equipment and laboratory equipment industries. Appendix D details the SIC codes used in each industry category. These industries were chosen as they have the highest concentration of firms engaging in R&D as well as the highest R&D intensities.

Panel B of Table 1 reports summary statistics for firms in these R&D-intensive industries. Compared with the overall sample, firms in these industries have higher R&D intensities and higher Tobin's q values.

[13]The industry classifications are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

TABLE 1. Summary statistics.

Panel A: All firms

	Mean	Std.
Log assets	6.099	1.940
Tobin's q	3.520	3.340
Profitability	0.333	0.427
R&D-to-sales	0.088	0.157
Investment	0.159	0.133
Observations	32,351	

Panel B: Firms in R&D-intensive industries

	Mean			
	R&D-to-Sales	Profitability	Tobin's q	Observations
Business services	0.109	0.298	4.084	960
Chips	0.127	0.287	3.670	4274
Hardware	0.114	0.308	3.565	2102
Medical equipment	0.101	0.430	4.675	2719
Pharmaceuticals	0.310	0.225	6.525	2120
Software	0.171	0.289	5.636	3182

Note: Panel A reports summary statistics for firms in the entire sample. The sample includes R&D-reporting firms in nonfinancial industries and contains 32,351 firm–year observations. Panel B reports selected summary statistics for firms in R&D-intensive industries.

3.3 *Calibrated parameters*

Some of the auxiliary parameters are calibrated to simplify the estimation. These include the discount rate, β, which is set to $1/1.04$ to match a return to capital of 4%. The steady-state investment rate equals the depreciation rate in the simulated data. As such, the depreciation rate δ is set equal to the investment rate in the data, 0.165. The tax rate parameter, τ, is calibrated to equal the ratio of aggregate income taxes to operating profits in the data. In the industry-level estimation, both the depreciation rate and the tax rate are modified to reflect the corresponding data values for those industries. Last, the constant term in the AR(1) equation for profitability, μ, functions only as a scaling parameter.[14] As such, μ is set such that the steady-state capital stock equals 1.

3.4 *Moments and identification*

When using the simulated method of moments, it is important to chose moments that are informative about the underlying parameters. This section discusses the moments used in the estimation and relates them to the underlying parameters.

The matched moments comprise the following: averages of R&D-to-sales, fixed costs, profitability, and Tobin's q; standard deviations of R&D-to-sales, profitability, and

[14]Changes in μ shift the steady-state capital stock, but do not affect any of the ratios used in the estimation, such as the R&D-to-sales ratio or Tobin's q.

investment; autocorrelations of R&D-to-sales, profitability, and investment; and correlations between R&D-to-sales and investment, investment and Tobin's q, and lagged R&D-to-sales and sales growth. So as to minimize the effect of outliers and reporting errors in the sample data set, all the firm-level variables underlying the calculation of these moments are top- and bottom-coded.

The moments involving the R&D-to-sales ratio help pinpoint the three R&D-related parameters in the model: λ, γ, and a. As seen in Proposition 1, changes in all these parameters influence the optimal R&D stock and, therefore, the average and standard deviation of the R&D-to-sales ratio. The correlation between lagged R&D-to-sales ratio and sales growth helps inform the impact of a successful innovation on profits, λ. The autocorrelation of the R&D-to-sales ratio varies with the obsolescence rate, γ, as a high obsolescence rate implies a lower autocorrelation. The success rate parameter, a, influences Tobin's q in the simulated data, as higher success rates translate to a higher contribution of R&D investment to firm value.

The fixed costs parameter, fc, is pinned down by the ratio of fixed costs to sales. The curvature of the profit function, θ, is mainly pinned down by the averages of profitability and Tobin's q. The autocorrelation, ρ, and standard deviation, σ, of the profitability process are identified by the corresponding moments for profitability. These two parameters also influence the average of Tobin's q, and the autocorrelation and standard deviation of the R&D-to-sales ratio. The standard deviation of investment helps pin down the investment adjustment cost parameter, b.

It should be noted that although the above discussion links specific parameters to specific moments to help provide intuition, the estimation employs all the moments to identify all the parameters jointly. Indeed, changes in any parameter can, and in most cases do, influence all of the moments. Section 5 examines whether the above identification argument fares well in practice.

4. Results

This section presents the results from estimating the structural model. It first presents results obtained from the entire sample, and then presents results obtained from selected R&D-intensive industries. Last, it presents results obtained from estimating an extension of the model, where R&D investments can lead to multiple profitability jumps per period.

4.1 *All R&D firms*

Table 2 presents the results from estimating the model on all firms in the sample. Panel A presents the parameter estimates, and Panel B presents the matched moments from the data and the model.

The estimate for λ indicates that the underlying profitability process z jumps by an economically significant 22.2% when firms realize innovations. The estimate for a translates to an average success rate of about 83%. Together, these imply an expected increase in the underlying profitability process due to R&D expenditures of 18.5%. Such a large

TABLE 2. One profitability jump per period.

Panel A: Parameter estimates

Parameter	θ	ρ	σ	λ	a	b	γ	fc	$\hat{\Psi}$
Estimate	0.396	0.587	0.380	0.222	5.293	0.497	0.322	0.409	2671
Std. err.	(0.002)	(0.006)	(0.003)	(0.003)	(0.253)	(0.031)	(0.018)	(0.004)	

Panel B: Moments

Moments	Data	Model
Averages		
R&D-to-sales	0.087	0.082
Fixed costs	0.241	0.229
Profitability	0.333	0.365
Tobin's q	3.477	3.571
Standard deviations		
R&D-to-sales	0.056	0.028
Profitability	0.253	0.309
Investment	0.105	0.101
Autocorrelations		
R&D-to-sales	0.366	0.709
Profitability	0.422	0.555
Investment	0.341	0.317
Correlations between		
R&D-to-sales and investment	−0.022	−0.108
Investment and Tobin's q	0.280	0.341
Lagged R&D-to-sales and sales growth	0.062	0.286
Success rate		0.833

Note: Panel A reports the estimated structural parameters and a goodness-of-fit statistic, $\hat{\Psi}$. Panel B reports the matched moments from the sample and simulated data sets. The sample includes R&D-reporting firms in nonfinancial industries and contains 32,351 firm–year observations. Section 3.1 details the construction of the sample and the variable definitions. The probability of success from R&D investment is given by a Bernoulli distribution. The estimation is carried out using simulated method of moments.

impact from R&D investment not only helps the model generate high levels of R&D expenditures, it also enables the model to generate the high Tobin's q levels observed in the data.[15] Indeed, an average value for Tobin's q of 3.57 would be hard to justify using only a physical investment perspective. For comparison, the model generates an average shadow price of capital, $1 + b\frac{I}{K}$, of only 1.08.

The estimated obsolescence rate for R&D investment, γ, is higher than the value of 15% traditionally employed in the production-function literature (see Griliches and Mairesse (1984)). Hall (2010) obtains depreciation rates in the range of 20–40% using a valuation-based approach. Further, the model incorporates successful innovations from past R&D investments in the z term, whereas all the benefits of past R&D investments accrue in the R&D stock in the production-function-based literature. As such, it is plau-

[15]See Hall (2001) and Corrado, Haltiwanger, and Sichel (2005) for evidence that intangible capital, more broadly, plays an important role in understanding the value of the aggregate capital stock.

sible to expect a higher obsolescence rate from a modeling approach that emphasizes the role of R&D in generating innovations. Conversely, the finding that $\gamma < 1$ indicates that R&D stocks influence innovations, not R&D flows, as would be the case if $\gamma = 1$.

The estimated curvature of the profit function, θ, is lower than the estimates obtained by Cooper and Haltiwanger (2006). Assuming a capital share of 1/3 and applying equation (2), one obtains an implied price elasticity of demand of 2.97 (= 1/0.337), within the range of estimates obtained in the literature (see Broda and Weinstein (2006) and Hendel and Nevo (2006)). The estimated autocorrelation and profitability shock terms are directly related to their matched moments. Last, the estimated adjustment cost parameter, λ, is within the range of 0–2 typically obtained in the literature (see Cooper and Haltiwanger (2006) and Whited (1992)).

In terms of the matched moments, the model matches the average moments quite well. The model generates a mean R&D-to-sales ratio that is a bit lower than the data, while generating somewhat higher mean profitability and Tobin's q levels. The model does not fare so well regarding the standard deviation moments, as it implies a lower standard deviation of R&D than in the data, suggesting that other sources of heterogeneity also influence firms' R&D decisions.

The model manages to match the correlation between lagged R&D-to-sales and sales growth fairly well. This moment captures the impact of R&D expenditures on subsequent sales growth and, therefore, on subsequent increases in profitability. The model also generates the modest correlation between investment and Tobin's q observed in the data; investment-based models typically have difficulty matching this moment, as these models imply a high correlation. Measurement error in Tobin's q may provide part of the explanation as to why the correlation between it and investment in the data is less than what would be implied by investment models (see Erickson and Whited (2000)). Finally, the model implies a somewhat surprising negative correlation between R&D-to-sales and investment. This arises because while the optimal policy for the R&D stock given in Proposition 1 is highly correlated with Tobin's q and investment, the correlation between the flow of R&D expenditures and investment is much weaker and can become negative.

4.2 *R&D-intensive industries*

Table 3 reports the parameter estimates obtained from the estimation of the model on the selected R&D-intensive industries, as detailed in Section 3.2.

The parameter estimates indicate that the model captures heterogeneity across these industries both in terms of their R&D-related parameters and other parameters. For instance, successful innovations have a much bigger immediate impact on the underlying profitability process in the pharmaceutical and software industries than in other industries. That said, innovations have a meaningful impact on profitability in all of the selected industries.

The model generates a range of estimates for the obsolescence rate for R&D, γ. While the estimate for some industries is similar to that obtained for all firms, in other industries the estimates are not significantly different from 1, indicating that R&D flows

TABLE 3. Parameters from industry-level estimation.

Parameter	θ	ρ	σ	λ	a	b	γ	fc	$\hat{\Psi}$
Business services									
Estimate	0.392	0.591	0.348	0.228	4.392	0.457	0.365	0.375	103
Std. err.	(0.009)	(0.024)	(0.017)	(0.022)	(1.019)	(0.071)	(0.089)	(0.020)	
Chips									
Estimate	0.450	0.599	0.387	0.207	8.750	0.585	1.000	0.337	435
Std. err.	(0.006)	(0.010)	(0.008)	(0.004)	(2.631)	(0.088)	(0.275)	(0.011)	
Hardware									
Estimate	0.421	0.617	0.438	0.246	4.144	0.674	0.378	0.409	238
Std. err.	(0.007)	(0.020)	(0.008)	(0.015)	(0.285)	(0.087)	(0.058)	(0.023)	
Medical equipment									
Estimate	0.260	0.599	0.242	0.384	9.514	0.345	0.534	0.479	294
Std. err.	(0.003)	(0.020)	(0.005)	(0.006)	(1.242)	(0.011)	(0.064)	(0.006)	
Pharmaceuticals									
Estimate	0.256	0.545	0.102	0.504	2.190	0.391	0.902	0.327	281
Std. err.	(0.002)	(0.012)	(0.003)	(0.008)	(0.245)	(0.023)	(0.108)	(0.011)	
Software									
Estimate	0.250	0.591	0.256	0.461	7.018	0.443	0.896	0.456	926
Std. err.	(0.002)	(0.014)	(0.006)	(0.005)	(1.373)	(0.059)	(0.173)	(0.005)	

Note: The table reports the parameter estimates obtained from the estimation of the model on firms in selected R&D-intensive industries constructed using four-digit SIC codes. Appendix D details the SIC codes used in each industry group. Section 3.1 details the construction of the sample and the variable definitions. The probability of success from R&D investment is given by a Bernoulli distribution. The estimation is carried out using the simulated method of moments.

influence innovations, not R&D stocks. Nonetheless, even in these industries, R&D investments can influence profitability and valuations for many years through the persistence of increases in profitability from innovations. That said, the high obsolescence rate in the pharmaceuticals industry is somewhat puzzling given the long duration of R&D projects in this industry. Mechanically, having a high obsolescence rate helps the model generate the high rate of R&D investment observed in the data. The estimates of a vary widely across the industries, translating into noticeable differences in the average success rate of innovations, which ranges from 0.67 in the pharmaceutical industries to 0.94 in the medical equipment industry. Broadly speaking, even firms in these R&D-intensive industries face some risk each year of not realizing a positive payoff from R&D investments through an innovation.

The estimates for the curvature parameter θ reflect changes in the average value of Tobin's q across these industries. Having a lower value of θ enables the model to generate a higher average Tobin's q, as lower θ values reduce the change in the optimal capital stock necessary following a successful innovation (or a large profitability shock). This also helps lead to higher R&D expenditures. The estimated parameter values for ρ and σ mainly reflect the autocorrelation and standard deviation of profitability in these industries. Last, changes in the adjustment cost parameter, b, mainly reflect differences in the standard deviation of investment. Notably, each of these parameter estimates is broadly similar to the estimates from all R&D firms reported in Table 2.

TABLE 4. Moments from industry-level estimation.

	Averages			Correlations Between		
	R&D-to-Sales	Profitability	Tobin's q	Lag R&D-to-Sales Sales Growth	Investment Tobin's q	Success Rate
Business services						
Data	0.107	0.299	4.042	0.277	0.107	
Model	0.101	0.331	4.098	0.211	0.292	0.799
Chips						
Data	0.125	0.287	3.636	0.331	0.042	
Model	0.112	0.326	3.681	0.267	0.356	0.693
Hardware						
Data	0.113	0.307	3.533	0.383	−0.064	
Model	0.110	0.354	3.710	0.471	0.269	0.808
Medical equipment						
Data	0.100	0.429	4.632	0.223	0.132	
Model	0.092	0.470	4.808	0.242	0.400	0.938
Pharmaceuticals						
Data	0.307	0.231	6.503	0.239	0.135	
Model	0.280	0.267	6.586	0.102	0.433	0.667
Software						
Data	0.170	0.289	5.607	0.296	0.014	
Model	0.164	0.341	5.893	0.195	0.409	0.914

Note: The table reports selected matched moments from the actual data and the simulated data derived from the estimation of the model on firms in selected R&D-intensive industries constructed using four-digit SIC codes. Appendix D details the SIC codes used in each industry group. Section 3.1 details the construction of the sample and the variable definitions. The probability of success from R&D investment is given by a Bernoulli distribution. The estimation is carried out using the simulated method of moments.

Table 4 reports a subset of the matched moments from the data and the model from the estimation of the model on the selected R&D-intensive industries.[16] The results indicate that the model can generate the very high levels of R&D intensity observed in some of these industries. Somewhat surprisingly, the model generates somewhat higher average values of Tobin's q and profitability than observed in the data. This may be partly because having higher levels of Tobin's q and profitability helps increase average R&D intensity.

The model matches the correlation between lagged R&D intensity and sales growth in most of the industries. This is driven partly by the role of R&D investments in generating profitability increases through innovations. While the model generates a relatively low correlation between Tobin's q and investment, it is nonetheless unable to generate correlations as low as those observed in the data.

4.3 *All R&D firms with multiple jumps per period*

One concern with structural estimation is that the findings are based on a specific model. As such, it is helpful to examine the sensitivity of the findings to the model spec-

[16]The unreported moments are available from the author on request.

ification. This section presents the findings obtained from estimating a model that relaxes the assumption that firms can obtain only one profitability jump per period. Extending the model in this manner helps tackle one limitation of the baseline model. Namely, the fact that R&D expenditures do not influence the size of the profitability jump conditional on obtaining an innovation. With multiple possible jumps, increases in R&D expenditures influence the probability of success and the size of the jump conditional on success.

The number of profitability jumps that firms obtain from R&D expenditures is now assumed to follow a geometric distribution, with success probability

$$p\left(\frac{S_i'}{K_i^\theta}\right) = 1 - \exp\left(-a\frac{S_i'}{K_i^\theta}\right).$$

This implies that the probability of obtaining n profitability jumps is given by $(1-p)p^n$. The profitability increase that firms obtain from innovations is linear in the number of jumps, n, with λ denoting the increase in profitability arising from a single jump. Formally, the transition equation for z is given by

$$\begin{aligned} &\log(z_i') = \mu + \rho\log(z_i) + \lambda n_i + \varepsilon_i, \\ &n_i \propto \mathsf{G}\left(p\left(\frac{S_i'}{K_i^\theta}\right)\right), \\ &\varepsilon_i \propto \mathsf{N}(0,\sigma^2), \end{aligned} \tag{12}$$

where $\mathsf{G}(p(\frac{S_i'}{K_i^\theta}))$ denotes a geometric distribution. Other than for this change, the model remains unchanged from that discussed above. One limitation of the extended model is that one cannot explicitly solve for the optimal R&D stock as in Proposition 1.[17]

Table 5 presents the results obtained from estimating the extended model on all firms in the sample. Panel A presents the parameter estimates, and Panel B presents the matched moments from the data and the model.

The estimated value for the profitability increase from a single jump, λ, is much lower than before. However, this is offset by an average number of profitability jumps of about 9.2, implying a total expected increase in profitability from R&D investments of about 20.3%, similar to that obtained in the model with one jump per period. The estimated obsolescence rate, γ, while somewhat lower than that obtained in Section 4.1, is still higher than the value of 0.15 that the literature often calibrates to. Finally, the estimates for the non-R&D parameters are mostly similar to before.

Turning to the matched moments, the model matches the various averages used in the estimation. As in Section 4.1, the model fails to generate the volatility of R&D intensity observed in the data. The model generates a small, albeit positive, correlation between lagged R&D intensity and sales growth. Overall, the similarity in the parameter

[17]The extended model is also much more computationally intensive to solve, as one needs to solve for value functions over a range of possible jumps. To maintain tractability, the estimation sets the number of maximum possible jumps at 10.

TABLE 5. Multiple profitability jumps per period.

Panel A: Parameter estimates

Parameter	θ	ρ	σ	λ	a	b	γ	fc	$\hat{\Psi}$
Estimate	0.414	0.657	0.356	0.022	10.353	0.429	0.229	0.417	2544
Std. err.	(0.011)	(0.008)	(0.004)	(0.001)	(0.263)	(0.073)	(0.006)	(0.012)	

Panel B: Moments

Moments	Data	Model
Averages		
R&D-to-sales	0.087	0.080
Fixed costs	0.241	0.229
Profitability	0.333	0.371
Tobin's q	3.477	3.644
Standard deviations		
R&D-to-sales	0.056	0.024
Profitability	0.253	0.309
Investment	0.105	0.110
Autocorrelations		
R&D-to-sales	0.366	0.442
Profitability	0.422	0.571
Investment	0.341	0.296
Correlations between		
R&D-to-sales and investment	−0.022	−0.163
Investment and Tobin's q	0.280	0.466
Lagged R&D-to-sales and sales growth	0.062	0.215
Average number of jumps		9.23

Note: Panel A reports the estimated structural parameters and a goodness-of-fit statistic, $\hat{\Psi}$. Panel B reports the matched moments from the sample and simulated data sets. The sample includes R&D-reporting firms in all industries and contains 32,351 observations. Section 3.1 details the construction of the sample and the variable definitions. The number of successful profitability jumps obtained from R&D investment is given by a geometric distribution. The estimation is carried out using the simulated method of moments.

estimates and the simulated moments obtained using the estimations with a single profitability jump and multiple profitability jumps gives comfort regarding the robustness of the results.

4.4 *Firm life cycles and growth*

A limitation of the model is that it does not incorporate firm life cycle dynamics, which have been shown to be important in the literature (see Cooley and Quadrini (2001) and Haltiwanger, Jarmin, and Miranda (2013)). One could potentially augment the model to incorporate a role for firm age, and estimate the richer model on the data used in this study combined with additional information on firm growth, entry and exit, and other life cycle moments (see Lentz and Mortensen (2008)). While such an approach could provide valuable insights, it would not be appropriate to estimate a rich life cycle model on the Compustat data set used in this study as those data reflect only publicly

TABLE 6. Sales growth in simulated and actual data.

	Data	Model
All firms	7.6%	9.3%
Selected industries		
Business services	9.3%	8.1%
Chips	9.6%	9.6%
Hardware	6.7%	12.1%
Medical equipment	9.0%	4.0%
Pharmaceuticals	15.1%	3.7%
Software	9.6%	5.0%

Note: The table presents mean sales growth rates from the data and the corresponding values from the estimated models on the sample of all firms and on the samples of firms in selected R&D-intensive industries. The parameter values used in the simulations are reported in Tables 2 and 3, respectively. All values are reported in percentages.

traded corporations. These firms are likely the most successful firms in the economy, and even among these firms, one observes them only after they become publicly traded. One would instead wish to turn to a Census data set of all firms in the economy to estimate such a model, though such data sets do not contain information on firm value.

That said, examining the model-implied growth rates and entry/exit rates is helpful for understanding strengths and weaknesses of the model. Table 6 presents the mean sales growth rates from the data and the corresponding values from the estimated models for all firms and for firms in selected R&D-intensive industries. As the mean sales growth rate moment was not used in the estimation, this comparison provides an out-of-sample evaluation of the model.

The results indicate that the model fares quite well on this dimension for the estimation on all firms. This is striking given that the only growth-related moment used in the estimation is the correlation between lagged R&D-to-sales and sales growth. Although the model captures firms in the steady state, it generates positive mean sales growth rates due to the fact that the jumps in the profitability process from innovations help generate asymmetric sales growth rates with nonzero means.

The model-implied sales growth rates match the corresponding data values for some of the industries but not others. In particular, the mean sales growth implied by the estimates for the pharmaceutical industry are far apart from the data, likely reflecting the fact that the mechanism in the model cannot capture the long gestation periods involved in drug development and the very high payoffs generated by successful new drugs.

The model fares less well on the entry/exit margin. Although the model contains a fixed cost, there is no exit (and thus no entry in equilibrium) at the estimated parameter values for all of the estimations. Economically, the continuation values of the firms are such that the fixed costs are insufficient to generate exit. Indeed, one may expect that while fixed costs are helpful for understanding exit among small, young firms, they would be unlikely to drive exit among large corporations. Turning to the data, Corbae and D'Erasmo (2014) report that the exit rate in the Compustat sample, excluding exits

due to mergers and acquisitions, equals 0.71%. They also report that more than half of these exits are due to firms defaulting on their debt.

One could address the absence of exit by expanding the model to include defaultable debt, though such an extension would be beyond the scope of this study. More simply, one could introduce an exogenous exit rate into the model and estimate this augmented model after calibrating the exit rate to the corresponding data value. Given that the exit rate among Compustat firms is less than 1%, one would expect that estimating this augmented model would yield results similar to those reported in the study. Finally, the absence of an entry/exit margin occurs more broadly in the structural investment literature; seminal studies such as Cooper and Haltiwanger (2006) and Bloom (2009) do not feature an entry/exit margin.

5. Identification

It is important to establish that the estimation procedure used in the study can indeed identify the various model parameters, particularly those related to R&D investment. This section tackles identification concerns using two methods: a graphical examination of the sensitivity of the simulated moments to model parameters and a reestimation of the model on simulated data.

5.1 *Sensitivity of moments to model parameters*

One potential concern is that the GMM objective function that is being minimized in the estimation is fairly flat with respect to some of the model parameters. This would imply that the matched moments are uninformative regarding those parameters. The low standard errors for the model parameters suggest that this is unlikely, as a flat GMM objective function would imply a high standard error, but it is helpful to verify that this is indeed so. Figure 1 plots the weighted sum-of-square differences between the data and the simulated moments over a range of values for the three R&D-related parameters, a, λ, and γ. The parameter values range from 0.975 to 1.025 times the estimated value. The figure indicates that the GMM objective function that is minimized by the estimator is indeed steeply sloped for each of the three parameters, indicating that the GMM objective function is sensitive to the model parameters. This implies that the moments used in the estimation are indeed informative about the R&D-related parameters in the model.

One further concern is that some pair of the R&D-related parameters may be colinear. That is, the GMM objective function may be mostly flat along some linear combination of λ, a, and γ. The distinct manners in which these three parameters enter the R&D policy function shown in Proposition 1 provide some comfort in this regard. Examining the covariance matrix for the parameter estimates indicates that λ indeed has a low correlation with the other parameters. However, the estimates for a and γ have a correlation of about 0.92, indicating some difficulty in separately identifying these two parameters. This reflects the fact that these two parameters have offsetting effects on the success probability shown in equation (4)—a rise in a offsets the negative impact of a rise in γ

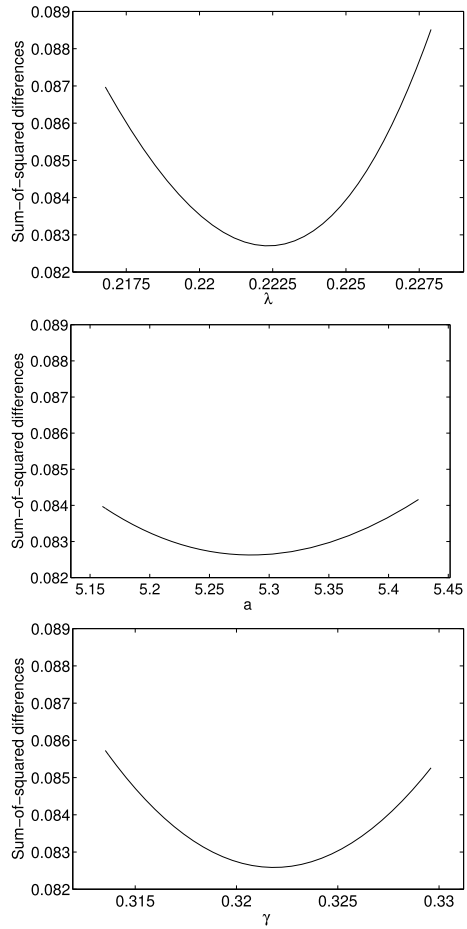

FIGURE 1. GMM objective function. The figures plot the value of the GMM objective function that is being minimized in the estimation reported in Table 2 as a function of a, λ, and γ. In each plot, the other parameters are held constant at their estimated values, while the x-variable varies over a 5% range centered on its point estimate.

on the R&D stock S_t. As such, the positive correlation between the estimates for a and γ has little impact on the implied success rate probabilities from the model and thus has little impact on the conclusion that firms face uncertainty in their R&D investment.

To further understand how the three R&D-related parameters are identified, Figure 2 plots some selected moments as a function of each of the three parameters. The figure indicates that, for the most part, the selected moments are informative about each of the R&D-related parameters. This variation in the moments with each of these parameters generates the variation in the GMM objective function seen in Figure 1.

Figure 2 also helps explain the low correlation between λ and the other two R&D-related parameters. While the average R&D-to-sales ratio increases with λ, it decreases with a and increases with γ. However, while average profitability increases with λ, it increases with a and decreases with γ, reflecting the effect of changes in steady-state

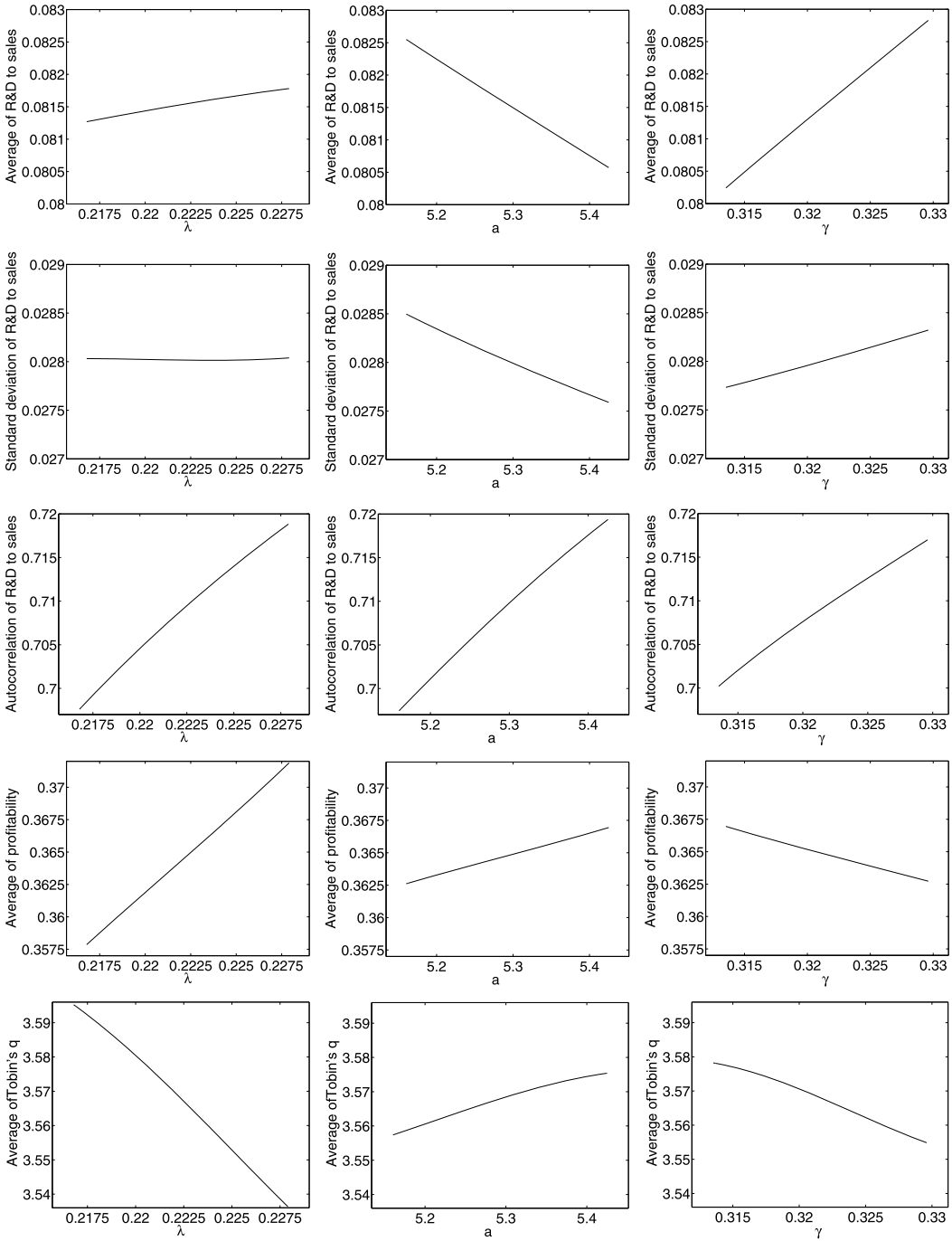

FIGURE 2. Selected moments. The figure plots selected moments from the estimation reported in Table 2 as a function of λ, a, and γ. Rows vary the selected moment, and the columns vary the R&D-related parameter. In each plot, the other parameters are held constant at their estimated values, while the x-variable varies over a 5% range centered on its point estimate.

firm size on measured profitability. The differential correlation between the effect of λ and the other two R&D-related parameters on these two moments leads to a relatively independent estimate for λ.

Figure 2 indicates that the autocorrelation of the R&D-to-sales ratio is helpful for identifying a and γ. While the other chosen moments have correlations with a and γ that differ in sign, the autocorrelation of the R&D-to-sales ratio has a positive correlation with both of these parameters, thus helping separate these two parameters.

5.2 *Estimation on simulated data*

The above analysis focuses on local identification of the R&D-related parameters in the model. Another potential concern relates to global identification of the model parameters. The use of the simulated annealing algorithm to search for the parameter vector that minimizes the GMM objective function partially alleviates this concern, as the simulated annealing algorithm uses a global search method to avoid getting trapped in local minima (see Kirkpatrick, Gelatt, and Vecchi (1983)).

One method of addressing global identification concerns involves reestimating the model on the simulated data set obtained from the initial estimation. Assuming the estimation procedure works well, one should recover the initial parameter estimates from this reestimation, as these parameters, by construction, generate the target matched moments used in the estimation. Table 7 reports the results of estimating the model on the simulated data set. This estimation is carried out using simulated data from the full sample estimation, as well as each of the industry-specific estimations.[18]

The results indicate that the estimation method is able to recover the parameters underlying the simulated data when applied to the sample of all firms. This indicates that the estimation method is successfully able to identify all of the model parameters when applied to the full sample. The estimation method is also able to recover the underlying parameters for some, but not all, of the industry estimates. In particular, the positive correlation between a and γ discussed above generates difficulty in recovering these two parameters from the estimation on the simulated data for a couple of the industry groups.

6. Counterfactual experiment

One benefit of an estimated structural model is that it can be used to carry out counterfactual policy experiments. This section uses the above estimated model to study the effect of an increase in the tax subsidy to R&D, τ_{rd}. The U.S. federal tax code provides a research and experimentation tax credit that is slated to expire at the end of 2013. The current budgetary environment makes the future of this tax credit uncertain, although supporters advocate expanding the tax credit and making it permanent.[19]

[18]In addition to the matched moments, the weighting matrix used to minimize the sum-of-squared difference is also recalculated when estimating the model on the simulated data.

[19]On September 8, 2010, President Obama called for the Research and Experimentation Tax Credit to be expanded and made permanent.

TABLE 7. Model estimation using simulated data.

Parameter	θ	ρ	σ	λ	a	b	γ	fc
All Firms								
Actual data	0.396	0.587	0.380	0.222	5.293	0.497	0.322	0.409
Simulated data	0.397	0.592	0.354	0.221	5.197	0.484	0.315	0.400
Selected Industries								
Business services								
Actual data	0.392	0.591	0.348	0.228	4.392	0.457	0.365	0.375
Simulated data	0.392	0.580	0.371	0.227	4.474	0.454	0.381	0.380
Chips								
Actual data	0.450	0.599	0.387	0.207	8.750	0.585	1.000	0.337
Simulated data	0.450	0.599	0.387	0.207	8.801	0.587	0.997	0.338
Hardware								
Actual data	0.421	0.617	0.438	0.246	4.144	0.674	0.378	0.409
Simulated data	0.431	0.646	0.343	0.233	4.015	0.660	0.362	0.361
Medical equipment								
Actual data	0.260	0.599	0.242	0.384	9.514	0.345	0.534	0.479
Simulated data	0.257	0.678	0.219	0.372	16.067	0.365	0.830	0.483
Pharmaceuticals								
Actual data	0.256	0.545	0.102	0.504	2.190	0.391	0.902	0.327
Simulated data	0.253	0.609	0.108	0.464	2.843	0.381	0.986	0.330
Software								
Actual data	0.250	0.591	0.256	0.461	7.018	0.443	0.896	0.456
Simulated data	0.264	0.471	0.380	0.470	3.563	0.452	0.495	0.451

Note: The table presents the results obtained from estimating the model on data obtained by simulating the model with the parameters given in Tables 2 and 3. The table reports the parameter estimates based on the actual data that are used to construct the simulated data and the corresponding parameter estimates from the simulated data sets. The weighting matrices for the estimations are also calculated using each of the simulated data sets.

In particular, this section examines both the short-run and the steady-state effects of an increase in the tax credit using the estimated model. These two effects may differ as changes in the steady-state distribution of firms can act as either a damping or amplifying mechanism for the initial short-run effects. For instance, in the model above, an increased tax credit encourages additional innovation, which leads to a shift in the steady-state profitability distribution in the economy. Investigating both the short-run and the steady-state effects is helpful, as while regression estimates typically identify the short-run effects, policy evaluation requires an understanding of long-run effects.

The short-run effect can be formally derived by differentiating the optimal R&D policy function given in Proposition 1 with respect to τ_{rd} to obtain

$$\frac{\partial}{\partial \tau_{\text{rd}}}\left(\frac{S'}{K^{\theta}}\right) = \frac{1}{a(1-\tau_{\text{rd}}-\tau)}.$$

One can rewrite the above expression in terms of a dollar impact on the optimal R&D stock of a \$1.00 R&D tax credit to obtain

$$\frac{1}{S'}\frac{\partial S'}{\partial \tau_{\text{rd}}} = \frac{K^{\theta}}{aS'(1-\tau_{\text{rd}}-\tau)}. \tag{13}$$

TABLE 8. Counterfactual experiment on a subsidy to R&D expenditures.

		$1.00 Impact		Steady-State Averages			
	τ_{rd}	Short Run	Steady State	R&D-to-Sales	Profitability	Tobin's q	Success Rate
All Firms							
Experiment	0.05	$1.19	$0.84	0.083	0.364	3.615	0.840
Selected Industries							
Business services							
Experiment	0.05	$1.28	$0.95	0.104	0.329	4.141	0.812
Chips							
Experiment	0.05	$1.86	$1.30	0.116	0.324	3.715	0.708
Hardware							
Experiment	0.05	$1.25	$0.89	0.113	0.353	3.762	0.816
Medical equipment							
Experiment	0.05	$0.62	$0.45	0.093	0.468	4.860	0.939
Pharmaceuticals							
Experiment	0.05	$0.92	$1.01	0.288	0.260	6.783	0.682
Software							
Experiment	0.05	$0.82	$0.58	0.166	0.341	6.018	0.916

Note: The table reports the results of an increase in the tax subsidy on R&D expenditure, τ_{rd}. The first panel reports the results from the estimations using all firms under the assumptions of a single profitability jump. The subsequent panels report the results from the estimations for the selected R&D-intensive industries. The "Experiment" rows report values obtained with a higher tax subsidy of $\tau_{rd} = 0.05$.

In comparison, the steady-state effect can be examined by comparing the change in the mean R&D expenditures—assuming a constant capital stock—before and after the counterfactual experiment.

Table 8 presents the results of a counterfactual experiment of an increase in the tax subsidy to R&D expenditures, τ_{rd}, from 2.5% in the estimated model to 5%. Although the Research and Experimentation Tax Credit uses a more complex formula than the proportional credit employed in the model, this experiment could be helpful for understanding the impact of an overall increase in the tax subsidy provided to R&D expenditures both in the short run and across steady states.

The increased R&D tax credit leads to an increase in R&D expenditures, reflecting the positive marginal effect shown in equation (13). In dollar terms, an additional $1.00 of R&D tax credits leads to a short-run increase in R&D expenditures of about $1.20. This finding is similar to that obtained by Hall and van Reenen (2000) and Bloom, Griffith, and van Reenen (2002), who find that a $1.00 increase in R&D subsidies leads to a $1.00 or more increase in R&D expenditures.[20] The ability of the model to replicate these empirical findings in the literature provides an indirect validation of the model.

The increase in the success rate leads to an overall upward shift in the steady-state distribution of z. This also leads to a small increase in the mean profitability and Tobin's q. This shift can have a mixed effect on the optimal R&D stock of the firm, which

[20]Conversely, Wilson (2009) finds no net effect of state R&D tax subsidies on R&D expenditures.

depends on the ratio of the expected jump in firm value from an innovation to the capital stock to the power θ. As such, the steady-state effect of the R&D tax credit may differ from the marginal effect. As the table indicates, the results indicate that the steady-state effect is noticeably smaller than the short-run impact, with a \$1.00 R&D tax credit generating only 84 cents of additional R&D expenditures. This implies that changes in the distribution of firms may mitigate the beneficial effects of R&D tax credits. One limitation of this analysis is that it ignores possible further general equilibrium effects—through changes in wages and the capital stock—of these policy changes.

The additional tax credit generates a small increase of less than 1 percentage point in the average success rate of innovations. This small increase partly reflects the fact noted above that the effect of the additional tax credit on R&D expenditures is not particularly large. Furthermore, the success rate function shown in equation (4) exhibits decreasing returns to scale, and given the already high rate of R&D expenditures observed in the economy, the marginal effect of additional R&D expenditures on the success rate is quite modest.

The counterfactual experiment on the industry-level estimates generates broadly similar findings. The short-run dollar impact ranges from about 62 cents to as high as \$1.86. While the corresponding long-run impact is somewhat smaller for most of the industries, it rises for the medical equipment industry, indicating that the difference between short-run and steady-state impacts in the model varies with the estimated parameter values. The increased tax credit leads to an increase in the average success rate of innovations in all industries; however, this increase is greater in industries that had lower initial success rates. This finding is consistent with the above argument that the R&D tax credits have only modest effects on success rates in the model when the estimated parameters already imply a high rate of innovation.

7. Conclusion

This study presents a dynamic model of investment in R&D and physical capital. R&D investments lead firms to generate stochastic innovations that increase profits. Firms invest in physical capital following such innovations to benefit from the increase in their profitability. The model is estimated on data on all firms that engage in R&D as well as firms in selected R&D-intensive industries. The model captures variation in moments on R&D expenditures, profits, and firm value across heterogenous samples. These results highlight the uncertainty that firms face from their R&D investments and that these investments play a key role in understanding firm profits and valuations.

The estimated model is used to carry out a counterfactual experiment on an increase in the tax credit to R&D expenditures. The increased tax credit leads to an increase in R&D expenditures, leading to higher profitability and valuations. The increased tax credit has only a modest effect on the rate of innovation, reflecting the already high rate of innovation implied by the model estimates. The findings also reveal that the effect of the increased tax credit may lessen over the long run as the increase in R&D expenditures also shifts the distribution of firms in the economy. This suggests that further research into understanding the dynamics of firms' R&D expenditures may be helpful for evaluating the effect of R&D tax credits over the long run.

Appendix A: Proofs

Proposition 1. *The optimal R&D stock of the firm when $S_i' > 0$ is given by*

$$\frac{\tilde{S}_i'}{K_i^\theta} = \frac{1}{a}\Bigg[\log(a) - \log\big((1-\tau_{\mathrm{rd}}-\tau)\big(1-\beta(1-\gamma)\big)\big) + \log\Bigg(\frac{\beta(E_z[G_c(K_i', z_i')|j_i=1] - E_z[G_c(K_i', z_i')|j_i=0])}{K_i^\theta}\Bigg)\Bigg].$$

Proof. The first-order condition for the optimal R&D stock yields

$$-(1-\tau_{\mathrm{rd}}-\tau) + (1-\tau_{\mathrm{rd}}-\tau)\beta(1-\gamma) + \beta\frac{\partial E_z[G_c(K_i', z_i')]}{\partial S_i'} = 0. \tag{A.1}$$

The impact of R&D spending on the expected value of the firm in the next period can be clarified by substituting the expression for $p(j_i)$ given in equation (4) into the expectation for $E_z[G_c(K_i', z_i')]$ given in equation (10):

$$\begin{aligned} E_z\big[G_c\big(K_i', z_i'\big)\big] = {} & E_z\big[G_c\big(K_i', z_i'\big)|j_i=1\big]\Bigg(1-\exp\Bigg(-a\frac{S_i'}{K_i^\theta}\Bigg)\Bigg) \\ & + E_z\big[G_c\big(K_i', z_i'\big)|j_i=0\big]\exp\Bigg(-a\frac{S_i'}{K_i^\theta}\Bigg). \end{aligned} \tag{A.2}$$

Recall that the R&D stock has no effect on the conditional expectation of $G_c(K_i', z_i')$ given j_i. The derivative of the above expression with respect to S_i' yields

$$\begin{aligned} \frac{\partial E_z[G_c(K_i', z_i')]}{\partial S_i'} = {} & \frac{a}{K_i^\theta}\exp\Bigg(-a\frac{S_i'}{K_i^\theta}\Bigg) \\ & \times \big(E_z\big[G_c\big(K_i', z_i'\big)|j_i=1\big] - E_z\big[G_c\big(K_i', z_i'\big)|j_i=0\big]\big). \end{aligned} \tag{A.3}$$

Substituting the above expression into the first-order condition given in (A.1) yields the optimal policy function for the firm's R&D stock,

$$\begin{aligned} & (1-\tau_{\mathrm{rd}}-\tau)\big(1-\beta(1-\gamma)\big) \\ & \quad = \beta\frac{a}{K_i^\theta}\exp\Bigg(-a\frac{\tilde{S}_i'}{K_i^\theta}\Bigg)\big(E_z\big[G_c\big(K_i', z_i'\big)|j_i=1\big] - E_z\big[G_c\big(K_i', z_i'\big)|j_i=0\big]\big), \\ & \frac{\tilde{S}_i'}{K_i^\theta} = \frac{1}{a}\Bigg[\log(a) - \log\big((1-\tau_{\mathrm{rd}}-\tau)\big(1-\beta(1-\gamma)\big)\big) \\ & \qquad + \log\Bigg(\frac{\beta(E_z[G_c(K_i', z_i')|j_i=1] - E_z[G_c(K_i', z_i')|j_i=0])}{K_i^\theta}\Bigg)\Bigg]. \end{aligned}$$

Some algebra reveals that the second-order condition with respect to S_i' is negative, ensuring that the first-order conditions yield the optimal policy in the interior region. □

Appendix B: Simulated method of moments

The indirect inference method of Gourieroux, Monfort, and Renault (1993) obtains parameter estimates by matching a set of selected moments from the data to those obtained by simulation. Denote the true values of the structural parameters by Ψ^*. The matched moments can be written as a solution to a minimization problem $Q(Y, M)$, where Y denotes the data and M denotes the moments to be matched. The data moments are then given by

$$\hat{M} = \arg\min_{M} Q(Y_N, M), \tag{B.1}$$

where Y_N denotes a data matrix with N observations. The corresponding moments for the simulated data set with parameter vector Ψ and $n = N \times S$ observations are given by

$$\hat{m}(\Psi) = \arg\min_{M} Q(Y_n, M). \tag{B.2}$$

The study picks $S = 8$, which is within the recommended range.

The structural parameters are then obtained by minimizing a quadratic form of the distance between the data and simulated moments,

$$\hat{\Psi} = \arg\min_{\Psi} N\big[\hat{M} - \hat{m}(\Psi)\big]' \hat{W} \big[\hat{M} - \hat{m}(\Psi)\big], \tag{B.3}$$

where $\hat{W}$ denotes a positive definite weighting matrix. The value of the above function at the minimum provides a goodness-of-fit measure. The optimal weighting matrix is given by

$$\hat{W} = \big[N \operatorname{var}(\hat{M})\big]^{-1}. \tag{B.4}$$

The above covariance matrix is calculated with the actual data set using the influence function method of Erickson and Whited (2000). The estimator is asymptotically normal for fixed S with covariance matrix given by

$$\begin{aligned} &\sqrt{N}\big(\hat{\Psi} - \Psi^*\big) \sim \mathsf{N}(0, \Sigma), \\ &\Sigma = \left(1 + \frac{1}{S}\right)\left[\frac{\partial^2 Q}{\partial \Psi \, \partial M'}\left(\frac{\partial Q}{\partial M}\frac{\partial Q}{\partial M}'\right)^{-1}\frac{\partial^2 Q}{\partial M \, \partial \Psi'}\right]^{-1}. \end{aligned} \tag{B.5}$$

While $\frac{\partial Q}{\partial M}$ can be evaluated analytically, numerical methods are required to obtain $\frac{\partial^2 Q}{\partial \Psi \, \partial M}$. Both partial derivatives are computed using simulated data evaluated at the data moments.

Appendix C: Numerical solution

The simulations require a numerical solution of the value function for R&D firms. The capital grid has 201 points and the profitability grid has 21 points. The capital grid is centered around an approximation of the median size of the firm, given the parameters. Simulations that result in steady-state firm sizes near the boundaries of the grid are

discarded in the estimation. The profit grid is formed using the quadrature method of Tauchen and Hussey (1991), with a mean value obtained by guessing the success rate. The endogenous jumps in z from an innovation are handled by interpolating firm value over two more grids constructed using the transition equation for profitability conditional on whether the firm innovates. The expected value of the firm is obtained using the law of iterated expectations.

The simulated sample is generated using the value and policy functions for R&D firms. The law of motion for profitability is generated directly using the transition equations. The firm's decisions are obtained using linear interpolation of the policy functions. The simulation is run for 100 years, with the initial 50 discarded as a burn-in sample. The value of the quadratic form of the distance between the data moments and the simulated moments is computed for each simulation. The program searches for the parameters that minimize this distance using the simulated annealing algorithm. Each estimation involved evaluating more than 50,000 candidate parameter sets and took 1–2 weeks of computing time.

The estimation of the model with multiple jumps per period follows a similar procedure. However, it is no longer possible to solve for the optimal R&D stock explicitly. Instead, the optimal R&D stock is solved for by using a grid search method, with 301 grid points for the optimal R&D stock.

Appendix D: Industry classification

The selected industry groups are constructed based on four-digit SIC codes. The list of SIC codes included in each industry category is as follows:

- Business services: 2750–2759, 3993, 4220–4229, 7218, 7300, 7310–7342, 7349–7353, 7359–7369, 7374, 7376–7385, 7389–7394, 7396–7397, 7399, 7519, 8700–8713, 8720–8721, 8730–8734, 8740–8748, 8910–8911, 8920–8999
- Chips: 3622, 3661–3666, 3669–3679, 3810, 3812
- Hardware: 3570–3579, 3680–3689, 3695
- Medical equipment: 3693, 3811, 3820–3827, 3829–3851
- Pharmaceuticals: 2830, 2831, 2833–2836
- Software: 7370–7373, 7375.

References

Abel, A. and J. C. Eberly (1994), "A unified model of investment under uncertainty." *American Economic Review*, 84, 1369–1384. [534]

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005), "Competition and innovation: An inverted-U relationship." *Quarterly Journal of Economics*, 120, 701–728. [535]

Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl (2009), "The effects of entry on incumbent innovation and productivity." *Review of Economics and Statistics*, 91, 20–32. [540]

Aghion, P., C. Harris, P. Howitt, and J. Vickers (2001), "Competition, imitation and growth with step-by-step innovation." *Review of Economic Studies*, 68, 467–492. [540]

Aghion, P. and P. Howitt (1992), "A model of growth through creative destruction." *Econometrica*, 60, 323–351. [532]

Akcigit, U. (2009), "Firm size, innovation dynamics, and growth." Working paper, University of Pennsylvania. [535, 541]

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2011), "R&D investment, exporting, and productivity dynamics." *American Economic Review*, 101, 1312–1344. [531, 535]

Bertsekas, D. P. (2000), *Dynamic Programming and Optimal Control*, Vol. 1. Athena Scientific, Belmont, MA. [538]

Bloom, N. (2009), "The impact of uncertainty shocks." *Econometrica*, 77, 623–685. [541, 552]

Bloom, N., R. Griffith, and J. van Reenen (2002), "Do R&D tax credits work? Evidence from a panel of countries 1979–1997." *Journal of Public Economics*, 85, 1–31. [533, 557]

Bloom, N., M. Schankerman, and J. van Reenen (2013), "Identifying technology spillovers and product market rivalry." *Econometrica*, 81, 1347–1393. [531]

Boldrin, M. and D. K. Levine (2008), "Perfectly competitive innovation." *Journal of Monetary Economics*, 55, 435–453. [537]

Broda, C. and D. E. Weinstein (2006), "Globalization and the gains from variety." *Quarterly Journal of Economics*, 121, 541–585. [546]

Brown, J. R., S. M. Fazzari, and B. C. Petersen (2009), "Financing innovation and growth: Cash flow, external equity and the 1990s R&D boom." *Journal of Finance*, 64, 151–185. [534]

Caballero, R. J. and E. M. R. A. Engel (1999), "Explaining investment dynamics in U.S. manufacturing: A generalized (S, s) approach." *Econometrica*, 67, 783–826. [539]

Cooley, T. F. and V. Quadrini (2001), "Financial markets and firm dynamics." *American Economic Review*, 91, 1286–1310. [550]

Cooper, R. W. and J. Ejarque (2003), "Financial frictions and investment: Requiem in Q." *Review of Economic Dynamics*, 6, 710–728. [541]

Cooper, R. W. and J. Haltiwanger (2006), "On the nature of capital adjustment costs." *Review of Economic Studies*, 73, 611–633. [534, 541, 546, 552]

Corbae, D. and P. D'Erasmo (2014), "Reorganization or liquidation: Bankruptcy choice and firm dynamics." Working paper, University of Wisconsin. [551]

Corrado, C., J. Haltiwanger, and D. Sichel (2005), *Measuring Capital in the New Economy*. NBER Studies in Income and Wealth. University of Chicago Press, Chicago, IL. [545]

Doraszelski, U. and J. Jaumandreu (2013), "R&D and productivity: Estimating endogenous productivity." *Review of Economic Studies*, 80, 1338–1383. [531, 535]

Eberly, J., S. Rebelo, and N. Vincent (2008), "Investment and value: A neoclassical benchmark." Working Paper 13866, NBER. [534, 541]

Erickson, T. and T. M. Whited (2000), "Measurement error and the relationship between investment and q." *Journal of Political Economy*, 108, 1027–1057. [546, 560]

Gomes, J. F. (2001), "Financing investment." *American Economic Review*, 91, 1263–1285. [534, 542]

Gourieroux, C., A. Monfort, and E. Renault (1993), "Indirect inference." *Journal of Applied Econometrics*, 8, S85–S118. [532, 541, 560]

Greenwood, J. and B. Jovanovic (1999), "The information-technology revolution and the stock market." *American Economic Association (Papers and Proceedings)*, 89, 116–122. [535]

Griliches, Z. (1979), "Issues in assessing the contribution of research and development to productivity growth." *Bell Journal of Economics*, 10, 92–116. [531, 535]

Griliches, Z. (1994), "Productivity, R&D, and the data constraint." *American Economic Review*, 84, 1–23. [541]

Griliches, Z. (2000), *R&D, Education and Productivity: A Retrospective*. Harvard University Press, Boston, MA. [531]

Griliches, Z. and J. Mairesse (1984), "Productivity and R&D at the firm level." In *R&D, Patents, and Productivity* (Z. Griliches, ed.), University of Chicago Press, Chicago, IL. [532, 545]

Grossman, G. M. and E. Helpman (1991), *Innovation and Growth in the Global Economy*. MIT Press, Boston, MA. [532]

Hall, B. H. (2010), "Measuring the returns to R&D: The depreciation problem." In *Contributions in Memory of Zvi Griliches* (J. Mairesse and M. Trajtenberg, eds.), NBER Books, Cambridge, MA. [545]

Hall, B. H. and J. Mairesse (1995), "Exploring the relationship between R&D and productivity in French manufacturing firms." *Journal of Econometrics*, 65, 263–293. [531]

Hall, B. H. and J. van Reenen (2000), "How effective are fiscal incentives for R&D? A review of the evidence." *Research Policy*, 29, 449–469. [533, 557]

Hall, R. E. (2001), "The stock market and capital accumulation." *American Economic Review*, 91, 1185–1202. [545]

Haltiwanger, J. C., R. S. Jarmin, and J. Miranda (2013), "Who creates jobs? Small vs large vs young." *Review of Economics and Statistics*, 95, 347–361. [550]

Hayashi, F. (1982), "Tobin's marginal q and average q: A neoclassical interpretation." *Econometrica*, 50, 213–224. [542]

Hendel, I. and A. Nevo (2006), "Measuring the implications of sales and consumer inventory behavior." *Econometrica*, 74, 1637–1673. [546]

Hennessy, C. A. and T. M. Whited (2005), "Debt dynamics." *Journal of Finance*, 60, 1129–1165. [541]

Hennessy, C. A. and T. M. Whited (2007), "How costly is external financing? Evidence from a structural estimation." *Journal of Finance*, 62, 1705–1745. [541]

Hobijn, B. and B. Jovanovic (2001), "The information-technology revolution and the stock market: Evidence." *American Economic Review*, 91, 1203–1220. [535]

Jones, C. I. (1995a), "R&D-based models of economic growth." *Journal of Political Economy*, 103, 759–784. [536]

Jones, C. I. (1995b), "Time series tests of endogenous growth models." *Quarterly Journal of Economics*, 110, 495–525. [536]

Kaplan, G. (2012), "Inequality and the lifecycle." *Quantitative Economics*, 3, 471–525. [541]

Kirkpatrick, S., C. D. Gelatt, and M. P. Vecchi (1983), "Optimization by simulated annealing." *Science*, 220, 671–680. [555]

Klette, T. J. and S. Kortum (2004), "Innovating firms and aggregate innovation." *Journal of Political Economy*, 112, 986–1018. [535, 536]

Kortum, S. (1997), "Research, patenting and technological change." *Econometrica*, 65, 1389–1419. [536]

Lach, S. and M. Schankerman (1989), "Dynamics of R&D and investment in the scientific sector." *Journal of Political Economy*, 97, 880–904. [532]

Lentz, R. and D. T. Mortensen (2008), "An empirical model of growth through innovation." *Econometrica*, 76, 1317–1373. [541, 550]

Moris, F. (2005), "The U.S. research and experimentation tax credit in the 1990s." InfoBrief NSF05-316, National Science Foundation, Arlington, VA. [537]

Pakes, A. and P. McGuire (1994), "Computing Markov-perfect Nash equilibria: Numerical implications of a dynamic differentiated product model." *RAND Journal of Economics*, 25, 555–589. [536]

Romer, P. M. (1990), "Endogenous technological change." *Journal of Political Economy*, 98, S71–S102. [532, 536]

Segerstrom, P. S. (1998), "Engogenous growth without scale effects." *American Economic Review*, 88, 1290–1310. [536]

Summers, L. H. and M. A. Salinger (1983), "Tax reform and corporate investment: A microeconometric simulation study." In *Behavioral Simulation Methods in Tax Policy Analysis* (M. Feldstein, ed.), University of Chicago Press, Chicago, IL. [542]

Tauchen, G. and R. Hussey (1991), "Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models." *Econometrica*, 59, 371–396. [561]

Thompson, P. (2001), "The microeconomics of an R&D-based model of endogenous growth." *Journal of Economics Growth*, 6, 263–283. [535]

Whited, T. M. (1992), "Debt, liquidity constraints, and corporate investment: Evidence from panel data." *Journal of Finance*, 47, 1425–1460. [542, 546]

Wilson, D. J. (2009), "Beggar thy neighbor? The in-state, out-of-state, and aggregate effects of R&D tax credits." *Review of Economics and Statistics*, 91, 431–436. [557]

Xu, D. Y. (2008), "A structural empirical model of R&D, firm heterogeneity, and industry evolution." Working paper. [531, 541]

Young, A. (1998), "Growth without scale effects." *Journal of Political Economy*, 106, 41–63. [536]

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