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Abstract

Entrepreneurs undertake more R&D when financiers are better informed about their projects because they expect to receive more funding for successful projects. Conversely, financiers learn more about projects when entrepreneurs perform more R&D because then the opportunity cost of mis-investing is higher. Thus R&D and financial analysis are mutually reinforcing. Evidence based on two quasi-natural experiments supports this interaction. Quantitatively, investors' learning accounts for over a quarter of the total effect of a policy designed to stimulate R&D. A calibration suggests that the interaction's contribution to income growth represents a third of the total contributions of learning and R&D.

JEL Classification: G20, O31, O4

Keywords: Financial Development, growth, technological progress, Innovation, capital allocation, learning

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ABSTRACT

Entrepreneurs undertake more R&D when financiers are better informed about their projects because they expect to receive more funding for successful projects. Conversely, financiers learn more about projects when entrepreneurs perform more R&D because then the opportunity cost of mis-investing is higher. Thus R&D and financial analysis are mutually reinforcing. Evidence based on two quasi-natural experiments supports this interaction. Quantitatively, investors' learning accounts for over a quarter of the total effect of a policy designed to stimulate R&D. A calibration suggests that the interaction's contribution to income growth represents a third of the total contributions of learning and R&D.

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1 Introduction

This paper studies the interplay between firms' research and development (R&D) efforts and investors' analyses of their prospects. This interplay operates as follows. An entrepreneur attempts more research when financiers are better informed about the profitability of projects because, in that case, she expects financiers to more effectively discriminate across projects and hence to provide more funding to successful ones. Conversely, financiers collect more information about projects when an entrepreneur undertakes more R&D because, in that case, the opportunity cost of mis-investing—that is, of funding unsuccessful projects while missing out on successful ones—is higher. Thus, knowledge about technologies (financial analysis) and technological knowledge (R&D efforts) are mutually reinforcing. We develop a model to formalize this insight and evaluate it empirically. There is strong evidence that this interaction truly occurs, and we estimate that its contribution to income growth represents about a third of the total contributions made by R&D and financial analysis.

The model is purposely simple. It highlights the ingredients needed to generate our effect and structures the quantitative analysis. It features competitive rational agents who conceive risky projects, learn about their prospects, and invest in them. Costs are incurred either when innovating (what we call “research”) or when engaging in financial analysis (what we call “learning”). Unlike previous papers (discussed later in this section), here the positive feedback between research and learning is not a consequence of risk sharing (since risk is fully diversified away) or of moral hazard (since efforts can be contracted for). Instead, that feedback simply follows from the complementarity of capital and productivity. Expressing output as $Y = AK^\alpha$ where α is a positive parameter, and A and K denote (respectively) the uncertain productivity and the amount of capital attracted by a project, shows that the return on financiers' funds increases with A (every unit of capital yields a larger payoff) whereas the rewards from research increase with K (a productivity-enhancing invention can be applied on a larger scale). The complementarity between A and K leads to the complementarity between research and learning, which is the focus of our study.

Over time, technologies improve along with investors' information about them and with the allocation of capital, which leads to growth in total factor productivity (TFP) and, in turn, to growth in income. We compute the contributions of learning and research and also of their

interplay. The results demonstrate that the growth rate of income in the economy with both learning and research is larger than the *sum* of growth rates in (i) the economy with research but no learning and (ii) the economy with learning but no research—an outcome that reflects once again the positive feedback between learning and research. This finding implies, for example, that an economy converging to a steady state when learning and research do *not* interact can experience unbounded growth once they *do* interact. Our model is consistent with known stylized facts about the link between finance and growth, to the extent that financial development is positively correlated with the quality of financiers’ knowledge about projects.¹

We evaluate empirically the model’s main predictions in a sample of publicly listed US firms. Specifically, the model predicts that (i) financiers learn more when firms perform more research and (ii) firms perform more research when financiers learn more. Assessing these relationships empirically requires proxies for research and learning as well as a methodology capable of addressing the endogeneity bias generated by this two-way relationship.² We measure firms’ research effort as their R&D expenditures, and financiers’ learning effort about a firm as the number of financial analysts who follow that firm. To address the endogeneity of these relationships, we instrument each variable using shocks from two quasi-natural experiments: one that shifts firms’ research effort and another that shifts learning by the financial sector.

The first of these experiments exploits the staggered implementation of R&D tax credits by US states between 1990 and 2006 (Wilson 2009). After confirming the beneficial effect of these tax incentives on R&D expenditures, we show that—following their passage and as predicted by our model—analysts significantly increased their coverage of firms eligible for the tax credits as compared with other firms in the country. More specifically, we estimate that the sensitivity of analyst coverage to R&D expenditures is 1.1; thus, a 10% increase in R&D expenditures induces, on average, a 11% increase in analyst following (the addition, roughly, of one new analyst).

Our second experiment uses the identification strategy pioneered by Hong and Kacperczyk

¹For the sake of parsimony, we do not explicitly model the financial sector. Instead, we interpret the amount of resources devoted to analyzing investment opportunities as a proxy for the extent of financial development. We call “financiers” the agents responsible for deploying capital in this economy.

²In the case of prediction (i) for example, a least-squares regression of learning on research yields inconsistent estimates because the regression’s residual is correlated with the regressor (research), as implied by prediction (ii).

(2010) and extended by, among others, Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013). The most recent of these papers considers mergers between and closures of brokerage houses that resulted in the dismissal of analysts. The authors provide evidence that the resulting drop in analyst coverage is largely exogenous to firms' policies. We document that the firms that lose analysts because of broker events significantly reduce their R&D expenditures relative to unaffected firms, in line with our model. Numerically, we estimate that the sensitivity of R&D expenditures to analyst coverage is 0.25; that is, a 10% decline in analyst coverage (roughly the loss of one analyst) triggers, on average, a 2.5% reduction in R&D expenditures.

Auxiliary predictions are also confirmed empirically. In the first experiment (positive shock to research effort), increased learning by financiers should result in funding that is both more highly correlated with firm quality and more dispersed across firms, as investors channel more funds to firms that they consider to be more efficient. This is indeed what we observe: following the passage of R&D tax credits, the correlation between new financing proceeds (measured as the sum of debt and equity issues normalized by assets) and firm quality (proxied by market value and Tobin's Q) as well as the cross-sectional dispersion of these proceeds are significantly higher among treated than control firms. Turning to the second experiment (negative shock to learning effort), the model predicts a reduction in the risk taken by entrepreneurs who realize that financiers are less capable of identifying the best projects. The data again support this prediction: following the loss of analysts due to broker disappearances, the return on assets, as well as the within-firm dispersions of patent citations and patent value—two proxies for the risk of firms' research—are significantly lower across treated than control firms. Both sets of findings lend support to the mechanism underlying our model.

The magnitude of the interaction effect is economically important. As an illustration, we estimate that the indirect effect of an R&D tax credit on R&D expenditures—one that operates through analysts' response—accounts for 28% of the size of that tax credit's total effect. With reference to the previous examples, a 10% increase in R&D expenditures triggered by an R&D tax credit has the effect of increasing coverage by about one analyst (11%), which in turn is responsible for nearly 2.8% (i.e., $11\% \times 0.25$) of the total 10% increase in R&D expenditures. We also quantify the contribution of the interaction effect to income growth. After calibrating the model using parameter estimates derived from our two experiments, we estimate that the interaction itself represents about one third (from 29% to 35%) of the total contributions of

learning and research to income growth.

Our analysis yields important insights on the effectiveness of policies aimed at promoting R&D (e.g., research subsidies or tax breaks). First, it suggests that such policies have a multiplier effect owing to the induced improvement in capital efficiency. Given our aforementioned estimates, the observed increase in R&D expenditures triggered by an R&D tax credit is about three-quarters due to the credit's direct effect and about one quarter (28%) due to the indirect effect of enhanced learning by the financial sector, which further stimulates R&D. Second, policies based on R&D incentives can be rendered more effective by coupling them with policies designed to increase capital efficiency—for example, encouraging equity research, improving accounting standards, and reducing impediments to trading financial assets.

We are not the first to model the interaction between financial analysis and innovation under imperfect information. In Bhattacharya and Chiesa (1995), de La Fuente and Marin (1996), Acemoglu and Zilibotti (1999), and Acemoglu, Aghion, and Zilibotti (2006), financiers supply capital to entrepreneurs whose effort they can monitor only at a cost. In Bhattacharya and Ritter (1983), King and Levine (1993), Ueda (2004), and Aghion, Howitt, and Mayer-Foulkes (2005), financiers do not observe entrepreneurs' ability. We assume away these problems of moral hazard and adverse selection, and show how the mutually reinforcing effects of learning and research arise as the first-best outcome in a setting without contracting frictions and without information asymmetry. In our setup, the entrepreneur and the financier coordinate in order to overcome the uncertainty inherent to the innovation process. At the time, it is unknown whether an invention will be a success; yet the entrepreneur needs to know that she will get financial backing should it prove successful. Only with such an understanding in place would an entrepreneur agree to exert the effort needed for a major breakthrough. Conversely, the financier is keener to investigate technologies with the potential to be breakthroughs.

Empirical research to date has focused mainly on the effect of the financial sector on corporate innovation. Kortum and Lerner (2000) and Lerner, Sorensen, and Stromberg (2011) find that venture capital and private equity activity stimulate firms' innovation. Banks, too, have been reported as having a beneficial effect. For example, Amore, Schneider, and Zaldokas (2013) document that the wave of US banking deregulation in the 1980s and 1990s spurred firms' innovation through an increase in credit supply. Several studies (Chava, Oettl, Subramanian, and Subramanian 2013; Hombert and Matray 2013; Cornaggia, Mao, Tian, and Wolfe

2015) qualify these findings by showing that the effect of banks depends crucially on the type of deregulation (i.e., whether it increases or decreases banks' local market power) and the type of firms studied (small vs. large, opaque vs. transparent, private vs. public). Other scholars examine the role of financial analysts in innovative activity. Derrien and Kesckés (2013) find, as we do, that a decline in analyst coverage reduces the firm's R&D expenditures (though that is not the focus of their study). He and Tian (2013) use data on patent output to argue that analyst coverage aggravates firms' "short-termism" and reduces the number of firms' patents. Clarke, Dass, and Patel (2015) qualify the latter result by showing that it is concentrated among the least productive innovators. Much less attention has been given to the reverse relationship: the effect of firms' innovation on financial sector activities. Our paper is the first to describe, empirically, a two-way linkage between the financial sector and corporate innovation. We show that shocks to the financial sector affect firms' innovation and vice versa.

The paper proceeds as follows. Section 2 presents the model. Section 3 lays out the empirical strategy. Section 4 describes the data. Section 5 reports the empirical results, which include a calibration of the model. Section 6 concludes. The three appendices discuss model fit, give formal proofs of our results, and present an extension of the model.

2 The Model

Our simple model describes the interaction between firms' research efforts and investors' information about them. It yields novel predictions that we then test using quasi-natural experiments, and allows us to quantify the interaction.

2.1 Setup

The economy consists of two sectors—a final goods sector and an intermediate goods sector—and two types of agents: entrepreneurs, who conceive the projects that constitute the intermediate sector; and financiers, who invest in those projects. The basic model features two periods; it is later extended to cover multiple periods so that we can evaluate its implications for long-run growth.

2.1.1 Agents

The population comprises a representative entrepreneur (“she”) and a representative financier (“he”). Both are risk neutral and consume only in period 2.

The Entrepreneur. The entrepreneur creates the technologies that produce intermediate goods. In period 1, she conceives a continuum of projects, with unit mass, indexed by $n \in [0, 1]$. The output of these projects is determined by a technology with decreasing returns to capital, $\tilde{Y}_n \equiv \tilde{A}_n(K_n)^\alpha$; here K_n is the amount of capital invested in project n in period 1, \tilde{A}_n is its random productivity (which can be learned in period 1, as we shall describe), \tilde{Y}_n is the quantity of intermediate good that project n yields in period 2 (net of capital depreciation), and α is a parameter—ranging between 0 and 1—that captures the extent of returns to scale.³

Projects are independent from one another (thus \tilde{A}_n is independent of \tilde{A}_m for any $m \neq n$), and they succeed with a 0.5 probability. Successful (resp. unsuccessful) projects yield a productivity $\tilde{A}_n = \bar{A}$ (resp. $\tilde{A}_n = \underline{A}$) for all n , where $\bar{A} > \underline{A} \geq 0$, as Figure 1 illustrates. Productivity in the cases of success and failure, \bar{A} and \underline{A} , are chosen by the entrepreneur. We assume that the entrepreneur has no influence on the probability of success but we demonstrate in Appendix C that the results of the model obtain when the entrepreneur controls, not productivity, but rather the probability of success. Creating a continuum of independent projects with productivity \bar{A} and \underline{A} costs $e_A(\bar{A} + \underline{A})$ in research. Here e_A is continuous, increasing, and convex; $e_A(0) = e'_A(0) = 0$; and $e'_A(+\infty) = +\infty$. Under this formulation, productivities in the case of success or failure are perfect substitutes in terms of their cost. We refer to \bar{A} and \underline{A} as “productivity” or (loosely) as the *research* effort. The entrepreneur raises the capital required to operate her technologies from the financier.

[[INSERT Figure 1 about Here]]

The Financier. The financier is endowed with wealth w , which he invests in projects set up by the entrepreneur. He allocates K_n units of capital to project n in period 1. At the time of investment, the financier does not know which projects will succeed. Instead, he re-

³A Cobb-Douglas function of this type is commonly employed to represent production in a setting with endogenous technology (see, among others, the textbooks of Barro and Sala-i-Martin (1995) and Jones (2002)). It subsumes the case of constant returns to scale, which can be obtained by driving α to 1 in the formulas that follow while noting that $\lim_{\alpha \rightarrow 1} [q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]^{1-\alpha} = q$.

ceives a continuum of imperfect signals \tilde{S}_n that reveal the successful projects. A signal is correct with probability q or incorrect with probability $1 - q$. That is, from the 0.5 successful (resp. unsuccessful) projects, $q/2$ are accurately identified as successes (resp. failures) while the remaining $(1 - q)/2$ projects are mis-labeled as failures (resp. successes). Observing signals of precision q costs $e_q(q)$. Here e_q is continuous, increasing, and convex; e'_q is convex; $e_q(1/2) = e'_q(1/2) = e''_q(1/2) = 0$; and $e'_q(1) = +\infty$. Note that $q = 1/2$ and $q = 1$ correspond to uninformative and perfect signals, respectively. As with the entrepreneur, the financier's chosen effort level applies to all the projects (i.e., $q_n = q_m$ for any $m \neq n$). Unlike research, learning does not affect the productivity of projects; instead, it enables a more efficient matching of capital with projects. We refer to q as the “precision” of information or (loosely) as the *learning* effort.

2.1.2 Technologies

The economy is home to two competitive sectors, an intermediate goods sector and a final goods sector. The former consists of the projects conceived by the entrepreneur and funded by the financier. These intermediate goods are used as inputs in the production of the final good via a riskless technology, $G \equiv Y^\beta$; here G is final output (used as the numéraire), Y denotes the use of the intermediate good, and $0 < \beta < 1$ is the factor share of the intermediate good in the production of the final good. Many identical firms compete in the final goods sector and aggregate to one representative firm.

2.1.3 Timing

At the start of period 1, the entrepreneur and the financier determine their research and learning efforts. Then the financier observes his signals and distributes his wealth across the projects. Importantly, at this stage, the financier does not know for certain which projects will succeed; he relies solely on his imperfect signals. In period 2, the successful projects are revealed, final goods are produced, and agents consume their share of the profits.

2.1.4 Discussion of the Model's Assumptions

Our model offers a parsimonious description of the interplay between firms' research efforts and investors' information about them. A central assumption is that effort levels (in both research and learning) are contractible. That is, they are determined *ex ante* cooperatively by the entrepreneur and the financier. As a result, the first-best outcome is achieved.⁴ More generally, there are no information asymmetries in the model: initially (i.e., at the time they choose their efforts), the entrepreneur and the financier are equally ignorant about which projects will be successful. The model's logic continues to apply when information is asymmetric (i.e., moral hazard) provided that the entrepreneur has no way of perfectly communicating her private information (i.e., her effort) to the financier.

Other assumptions can be relaxed without making any significant difference in our findings. As mentioned above, those results continue to hold when the entrepreneur controls not productivity but rather the likelihood of success, as shown in Appendix C. Our assumption that agents exert equal effort across projects simplifies the analysis by ensuring that they actually develop a large number of projects and do not simply concentrate their efforts on only a few of them. Alternatively, we could assume the existence of an upper bound on how much capital a project can attract. The main findings obtain also under a more general cost structure for research, $e_A(\bar{A}, \underline{A})$, as long as e_A is increasing and convex in each variable. Our assumptions on the cost functions are not necessary but merely sufficient to guarantee the existence of an interior equilibrium and its unicity. Risk neutrality can be relaxed, in favor of any increasing concave utility function, because our setup incorporates no aggregate risk. We could also drop the final goods sector, since its only purpose is to aggregate the output produced by multiple projects, and assume instead that agents derive utility directly from the consumption of intermediate goods.

2.2 Equilibrium Characterization

An equilibrium is defined by three conditions, which we describe next.

1. *Market clearing in the intermediate goods sector.* Final goods producers maximize their profit. Since intermediate goods trade in a competitive market, their equilibrium price in

⁴This assumption of contractible efforts implies that multiple equilibria do not arise.

period 2 is $\rho = \beta Y^{\beta-1}$, where $Y = \int_n \tilde{A}_n(K_n)^\alpha$ sums up output over all projects. There is no aggregate risk in this economy, so both ρ and Y are deterministic.

2. *Capital allocation.* After observing his signals $\{\tilde{S}_n\}_{n \in [0,1]}$, the financier distributes his wealth w across the entrepreneur's offered projects so as to maximize his total expected profits while taking ρ , \bar{A} , \underline{A} , and q as given:

$$\pi(q, \bar{A}, \underline{A}, w) \equiv \max_{\{K_n\}_{n \in [0,1]}} E \left[\rho \int_n \tilde{A}_n(K_n)^\alpha \mid \{\tilde{S}_n\}_{n \in [0,1]} \right] \quad \text{subject to} \quad \int_n K_n = w. \quad (1)$$

As with output (see condition 1), π is deterministic.

3. *First-best effort levels.* The entrepreneur and the financier cooperatively determine their effort levels (before the signals \tilde{S}_n are observed) in order to maximize the ex ante total surplus. That surplus is equal to the expected profit net of effort costs when taking the equilibrium price of intermediate goods, ρ , as given (the model is agnostic about how this surplus is shared between the entrepreneur and the financier):

$$\max_{q, \bar{A}, \underline{A}} \pi(q, \bar{A}, \underline{A}, w) - e_q(q) - e_A(\bar{A} + \underline{A}). \quad (2)$$

The equilibrium is characterized by our first proposition, as follows. (The proofs for all results are given in Appendix B.)

PROPOSITION 1 *In equilibrium, the learning effort q and the research effort (\bar{A}, \underline{A}) are the unique solutions to the following system of equations:*

$$\beta w^{\alpha\beta} V(q)^\beta = 2^{\beta(1-\alpha)} \bar{A}^{1-\beta} e'_A(\bar{A}) \quad \text{and} \quad \underline{A} = 0; \quad (3)$$

$$\beta w^{\alpha\beta} \bar{A}^\beta [q^{\alpha/(1-\alpha)} - (1-q)^{\alpha/(1-\alpha)}] = 2^{\beta(1-\alpha)} V(q)^{1/(1-\alpha)-\beta} e'_q(q). \quad (4)$$

where $V(q) \equiv (q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)})^{1-\alpha}$.

*The financier allocates $2w(q/V(q))^{1/(1-\alpha)}$ units of capital to a project deemed successful by his signal and allocates $2w((1-q)/V(q))^{1/(1-\alpha)}$ to a project deemed unsuccessful.*⁵

The entrepreneur chooses to concentrate her effort on improving returns in case of success,

⁵In the case of constant returns to scale in the intermediate goods sector (i.e., if $\alpha = 1$), these equations collapse to $\beta w^\beta q^\beta = \bar{A}^{1-\beta} e'_A(\bar{A})$, $\underline{A} = 0$, and $\beta w^\beta \bar{A}^\beta = q^{1-\beta} e'_q(q)$, with the financier allocating $2w$ units of capital to a project deemed successful and none to a project deemed unsuccessful.

setting \underline{A} to 0. Indeed, increasing the productivity in case of success, \bar{A} , is more beneficial than increasing it in case of failure, \underline{A} (because successful projects receive more capital), yet it costs the same (because the cost of research e_A is a function of the sum $\bar{A} + \underline{A}$). From now on, the research effort will designate \bar{A} . In equilibrium ($\underline{A} = 0$), the amount invested depends only on the learning effort q ; the research effort does not matter because it scales, by an *identical* factor, the values of projects expected to succeed and of those expected to fail. We now describe properties of the equilibrium.

2.3 Equilibrium Properties

The next proposition describes how learning and research efforts interact in equilibrium.

PROPOSITION 2 *The research effort is increasing in the learning effort. Conversely, the learning effort is increasing in the research effort.*

The first part of this proposition follows from noting that the function V (defined in Proposition 1) is increasing in the learning effort q (for any $q > 1/2$); hence, by equations (3), the research effort \bar{A} increases with q when we hold wealth constant. Intuitively, research is stimulated when the financier is better informed, because then the entrepreneur knows that he will be more discriminating and allocate more funds to good projects (and less to bad ones). Putting it differently, the higher the learning effort, the more closely capital tracks a project's productivity, and therefore the more convex is its profit as a function of productivity (since profit takes the form AK^α , and K is increasing in A). This leads the entrepreneur to increase the variance of productivity through a Jensen inequality effect, and thus to increase \bar{A} . Equation (4) shows that, conversely, the learning effort q increases with the research effort \bar{A} when holding wealth fixed. Indeed, a higher research effort encourages the financier to learn by magnifying the return differential between successful and failed projects—thus raising the opportunity cost of mis-investing. Therefore, knowledge about technologies and technological knowledge are mutually reinforcing.

The positive feedback effect between research and learning follows from the complementarity of productivity \tilde{A}_n and capital K_n in the production of intermediate goods. Since $\tilde{Y}_n \equiv \tilde{A}_n(K_n)^\alpha$, it follows that the return on the financier's funds increases with \tilde{A}_n (because the larger is this term, the more productive is every unit of capital). Similarly, the reward for

innovating increases with K_n because then the invention is applied on a larger scale. Thus the complementarity between \tilde{A}_n and K_n leads to the complementarity between learning and research.⁶

The following proposition characterizes the distribution of capital across projects.

PROPOSITION 3 *Capital is more closely matched to projects' productivity, and more dispersed across projects when the learning effort is higher (holding both wealth and the research effort fixed). In contrast, neither the quality of the match between capital and productivity nor the dispersion of capital depends on the research effort (holding both wealth and the learning effort fixed). Formally:*

$$\frac{\partial \text{Var}(K_n)}{\partial q} > 0 \quad , \quad \frac{\partial \text{Var}(K_n)}{\partial \bar{A}} = 0.$$

$$\frac{\partial \text{Corr}(\tilde{A}_n, K_n)}{\partial q} > 0 \quad \text{and} \quad \frac{\partial \text{Corr}(\tilde{A}_n, K_n)}{\partial \bar{A}} = 0.$$

Specifically, the correlation between capital and productivity, $\text{corr}(\tilde{A}_n, K_n)$, equals $2q - 1 > 0$; projects deemed successes receive $[q/(1 - q)]^{1/(1-\alpha)} > 1$ more funding than those deemed failures. Both expressions are increasing in the learning effort q . Intuitively, a better-informed financier allocates more funds to projects deemed successes and fewer funds to those deemed failures, leading to a distribution of capital which is both more highly correlated with productivity and more uneven. If the intermediate goods sector exhibits constant returns to scale (i.e., if $\alpha = 1$) then the dispersion is extreme, with projects considered to be failures receiving no funding at all. In contrast, the research effort has no bearing on the capital dispersion. The reason is that, in equilibrium ($\underline{A} = 0$), the amounts invested are not affected by the research effort (\bar{A}).

PROPOSITION 4 *The return on capital is more dispersed across projects when either learning*

⁶This intuition is easily formalized for the case of constant returns to scale in the intermediate goods sector (i.e., $\alpha = 1$). In that case, the average quantity of goods produced by a project can be broken down into the contributions of: projects' average productivity ($E[\tilde{A}_n] = (\bar{A} + \underline{A})/2$); average stock of capital per project ($E[K_n] = w$); and quality of the match between projects and capital, as captured by $\text{cov}(\tilde{A}_n, K_n) = (q - 1/2)(\bar{A} - \underline{A})w$. Thus we have

$$E[\tilde{A}_n K_n] = E[\tilde{A}_n]E[K_n] + \text{cov}(\tilde{A}_n, K_n) = [q\bar{A} + (1 - q)\underline{A}]w = q\bar{A}w.$$

Thus, average output increases with the *product* of (a) the precision q of the financier's information and (b) the productivity \bar{A} of the successful project.

or research efforts are higher (holding wealth fixed). Formally:

$$\frac{\partial \text{Var}[\tilde{A}_n(K_n)^{\alpha-1}]}{\partial q} > 0 \quad \text{and} \quad \frac{\partial \text{Var}[\tilde{A}_n(K_n)^{\alpha-1}]}{\partial \bar{A}} > 0.$$

The financier allocates more capital to projects he deems successes than to those he deems failures. Because of decreasing returns to scale, successful projects incorrectly labelled as failures yield a higher return than correctly identified successful projects. Hence, more learning leads to a more polarized capital allocation (Proposition 3), and in turn, to a more dispersed distribution of returns. Note that, under constant returns to scale, this distribution depends only on the research effort and no longer on the learning effort. Likewise, a higher research effort magnifies the return difference between correctly and incorrectly identified successful projects.⁷

2.4 Dynamic Extension

We present a dynamic extension of the model in order to evaluate, qualitatively and quantitatively, how the interplay between learning and research influences long-term growth. For this purpose we chain together a sequence of static models. Specifically, the economy is now populated by overlapping generations of entrepreneurs and financiers who live for two periods, as illustrated in Figure 2. Projects last two periods and are liquidated immediately after production. The final goods sector now employs labor (L_t), in addition to intermediate goods, according to the technology $G_t \equiv L_t^{1-\beta} Y_t^\beta$. The financier supplies one unit of labor inelastically in exchange for a competitive wage w_t , which he then invests in the entrepreneur's projects. Thus we endogenize the financier's wealth by assuming that it is equal to his labor income w_t . In turn, the wage is equal to the marginal product of labor, or $(1 - \beta)Y_t^\beta$, where $Y_t = \int_n \tilde{A}_{n,t-1}(K_{n,t-1})^\alpha$ is determined by the efforts chosen by agents from the previous generation. There is no population growth. One generation's research and learning efforts determine the stock of capital for

⁷Both types of projects receive the same amount of capital so return differences are entirely attributable to differences in productivity. A similar pattern obtains with unsuccessful projects but their return is zero regardless of how much capital they attract. Note also that under constant returns to scale, the distribution of returns continues to depend on the research effort.

the next generation and hence the productivity of that latter generation's labor.

[[INSERT Figure 2 about Here]]

2.4.1 Sources of Growth

Income in period $t + 1$, denoted w_{t+1} , is related to the precision q_t of information and to productivity \bar{A}_t in period t as described in the following expression:

$$w_{t+1} = (1 - \beta)Y_{t+1}^\beta = (1 - \beta) \times w_t^\beta \times \text{TFP}_q(q_t) \times \text{TFP}_A(\bar{A}_t), \quad (5)$$

where $\text{TFP}_A(\bar{A}_t) \equiv \bar{A}_t^\beta$ and $\text{TFP}_q(q_t) \equiv V(q_t)^\beta$.

Together with equations (3) and equation (4)—in which all three variables (\bar{A}_t , q_t , and w_t) are contemporaneous—and given an initial income level w_0 , equation (5) fully describe the economy's dynamics. That expression identifies the three forces that determine income growth. First, current income matters for the next period's income in the usual neoclassical way because it determines the aggregate capital stock: the marginal product of labor increases with current income but at a declining rate (the w_t^β term). The other two forces operate through TFP and can be viewed as the effects of research (TFP_A) and of learning (TFP_q).

The research component (TFP_A) is the focus of the endogenous growth literature, which acknowledges that technology can be improved by purposeful activity (e.g., R&D). In the framework developed here, this channel can be identified by freezing q_t . Our model associates the incentive to innovate with the financial sector's state; in this the model underscores that the economy's productivity, \bar{A}_t , depends on the quality q_t of investment knowledge. The learning component (TFP_q) is the focus of the financial development literature, which highlights the role of frictions in reducing the efficiency of investments. Examples include information limitations (Greenwood and Jovanovic 1990) and investment indivisibilities (Acemoglu and Zilibotti 1997). This channel can be identified in our model by freezing \bar{A}_t . An alternative interpretation of this model is that it shows how the incentive to mitigate investment inefficiencies depends on the level of the technology—in other words, how q_t depends on \bar{A}_t .

This extended model is consistent with four observations documented in the literature on finance and growth (see Appendix A for more details and references). To start with, finan-

cial development promotes economic growth, and this effect runs not through capital growth but rather through TFP growth. The subsequent three observations shed light on the link between finance and TFP. First, financial development stimulates investments in R&D, which in turn contributes to TFP. Second, financial development also enhances TFP by improving capital efficiency. Countries with more developed financial sectors allocate capital more efficiently across industries and firms, and a more efficient distribution of capital at the micro level translates into higher TFP at the macro level. Finally, financial development improves capital efficiency (among other ways) by alleviating informational problems.

We emphasize that, since learning and research affect each other in our model, both make direct *and indirect* contributions to economic growth. This means that capturing the total effect of learning requires that one accounts also for its positive influence on entrepreneurs' incentive to innovate (i.e., its effect on TFP_A). Likewise, the full benefit of research consists of its direct effect through TFP_A *plus* its indirect effect through TFP_q . This point has some important implications for the effectiveness of policies aimed at stimulating innovations. First, it suggests that innovation policies—such as research subsidies and tax breaks—have a multiplier effect thanks to the resulting improvement in capital efficiency. Second, innovations are encouraged also by policies designed to increase capital efficiency; examples include facilitating trade in financial assets and improving accounting standards.

2.4.2 Dynamics

We study the dynamics of income, research, and learning—and their interplay—along the economy's growth path in the case of constant returns to scale in the intermediate goods sector ($\alpha = 1$). In that case, equations (3)–(5) simplify to

$$\beta q_t^\beta w_t^\beta = \bar{A}_t^{1-\beta} e'_A(\bar{A}_t), \quad (6)$$

$$\beta \bar{A}_t^\beta w_t^\beta = q_t^{1-\beta} e'_q(q_t); \quad (7)$$

$$w_{t+1} = (1 - \beta) \times w_t^\beta \times q_t^\beta \times \bar{A}_t^\beta. \quad (8)$$

A steady-state equilibrium satisfies equations (6)–(8) together with the condition $w_{t+1} = w_t$. A trivial solution to this system obtains when income equals zero and neither learning nor

research take place ($w_t = \bar{A}_t = 0$ and $q_t = 1/2$). A nontrivial steady state also exists if

$$\frac{1}{\varepsilon_A(\bar{A})} + \frac{1}{\varepsilon_q(q)} \neq \frac{1}{\beta} - 1 \text{ for all } \bar{A} > 0 \text{ and } 1 > q > \frac{1}{2}, \quad (9)$$

where $\varepsilon_A(A) \equiv 1 + Ae''_A(A)/e'_A(A)$ and $\varepsilon_q(q) \equiv 1 + qe''_q(q)/e'_q(q)$ denote 1 plus the elasticity of (respectively) e'_A and e'_q with respect to A and q . We use an asterisk (*) to mark steady-state quantities and also drop the argument to signify functions evaluated at the steady state; thus $\varepsilon_A \equiv \varepsilon_A(\bar{A}^*)$ and $\varepsilon_q \equiv \varepsilon_q(q^*)$. Our final proposition characterizes the economy's dynamics.

PROPOSITION 5 *Assume that returns to scale in the intermediate goods sector are constant (i.e., $\alpha = 1$) and that condition (9) holds. Then the economy admits two steady-state equilibria, 0 and $w^* > 0$. System dynamics in the neighborhood of a steady state are governed by the following expressions*

$$\ln(\bar{A}_t) \approx \frac{\beta}{\varepsilon_A - \beta} [\ln(q_t) + \ln(w_t)] + \text{constant}, \quad (10)$$

$$\ln(q_t) \approx \frac{\beta}{\varepsilon_q - \beta} [\ln(\bar{A}_t) + \ln(w_t)] + \text{constant}'; \quad (11)$$

$$\ln\left(\frac{w_{t+1}}{w^*}\right) \approx (\gamma + 1) \ln\left(\frac{w_t}{w^*}\right), \quad \text{where } \frac{1}{\gamma + 1} = \frac{1}{\beta} - \frac{1}{\varepsilon_A} - \frac{1}{\varepsilon_q}. \quad (12)$$

Three cases are possible.

- *Case 1: $\frac{1}{\varepsilon_A} + \frac{1}{\varepsilon_q} < \frac{1}{\beta} - 1$. In this case, w^* is a stable steady state but 0 is not. Income converges to w^* .*
- *Case 2: $\frac{1}{\beta} > \frac{1}{\varepsilon_A} + \frac{1}{\varepsilon_q} > \frac{1}{\beta} - 1$. Here 0 is a stable steady state but w^* is not. If $w_0 > w^*$ then the economy grows without bound, but if $w_0 < w^*$ then the economy contracts toward 0.*
- *Case 3: $\frac{1}{\varepsilon_A} + \frac{1}{\varepsilon_q} > \frac{1}{\beta}$. In this case, the economy is unstable and oscillating.*

The term γ measures the speed with which income converges to its steady state, in a neighborhood thereof, conditional on a given level of income. In Case 1 ($-1 < \gamma < 0$), the economy converges to a steady state in which income no longer grows. Therefore, learning and research have only transitory effects on growth. This follows because their costs rise quickly

with effort levels (ε_A or ε_q large) whereas the marginal product of intermediate goods falls rapidly with those efforts (β low). In Case 2 ($\gamma > 0$), learning and research instead have a permanent effect and so ongoing growth is possible. Income grows without bound if its initial value w_0 exceeds w^* but shrinks toward 0 otherwise. If we focus on Cases 1 and 2 and interpret the learning effort q and its cost $e_q(q)$ as measures of financial development, then the model predicts that the financial sector develops in tandem with the real economy.⁸ Finally, the system oscillates and is unstable in Case 3 ($\gamma < -1$). The following corollary breaks down the convergence rate of income into its various components.⁹

COROLLARY 6 *The speed with which income converges in a neighborhood of the steady state γ can be decomposed as $\gamma = \gamma_K + \gamma_A + \gamma_q + \gamma_{Aq}$ where*

- $\gamma_K \equiv -(1 - \beta) < 0$ is the contribution of capital accumulation to growth;
- $\gamma_A \equiv \frac{\beta^2}{\varepsilon_A - \beta}$ is the contribution of research in the absence of learning;
- $\gamma_q \equiv \frac{\beta^2}{\varepsilon_q - \beta}$ is the contribution of learning in the absence of research; and
- $\gamma_{Aq} \equiv \frac{\beta^2(\beta + \gamma + 1)}{(\varepsilon_A - \beta)(\varepsilon_q - \beta)}$, the residual, is the contribution of the interaction between research and learning.

The terms γ_A , γ_q , and γ_{Aq} are positive except in the case of oscillating dynamics.

Income grows at the rate $\gamma_K + \gamma_A$ when investors do not learn, and it grows at the rate $\gamma_K + \gamma_q$ when entrepreneurs do not innovate. When learning and research both occur but without interacting, income grows at the rate $\gamma_K + \gamma_A + \gamma_q$ (the terms q_t and \bar{A}_t are replaced with constants in equations (6) and (7), respectively). Focusing on the non-oscillating dynamics (Cases 1 and 2 in Proposition 5) and leaving aside the neoclassical effect on capital accumulation (represented by the term γ_K), the growth rate of income in the economy with both learning

⁸The term $e_q(q_t)$ can be interpreted as the amount of resources devoted to analyzing investment opportunities. Alternatively, we could add to the economy a competitive intermediary who invests funds on behalf of the financier. This intermediary collects information about projects' returns and is paid a fee to compensate for the disutility of learning. There is free entry in the intermediary sector. In Appendix B.5, (23) implies that $d \ln(q_t/q^*)/d \ln(w_t/w^*)$ is positive except in the case of oscillating dynamics.

⁹Corollary 6 subsumes the two polar cases discussed previously. If $\varepsilon_q = +\infty$ then q_t is frozen as in the "endogenous growth" case and $\gamma_q = 0$, so the economy grows at the rate $\gamma_K + \gamma_A$. If instead $\varepsilon_A = +\infty$, then \bar{A}_t is frozen as in the "financial development" case and $\gamma_A = 0$, so the economy grows at the rate $\gamma_K + \gamma_q$.

and research, or $\gamma_A + \gamma_q + \gamma_{Aq}$, exceeds the *sum* of the growth rates in the no-learning economy (γ_A) and in the no-research economy (γ_q). This outcome reflects the mutual influence of learning and research. In Section 5.6 we calibrate the model to assess the importance of this interaction effect for income growth.

3 Empirical Strategy

Our theoretical analysis emphasizes the complementarity between an entrepreneur's R&D efforts and the financial sector's information-gathering activities. For the purpose of the empirical work, we use a sample of US firms and test the four hypotheses that follow from Propositions 2–4. Hypotheses 1 and 2 are direct implications of Proposition 2 and correspond to our paper's central predictions about the mutually reinforcing effect of learning and research. The first of these hypotheses states that firms perform more research when financiers learn more; the second states the converse—namely, that financiers learn more when firms perform more research.

Hypothesis 1. An increase in learning effort leads to an increase in research effort.

Hypothesis 2. An increase in research effort leads to an increase in learning effort.

Propositions 3 and 4 allow us to formulate auxiliary tests of the model, as stated in the next two hypotheses.

Hypothesis 3. An increase in the research effort leads, through an increase in the learning effort, to a tighter match between capital and productivity, and to a more dispersed distribution of capital across projects.

Hypothesis 4. An increase in the learning effort leads to a more dispersed distribution of return on capital across projects.

Hypothesis 3 is derived from Propositions 2 and 3: although the research effort does not influence the dispersion of capital directly (i.e., holding fixed the learning effort), it does so indirectly once the learning effort is allowed to adjust (as in our empirical experiments). Hypothesis 4 is derived from Propositions 2 and 4, given that the distribution of returns is determined by the learning effort directly (i.e., holding fixed the research effort), as well as indirectly through

its effect on the research effort. As such, testing it can lead to rejecting the model—or to failing to do so—but it does not help identify the mechanism at play. We shall therefore also examine the risk of firms' research to verify whether an increase in the learning effort encourages more risk taking by the entrepreneur, as the model predicts.

Testing the first two hypotheses, which concern the relationships between research and learning, requires that we account for the biases induced by an OLS estimation of these relationships. First, any shock to capital (w_t in the model) will stimulate learning and research independently, thereby generating a spurious correlation between them. Moreover, that two-way relationship generates an endogeneity bias. For example, a least-squares regression of learning on research yields inconsistent estimates because—as shown by (11)—the regression's residual is correlated with the regressor (i.e., research). Similarly, in (10) we see that the regressor (i.e., learning) is correlated with the residual from the regression of research on learning. Our strategy for addressing these issues is to exploit exogenous changes to firms' environment, as is commonly done in the literature on finance and growth. These shocks suddenly shift firms' research incentive and the financial sector's learning incentive.

We use R&D expenditures to measure a firm's research effort. We proxy for investors' learning effort about a firm's prospects with the number of equity analysts covering the firm. A long literature indeed finds that analysts produce information that matters to investors and that their reports affect stock prices and firms' financing (e.g., see Womack 1996 for an early example, or Chang, Dasgupta and Hilary 2006 for a more recent one). Nonetheless, we acknowledge that equity analysts' coverage of publicly-traded firms is an imperfect measure of the production of information about firms' research effort—one that is motivated by data availability. While the results we obtain with this proxy support our theory, we see two caveats to using our estimates for quantifying the mechanisms at work (e.g., for calibrating our model). First, information about public firms is also produced by other agents such as bankers, bondholders, rating agencies, large shareholders. Second, beyond public firms, research is also carried out by private firms, and these firms are followed by other information producers, including venture capitalists, corporate incubators, wealthy individual investors, and government agencies. Our quantification remains valid to the extent that the elasticity of information production with respect to firms' research, as well as the elasticity of firms' research with respect to information production, are comparable across information producers, and between public and private

firms.

3.1 More Research Leads to More Financial Analysis

To test whether more research by firms leads to more learning by the financiers, we examine whether analysts' coverage of firms changes when firms increase their R&D expenditures following the enactment of R&D tax credits across US states between 1990 and 2006.¹⁰ These policy changes provide a source of variation in firms' research activities—a source that is plausibly exogenous to firms' analyst coverage.

States' R&D tax credits proceeded from the implementation of federal tax credits in 1981. Minnesota introduced its own tax credit in 1982, followed by 32 other states as of 2006 (Wilson 2009). These credits allow firms to reduce their state tax liability by deducting a portion of R&D expenditures from their state tax bill. State taxes are usually based on revenues or business activities (such as the presence of employees or real estate) in the state.¹¹

Following Wilson (2009) and Bloom et al. (2013), we exploit increases in state R&D tax credits as a plausibly exogenous source of variation in firms' research effort. From the standpoint of an individual firm, changes in state R&D tax credits alter R&D behavior in ways that are likely *not* related to variables (e.g., market conditions) that could independently affect the coverage decision of brokerage firms.¹² Studies of R&D tax credits applied nationwide in the United States and elsewhere show that such credits stimulate R&D expenditures (Hall and Van Reenen 2000; Wilson 2009; Bloom, Schankerman, and Van Reenen 2013). At the state level, previous research suggests a positive effect of these credits on in-state R&D expenditures (Wilson 2009) and on the number of high-tech establishments in the state (Wu 2008). More recently, Bloom et al. (2013) use changes in state and federal tax credits as an instrument to identify R&D spillovers between firms within geographic and product markets.

Table 1 summarizes information on state tax credits. The table reports the year when first

¹⁰We start the R&D sample in 1990 to align it with our second experiment (brokerage house closures and mergers). The sample stops in 2006 because that is the last year for which state tax credit information is reported in Wilson (2009).

¹¹See Heider and Ljungqvist (2015) for more details on state corporate taxes. Some states allow loss-making firms to convert tax credits into cash and/or to carry those credits forward.

¹²In a robustness test, we also control for changes in state economic conditions (gross state product and unemployment rate) and find that our estimates are little affected.

introduced, the size of the credits, and subsequent changes.¹³ Tax credit rates range from 3% in Nevada and South Carolina to 20% in Arizona and Hawaii.

[[INSERT Table 1 about Here]]

We first confirm that increases in state tax credits are indeed associated with increases in R&D expenditures for firms headquartered in those states. Then we compare the change in analyst coverage of firms located in states that passed a tax credit with the change in coverage of comparable firms located in states that did not. The staggered implementation of tax credits across states allows us to control for aggregate shocks contemporaneous with implementing a tax credit—shocks that may influence firms’ analyst coverage and confound the effect of R&D. To the extent that (absent treatment) analyst coverage of firms in different states follows similar trends, and given the assumption that passage of a state R&D tax credit is not correlated with other changes driving the coverage of firms in the state, our difference-in-differences estimation enables us to isolate the effect of firm’s research effort on analyst coverage. In effect, for each year we use changes in analyst coverage of firms in states that do not experience a change in R&D tax credit as a counterfactual to firms located in states that did enact an R&D tax credit in that year. By comparing the changes in analyst coverage of treatment and control firms, we obtain an estimate of the causal effect of firms’ research effort on such coverage.

Our analysis is conducted at the firm level, and we focus on US-listed manufacturing firms that consider research and development activities to be a material factor in their business.¹⁴ Whenever a state implements a tax credit, we compare the change in coverage of firms affected by that tax credit (treated firms) with the coverage of firms in other states (control firms). Following Heider and Ljungqvist (2015), we reduce the potential endogeneity of a state choosing a certain level of tax credit by abstracting from the actual levels. Instead we use a binary indicator variable set equal to 1 for years in which the state introduces or increases its R&D tax credit (and equal to 0 for other years).¹⁵ Like Heider and Ljungqvist (2015), we estimate our main

¹³We thank Daniel Wilson for making these data available (see <http://www.frbsf.org/economic-research/economists/daniel-wilson/>).

¹⁴Hence we exclude from the analysis any firm that either does not report R&D expenditures or reports zero R&D expenditures.

¹⁵We do not consider *reduced* tax credits because very few states implemented them over our sample period (29 firm-year observations, versus 635 of increased tax credits).

regression in first differences to control for all time-invariant characteristics. All regressions include year dummies, and standard errors are clustered at the 3-digit industry level. The main specifications also feature lagged time-varying controls, which include the logarithm of sales and a dummy variable indicating whether the firm reported accounting losses (which affects the firm’s tax liability and hence possibly the benefit of a tax credit). The regression takes the following form:

$$\Delta \ln(Coverage_{i,s,t}) = \beta TC_{s,t}^+ + \eta_t + \sum_j \gamma_j \Delta X_{i,t-2}^j + \varepsilon_{it};$$

here $TC_{s,t}^+$ is a dummy variable that takes the value 1 only if state s (in which firm i is located) implemented or increased its R&D tax credit in year $t - 1$, the η_t are year dummies, and $X_{i,t-2}^j$ are the firm controls described previously. Our coefficient of interest is β , which measures the difference between the change in analyst coverage for firms in the treated state relative to the change in coverage for firms in other states.

That difference-in-differences estimate is robust to many potential confounds. Aggregate time-varying shocks and time-invariant firm attributes are captured by the year dummies and the differencing of the data. We also control for time-varying changes in firm characteristics, such as size and negative profitability, by including these (lagged) variables in our specifications. A remaining possible concern with our methodology is the finding by Wilson (2009) that, at the state level, a portion of the increase in in-state R&D is due to a decrease in out-of-state R&D. In our context, it is possible that, following the passage of an R&D tax credit, firms relocate to states with high tax credits at the expense of other states. For example, firms could hire more researchers in states that enact a tax credit, presumably by offering higher compensation or better work conditions to researchers from other states. Yet what matters to our analysis is whether firms located in treated states increase their R&D, regardless of where the extra R&D occurs. We show empirically that this is the case. Furthermore, if some firms were simply substituting R&D across states without increasing their overall R&D spending, then our estimates would be biased toward *not* finding an effect of tax credits on R&D expenditures and analyst coverage in treated states.

In short: changes in state R&D tax credits offer a good setting for our assessment of how the firm’s research effort affects the financial sector’s learning effort.

3.2 More Financial Analysis Leads to More Research

The second prediction of our model is that more learning by financiers increases firms' research effort. The ideal experiment for testing this prediction is one in which the financial sector's ability to learn about firms' innovative projects changes for exogenous reasons. The identification strategy pioneered by Hong and Kacperczyk (2010)—and then extended by Kelly and Ljungqvist (2012), Derrien and Kecskés (2013), and others—approaches this ideal. Derrien and Kecskés exploit closures of and mergers between brokerage houses that result in the removal or dismissal of analysts. Indeed, closures often lead to the removal of analysts who are not rehired by a new broker, and many mergers lead to the dismissal of analysts who follow the same stocks as those working for the other merging entity. Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013) provide convincing evidence that the drop in analyst coverage resulting from such events is largely exogenous to any policies implemented by the covered firms.

The loss of analysts has significant implications for the information environment of affected firms. Hong and Kacperczyk (2010) show that reduced competition among analysts after brokers merge results in worse forecast accuracy, and Derrien and Kecskés (2013) that the quality of the research produced by disappearing analysts is slightly above average, suggesting that information about affected firms might indeed be lost. Moreover, equity analysts not only produce new information, they also play an important role in disseminating existing information, including public data. For example, many-analyst firms have returns that lead those of few-analyst firms (Brennan, Jegadeesh, and Swaminathan 1993), and exhibit less price momentum, indicating that stock prices of firms covered by more analysts adjust to public information faster (Hong, Lim, and Stein 2000; see also Brennan and Subrahmanyam 1995, Hou 2007, Menzly and Ozbaz 2010). Consistent with this view, Kelly and Ljungqvist (2012) report an increase in measures of information asymmetry following broker closures. Thus—and this is what matters for our purpose—declines in coverage due to broker closures and mergers cause a deterioration of information about firms.

To assess how reduced analyst coverage alters a firm's research effort, we study firms affected by the events identified by Derrien and Kecskés over our sample period.¹⁶ But unlike

¹⁶For broker closures, treated firms are those for which the analyst disappears from the analyst database during the year after the broker closure date. For broker mergers, treated firms are those that are covered by both the target

those authors, we focus on innovative firms (as described in Section 4). Adopting the same specification as in our first experiment, our difference-in-differences estimator compares the change in research effort at treated firms to the change experienced by control firms unaffected by the event. The regression takes the following form:

$$\Delta \ln(R\&D_{i,t}) = \beta AN_{i,t}^- + \eta_t + \sum_j \gamma_j \Delta X_{i,t-2}^j + \varepsilon_{it};$$

here $AN_{i,t}^-$ is a dummy variable that takes the value 1 only if a firm i is subject to a broker event in year $t - 1$, the η_t are year dummies, and $X_{i,t}^j$ are the firm controls described previously.¹⁷ Our coefficient of interest is β , which measures the difference between the change in R&D for firms treated by broker events relative to the change in coverage for other firms.

Overall, the broker events provide a good setting in which to assess how the amount of information produced by the financial sector affects the research effort of firms. Together, our two experiments enable a study of the two-way interaction between firms' research and financial analysis.

4 Data

We evaluate the interaction between analyst coverage and firms' R&D on a single set of innovative manufacturing firms with which we evaluate the effect of both shocks (i.e., R&D tax credit changes and broker events). With this approach, our estimates of the interaction effect are not biased by differences in firm characteristics across the two experiments. When constructing our sample we ensure that—for both experiments—the treatment and control firms are sufficiently similar. This requirement is especially important for the second experiment given that (as reported by Hong and Kacperczyk 2010) brokerage closures primarily affect firms that are larger than the average Compustat firm. When covariates (such as size) do not exhibit sufficient overlap between treatment and control groups, the result can be imprecise estimates (Crump,

broker and the acquirer broker before the merger and for which one of their analysts disappears during the year after the brokers merge. As the Derrien and Kecskés (2013) note: “this eliminates the possibility that only one broker covers the firm before the merger and the analyst is terminated because he anticipates specific corporate policies for the firms that he covers.”

¹⁷ $AN_{i,t}^-$ takes the value 1 in the first full fiscal year following the shock.

Hotz, Imbens, and Mitnik 2009). A practical solution suggested by these authors to remedy this problem is first to estimate a propensity score on all firms (i.e., estimate the probability of a firm being treated, conditional on observable characteristics) and then to restrict the analysis to firms with a score between 0.1 and 0.9 in both experiments. We adapt this methodology to our setting and estimate the propensity score of all firms for each experiment. Our final sample includes 844 innovative firms with a propensity score on the $[0.1, 0.9]$ interval for both experiments.¹⁸

We focus on the firms that report strictly positive R&D expenditures. Firms typically report R&D expenditures in their financial statements when those expenditures are material to their business (Bound, Cummins, Griliches, Hall, and Jaffe 1984). Thus, keeping only those sample firms with strictly positive R&D expenditures ensures that the tests focus on firms for which our model is most relevant. We exclude firms with year-to-year R&D growth exceeding 200%; thus we reduce the estimation noise introduced by mergers or by radical strategic decisions that have little to do with changes in analyst coverage or in state R&D tax credits. Firms' locations are identified with the location of their headquarters as reported in Compact Disclosure and in Compustat when not available from Compact Disclosure.¹⁹ Because many listed firms locate in Delaware for reasons unrelated to their operations, our sample also excludes firms located in that state.²⁰

We use (the logarithm of) R&D expenditures to measure firms' research effort. To measure analyst coverage, we count the number of unique analysts making a yearly earnings forecast during the firm's fiscal year (and take the logarithm).²¹ We deflate all accounting variables, which are taken from Compustat, using the Consumer Price Index. Analyst data are from I/B/E/S.

[[INSERT Table 2 about Here]]

¹⁸The propensity score is estimated by way of a logit regression. The treated indicator takes the value 1 if the firm is treated on any occasion during the sample period (and takes the value 0 otherwise). The covariates included in the logit regression are industry dummies, the logarithm of sales, and an accounting loss indicator (i.e., a dummy variable that takes the value 1 if the firm reports negative earnings before interest and taxes), all based on the first year each firm appears in the sample.

¹⁹Howells (1990) and Breschi (2008) show that large firms locate their R&D facilities close to the company's headquarters and do not disperse geographically. See also Acharya, Baghai, and Subramanian (2014).

²⁰However, including firms located in Delaware in the sample does not materially affect the results.

²¹All firms in our sample are followed by at least one analyst in all years. We require firms to have at least four consecutive observations of analyst coverage and R&D expenditures.

Table 2 presents the summary statistics for our sample. Since we require firms to be followed by at least one analyst and to have positive R&D expenditures, it follows that our typical firm is both large (the median amount of sales is \$578 million in the sample versus \$77 million for Compustat manufacturing firms) and innovative.

5 Empirical Results

Figure 3 is a scatter plot of our measures of financial analysis (number of analysts following a firm) and firms' research effort (level of R&D expenditures) adjusted for aggregate trends in R&D and analyst coverage (year fixed effects), and the amount of firms' sales.²² The figure illustrates that, as our theory suggests, the two variables are positively correlated in the data: the correlation between the (adjusted) variables is 0.51. Next we investigate whether this correlation reflects a causal relationship.

[[INSERT Figure 3 about Here]]

5.1 More Research Leads to More Financial Analysis

We are interested in the effect that changes in R&D tax credits have on learning by the financial sector, where the latter is measured by analyst coverage. We first confirm in Table 3 that increases in a state's R&D tax credit lead to increases in R&D expenditures by firms located in that state. The coefficient of interest is that for the variable TC^+ , which captures the total effect of a tax credit increase on the R&D of firms located in the treated state one year after the tax credit's passage—as compared with firms not experiencing a change in their state's tax credits during that same year. Following enactment of an R&D tax credit, treated firms increase their R&D expenditures by 4.6% relative to control firms (p-value = 0.014).^{23,24} The change takes

²²The variables plotted on the chart are the firm-average residuals from regressions of the variable of interest on year fixed effects and the logarithm of sales. Therefore, each dot represents a firm.

²³The effect ranges from 3.9% to 4.6%. To facilitate comparison with the two-stage least-squares instrumental variables estimation of Section 5.4, we focus the tables' interpretation on the magnitudes in Column (2) and use Column (3) to verify the timing of the changes triggered by the shock.

²⁴Wilson (2009) finds that a 1% increase in tax credits results in about a 1.7% increase of in-state R&D in the short term. In our sample, the average tax credit increase is 4.49%; hence our coefficient implies that, in this sample of large firms, a 1% increase in tax credits leads to firms increasing their R&D expenditures by about 1%.

place in the year after the tax credit is implemented, as indicated by the insignificant estimated coefficients for both the lead and the lag of the shock variable. As expected (and in accord with Bloom et al. 2013), firms increase their research effort in response to increased tax credits.

[[INSERT Table 3 about Here]]

We now turn to our first testable hypothesis, according to which an increase in the research effort leads to an increase in the learning effort. The values reported in Table 4 are consistent with this hypothesis because they show that, after passage of state R&D tax credits, firms in treated states are covered by 5.1% more analysts than are firms located in other states (p-value = 0.006). Given that the average firm in the sample is followed by ten analysts, each firm is followed by an additional 0.51 analysts after enactment of a tax credit. Column (3) confirms that this increase in analyst coverage is concentrated in the year following passage of the tax credit.

[[INSERT Table 4 about Here]]

5.2 More Financial Analysis Leads to More Research

To evaluate our second hypothesis, which posits an effect of financial analysis on the research effort of firms, we use reductions in analyst coverage triggered by brokerage closures and mergers. Table 5 confirms that treated firms (i.e., those followed by analysts employed at closing or merging brokers) experience a reduction in analyst coverage in the year following a closure or merger. On average, treated firms lose about 10.0% more analysts than do control firms (p-value < 0.001). Given that the average firm employs about 11 analysts, treated firms lose (on average) about one analyst as compared with control firms. This is the magnitude we would expect given the construction of the broker experiment.

[[INSERT Table 5 about Here]]

Table 6 presents the main results regarding firms' research effort. We find that the R&D expenditures of treated firms fall by 2.5%, relative to control firms, after losing an analyst (p-value = 0.044). This effect is commensurate with those reported for other variables in studies

using a similar set of events. For example, Kelly and Ljungqvist (2012) document a 2.6% decrease in stock price upon announcement of the loss of an analyst. Our results also confirm, and strengthen on a sample of innovative firms, those of Derrien and Kecskés (2013) regarding R&D: they find a 0.21% decline in the ratio of R&D expenditures to assets using a broader sample of firms which includes firms with nonmaterial R&D.²⁵

[[INSERT Table 6 about Here]]

These results provide support for our second hypothesis—namely, that a higher learning effort by the financial sector encourages firms to innovate. Together, our empirical investigations support the two predictions at the core of our model: Wall Street financial analysis and Main Street R&D interact and reinforce each other.

5.3 Robustness

Table 7 displays the result of robustness tests, starting with the R&D shock, then turning to the learning shock. To ease comparison with our findings, Column (1) reproduces the baseline regression of analyst coverage on R&D tax credits, and Column (4) that of R&D expenditures on broker events.

One issue with using regional variations (such as the implementation of state R&D tax credits) to study firm outcomes is that regions differ in industry compositions. An industry-related trend in a state could spuriously generate an association between the passage of a tax credit and observed corporate variables such as, in our case, analyst coverage (e.g., Lerner and Seru, 2015). Column (2) of Table 8 addresses this concern by directly controlling for industry

²⁵Using patenting as a measure of innovation output in an experiment similar to ours, He and Tian (2013) find a negative relationship between analyst coverage and patenting activity. Clarke et al. (2015) show that this relationship is driven by poor-quality innovators (i.e., firms that are granted many patents but receive no citations) and actually *reversed* for high-quality innovators (i.e., these firms innovate more when they are followed by more analysts as we argue here). One interpretation of those findings (and of the results reported here and in Derrien and Kecskés 2013) is that firms (especially, low-quality innovators) use patents as a means of communication with investors, and adjust their patenting policy to their informational environment; so for a given research effort (i.e., a given level of R&D expenditures), a firm increases its patenting activity to compensate for the loss of information that analysts no longer produce. This interpretation is consistent with the findings of Balakrishnan et al. (2014) that firms respond to the loss of analysts due to broker closures by providing more timely and informative earnings guidance. In line with the existence of a trade-off between patenting and secrecy, Saidi and Zaldokas (2015) document that firms issue fewer patents—though without altering their investment in innovation—when their lenders are better informed.

trends in the regression, specifically, by adding industry fixed effects to our first-difference regressions. Including the fixed effects reduces the magnitude of the coefficient estimate on $TC+$ from 0.051 to 0.044, but it remains statistically significant at the 5% level. Next, although previous studies have used state R&D tax credits as a source of variation in research effort exogenous to corporate policies (e.g. Bloom et al. 2013), Column (3) addresses the concern that these tax credits may be correlated with state economic conditions by also controlling for changes in state gross product and unemployment rate in the year of the tax credit increase. The coefficient on analyst coverage decreases slightly to 0.046 but again remains statistically significant at the 5% level.

Turning to the learning shock, a potential concern is that, to the extent that physical capital and R&D expenditures are complements, analyst coverage could affect firms' R&D, not through the learning channel we propose, but indirectly through its effect on capital expenditures. In support for this interpretation of our findings, Derrien and Kecskés (2013) report a drop in capital expenditures in reaction to a decrease in analyst coverage. We first note that this drop might actually be attributable to our learning story for many firms in our sample, namely those operating in technology-intensive industries where a significant proportion of capital is innovative. In the semi-conductor industry for example, fabrication plants are so technologically advanced that their cost could qualify as R&D rather than capital expenditures. Notwithstanding this interpretation, in Column (5) we isolate the direct effect of analyst coverage on R&D expenditures by controlling for the change in capital expenditures that follow broker events. The magnitude and statistical significance of the coefficient estimate remain unchanged. Likewise, they stay close to their baseline levels after controlling for other variables that Derrien and Kecskés (2013) show are affected by broker events and may be determinants of R&D (acquisition spending, long-term debt, and cash balances) in Column (6).

5.4 Quantifying the Indirect Effect of a Tax Credit through Learning

Our common set of firms allows us to combine elasticities derived from different experiments, and use our estimates to decompose the effect of an R&D tax credit into a direct effect and an indirect effect that operates through learning. Toward that end, we first obtain the sensitivity of R&D expenditures to analyst coverage, and that of analyst coverage to R&D expenditures, by

directly estimating the following two equations via two-stage least squares²⁶:

$$\Delta \ln(Coverage_{i,t}) = \beta_1 \Delta \ln(RD_{i,t}) + \eta_{1,t} + \sum_j \gamma_{1,j} \Delta X_{i,t-2}^j + \varepsilon_{1,it}, \quad (13)$$

$$\Delta \ln(RD_{i,t}) = \beta_2 \Delta \ln(Coverage_{i,t}) + \eta_{2,t} + \sum_j \gamma_{2,j} \Delta X_{i,t-2}^j + \varepsilon_{2,it}. \quad (14)$$

In (13), we instrument R&D expenditures with the tax credit shocks, and in (14), we instrument analyst coverage with the broker events.

[[INSERT Table 8 about Here]]

Table 8 displays the results. This instrumental variables procedure yields an estimate of the sensitivity of analyst coverage to R&D expenditures of 1.118; that is, a 10% increase in R&D expenditures induces an 11.2% increase in analyst coverage (a gain of about one new analyst). In Column (4) of Table 8 we see that the sensitivity of R&D expenditures to analyst coverage is 0.250; in other words, a 10% increase in analyst coverage (a gain of about one analyst) induces a 2.5% increase in R&D expenditures.

The values reported in Table 4 (Column (2)) show that the passage of a tax credit increases analyst coverage by 5.1% on average. Hence the indirect effect of the tax credit—operating through analysts’ response and denoted $\Delta \ln(RD)^*$ —equals approximately $0.250 \times 5.1\% = 1.3\%$. To put this number in perspective, we compare it to the total effect of the tax credit on $\Delta \ln(RD)$, which equals 4.6% according to Table 3 (Column (2)). Thus the indirect effect of the tax credit, through the response of analysts, is slightly more than a quarter ($28\% = 1.3\%/4.6\%$) of the size of its total effect. Suppose, for example, that some policy triggers a 10% increase in R&D expenditures (as a total effect); as much as 2.8% of that increase, is (indirectly) due to the “catalyzing” effect of financial analysis. These results speak to the importance of maintaining learning incentives in order to enjoy the full benefits of R&D tax credits. They also show how policies that seek to improve the functioning of financial markets can serve as catalysts for other policies aimed at boosting firm investment.

²⁶In section 5.1, we regressed analyst coverage on R&D tax credits; here we regress analyst coverage on the predicted values from a first-stage regression of R&D expenditures on R&D tax credits. Likewise we regressed, in section 5.2, R&D expenditures on broker closures; here we regress R&D expenditures on the predicted values from a first-stage regression of analyst coverage on broker closures.

5.5 Additional Tests

Next we investigate whether our empirical findings can be explained by the specific mechanism outlined in our theory. For that purpose, we evaluate Hypotheses 3 and 4.

5.5.1 Distribution of Long Term Financing Following the R&D Shock

Hypothesis 3 predicts a positive association between the learning effort and the dispersion of capital. To assess this prediction, we examine firms' capital proceeds using data on firms long-term financing, retrieved from Compustat. Specifically, we define a firm's net new financing proceeds as the highest of the sum of its stock and long-term debt issues, and zero (proceeds might be negative if the firm buys back or redeems securities). We then adapt the methodology of Bertrand, Duflo, and Mullainathan (2004) for multiple treatment groups. Using the R&D shock, we retain, for the first event that affects each firm, observations from two years before the shock to two years after, as well as firms that are never treated. We then proceed in three steps. First, pooling all these observations, we regress (the log of one plus) firms' net new financing proceeds on a treatment dummy, year dummies, industry dummies, the logarithm of sales, and then extract the residuals. Second, for each treated firm (from here on, control firms play no role), we average the residuals over the two years before, and also over the two years after the treatment year. Third, we test for whether the cross-sectional standard deviations of the residuals are equal before and after the shock. The first row of Table 9 shows that the F -test for equality of variances is rejected in the predicted direction: after the passage of R&D tax credits, new financing proceeds are significantly more dispersed across treated firms as compared to control firms, consistent with Hypothesis 3 (p -value <0.000).

Next, we assess whether financing proceeds also track firm quality more closely following the R&D shock, as predicted by Hypothesis 3. We estimate a regression of the proceeds raised over the two years preceding the shock on firm value at the end of these two years, and a similar regression after the shock (that is, we regress the proceeds raised over the two years following the shock on firm value at the end of these two years). These regression coefficients capture how well capital matches firm quality in each period. We measure a firm's value using its market value and Tobin's Q , purged from any effect of firm size. We expect to find regression coefficients that are not only positive (as better firms attract more capital), but also larger

regression coefficient after the shock compared to before. Indeed, Row (ii) of Table 9 reports positive coefficients and shows that the quality of the match significantly increases after the passage of R&D tax credits (p-value<0.000).²⁷

Together, these findings provide support for the mechanism outlined in our model: as firms increase their research effort, increased learning by financiers results in funding that is both more dispersed across firms and more highly correlated with firm quality.

[[INSERT Table 9 about Here]]

5.5.2 Dispersion in Return on Capital and Innovation Risk following the Learning Shock

According to Hypothesis 4, firms' return on capital should become less dispersed as financiers reduce their learning effort. We evaluate that prediction using the same methodology as used to test Hypothesis 3. Measuring the return on capital with firms' return on assets (RoA), we assess how the cross-sectional standard deviation of RoA changes after the learning shock (broker events). The results are reported in Row (iii) of Table 9. As predicted by the model, the standard deviation of RoA residuals significantly decreases following the shock (p-value = 0.056).

The finding on RoA is consistent with the model but does not tell us whether the observed decline in the dispersion of returns is due to financiers allocating capital less selectively (i.e., direct effect of the reduction in learning effort), or to firms innovating less in response to the loss of analysts (i.e., reduction in research effort induced by the reduction in learning effort). To isolate the latter, we take a closer look at firms' research activities. In the model, learning stimulates research by encouraging risk taking; hence we check whether firms curb the risk of their research in response to the loss of analysts.

We proxy the riskiness of a firm's research with the standard deviations of its patent values and of its patent forward citations. A patent value represents the value attributed to the patent

²⁷We assess the statistical significance of the increase in the slope with a Chow test. As with the above test of dispersion in financing proceeds, we first extract net proceeds residuals and Tobin's Q residuals, and perform the Chow test with these residuals. The control variables employed to obtain the residuals are the same as in the dispersion test above (i.e., treatment dummy, year dummies, industry dummies, the logarithm of sales). Proceeds' residuals are aggregated over the two-year periods. Tobin's Q residuals are taken at the end of each two-year period. For brevity, Table 9 reports only results based on Tobin's Q. Results based on firms' market value are qualitatively similar.

by the stock market and is inferred from the firm’s stock price reaction to patent news. Forward citations denote the number of citations received by a patent from the date it is accepted until 2011. These patent metrics are collected from Kogan et al. (2017).²⁸ A higher within-firm standard deviation of patent values or of citation numbers is symptomatic of riskier research: firms which develop riskier innovations end up with a patent portfolio made up of both more successful and more unsuccessful patents, thereby increasing their (within-firm) dispersion in patent values and citations.

We assess how the standard deviations of patent values and citation numbers change from two years before to two years after the broker events. Adapting our previous methodology, we find, in Row (iv), that both standard deviations decrease after the loss of analysts (p-values of resp. 0.056 and 0.049).²⁹ Thus, these findings indicate that learning by the financial sector is positively associated not only with firms’ research effort, but also with the risk of that research.

In sum, the results of these auxiliary tests are consistent with the channel described in our model: research and learning amplify return and funding differences across firms.

5.6 Calibration

We conclude the empirical analysis by calibrating our model to evaluate the importance—to long-term growth—of the interplay between financial analysis and firms’ research effort. We must determine four parameters (α , β , ε_A , and ε_q) in order to compute γ , or how rapidly income converges to the steady state, as well as the components of γ (γ_K , γ_A , γ_q , and γ_{Aq}).

We start with α , which controls the degree of returns to scale in the intermediate goods sector and hence how profits are shared between firms. In the model, only successful firms (half of all firms) earn a profit, and this profit is higher for the fraction q recognized as successful by the financier. These $q/2$ firms account for a proportion $F = q^{1/(1-\alpha)} / [q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]$ of aggregate profits. This proportion increases in α , starting from q when $\alpha = 0$ (a fraction $q/2$ of firms earn a fraction q of the profits) and reaching 1 when $\alpha = 1$ (these firms capture all the

²⁸The data are available at <https://iu.app.box.com/v/patents>.

²⁹To adjust patent metrics for the average characteristics of patents from the same year and technological class, we add technological class-year fixed effects to the initial regression from which we extract value and forward citation residuals. Then, for each firm, we pool the residuals from patents applied for in the two years before the shock and in the two years after the shock, and calculate the cross-sectional standard deviation of value and forward citation residuals at the firm level for each of the two periods. We then compare the average standard deviations before and after the shock.

profits). Empirically, the return on innovation is extremely skewed. For instance, Scherer and Harhoff (2000) estimate that 10% of the inventions capture from 48% to 93% of total returns in their sample. We accordingly set $\alpha = 1$ so as to generate the most skewed distribution of profits.

To parameterize the costs of research e_A and learning e_q , we use estimates of the sensitivities of learning to research and of research to learning derived from our two experiments. More specifically, we assume that the economy is initially in steady state and that it is perturbed by a shock (changes in R&D tax credits or in broker closures) at the end of period T . We interpret these shocks as a *rescaling* of the costs of innovating or learning (i.e., parallel shifts in the logarithms of those costs). The perturbed economy then converges toward a new steady state. Our model is used to compute the change in the learning and research efforts from period T to the next period, $T + 1$. In period T , before the shock, the economy is fully described by the equations characterizing the initial steady state (system (19) in Appendix B.5). The economy's evolution is then governed (approximately) by (10)–(12), from Proposition 5, under the parameters of the new steady state. We show in Appendix B.7 how to relate ε_A and ε_q (i.e., 1 plus the elasticities of the cost functions evaluated at the new steady state) to the elasticity of R&D expenditures with respect to analyst following in the broker closure experiment—and to the elasticity of analyst following with respect R&D expenditures in the R&D tax credit experiment—based on the derived estimates displayed in Table 8. Solving a system of two equations yields estimates of ε_A and ε_q .

There is one parameter still to calibrate: β , which measures the share of capital in total income. We consider a range of values comprising $1/3$, the estimate commonly used when capital is assumed to be exclusively physical, and $2/3$, which corresponds to a broader definition that includes both physical and human capital (e.g., Mankiw, Romer, and Weil 1992). Table 10 displays the results of the calibration exercise for different values of β . Panel A reports growth rates of income per period; Panel B reports growth rates per annum while assuming that one period lasts 30 years.³⁰

[[INSERT Table 10 about Here]]

Columns (2) and (3) of Panel A give the estimates of ε_A and ε_q . If $\beta = 1/3$ then $\varepsilon_A = 2.02$ and $\varepsilon_q = 0.76$; these values rise to 4.55 and 1.72 (respectively) as β increases to $2/3$. Indeed,

³⁰The annual rate is equal to $(1 + \textit{Per-period rate})^{1/30} - 1$.

learning and research in our model are more responsive to one another under more slowly decreasing returns to scale (i.e., higher β). This dynamic must be offset by cost functions that are more elastic in order to match the observed sensitivities.

When $\beta = 1/3$, the speed of income's convergence to steady state is -18% per period or -0.67% per annum, where the minus sign indicates that income grows at a slower rate for higher levels of income (and hence that it converges to a steady state). It is larger than the 2% annual convergence rate reported by Barro (2015), but it is reasonable after one accounts for population growth of 1.8% per year (which is assumed away in the model). In comparison, income converges at $6.4\% - 67\% = -60.6\%$ per period if agents innovate but do not learn and at $25\% - 67\% = -42\%$ per period if agents learn but do not innovate; here -67% captures the neoclassical effect of diminishing returns to capital. Obviously, the attenuation of income growth is slower when agents carry out both tasks than when they undertake only one. Table 10 reveals that learning has a much larger effect on income growth than does firms' research effort: 25% versus 6.4% for $\beta = 1/3$. The reason is that, in the data, analyst following is much more responsive to R&D expenditures (elasticity of 1.12 in the R&D tax credit experiment) than R&D expenditures are to analyst following (elasticity of 0.25 in the broker closure experiment).

The effect of the research–learning interaction amounts to 17% per period. This number represents the difference between -18% , or the actual convergence rate, and -35% , or the rate that obtains in a fictitious economy where agents learn and innovate but where research improvements do not lead to learning improvements, and vice versa, except through current income. This effect accounts for some 35% ($=17\% / (6.4\% + 25\% + 17\%)$) of the total effect of learning and research. The interaction's relative contribution to income growth is reduced for higher levels of β , but still remains large (its lower bound is 26%). When $\beta = 2/3$, for example, the interaction effect represents nearly 30% of the total effects of learning and research.

Table 10 shows that, under higher levels of β , the economy can escape the attraction of a steady state and (in theory) expand forever. Even more interesting is that, if β lies between 0.4 and 0.5, then any growth that persists is due *only* to the interaction between learning and research. Suppose that $\beta = 0.5$, for instance. Then income is estimated to diverge (at a rate of 13% per period). But income would be estimated to converge (at a rate of -7% per period) if we fail to account for that interaction.

Although this calibration exercise leaves out many important features of a realistic econ-

omy (e.g., we assume a 100% savings rate and that there is no population growth), it is not clear that incorporating those features would affect the *relative* importance of learning, research, or their interaction. We therefore conclude that the interplay between research and learning is an important contributor to income growth.

6 Conclusion

We develop and test a model of financial development and technological progress. Its main insight is that knowledge about technologies (financial analysis) and technological knowledge (R&D) are mutually reinforcing. In other words: entrepreneurs innovate more when financiers are better informed about their projects, because the former expect to receive more funding if their projects are successful. Conversely, financiers collect more information about projects when entrepreneurs innovate more because then the opportunity cost of mis-investing (allocating capital to unsuccessful projects and missing out on successful ones) is greater. This positive feedback promotes economic growth and is economically significant: a calibration indicates that the feedback effect's contribution to income growth represents about a third of the total contributions of information collection and R&D.

We test predictions derived from the model by exploiting two quasi-natural experiments that permit us to isolate the effect of research on learning from that of learning on research. In addition to providing support for the model, these experiments allow us to estimate that the feedback effect is about a quarter of the size of the total effect of a policy designed to stimulate R&D. For example, a 1% increase in R&D expenditures triggered by an R&D tax credit increases analyst coverage by 1.1%, which in turn, is responsible for up to 0.3% of the 1% increase in R&D expenditures.

These results open several avenues for further research. Our empirical analysis has focused on the information produced by a particular group of agents (equity analysts) whose collecting of information we take to be representative of the broader investor community. Yet there is, of course, a wide diversity of information producers; examples include venture capitalists, banks, and large investors. It would be enlightening to identify differences among these information producers, especially since the financial structure in some countries is tilted toward certain types of intermediaries.

More generally, our paper illustrates the importance of thinking about the development of real and financial sectors within an integrated framework. Since at least Greenwood and Jovanovic (1990) it has been understood that these sectors tend to evolve in tandem. Our contribution is to document how one specific dimension of the real economy (its propensity to innovate) interacts with one specific function fulfilled by the financial system (information gathering). Further empirical work is needed to deepen our understanding of how other aspects of the real economy and of the financial sector depend on each other.

A Detailed Discussion of the Model's Fit with Stylized Facts about Finance and Growth

The dynamic extension of our model is consistent with the following observations on the link between finance and growth.

Financial development causes growth by improving TFP. A large literature, surveyed by Levine (1997, 2005), shows that financial development promotes economic growth. Country-level, industry-level, firm-level, and event-study investigations suggest that financial intermediaries and markets have a considerable effect on real growth in gross domestic product (e.g., Jayaratne and Strahan 1996; Levine and Zervos 1998; Rajan and Zingales 1998; Beck, Levine, and Loayza 2000; Fisman and Love 2004). Moreover, Levine and Zervos (1998) and Beck et al. (2000) find that the relation of financial development to TFP growth is strong whereas its link to capital growth is tenuous. Thus it appears that financial development contributes to growth by increasing total factor productivity, not by increasing capital accumulation.

Financial development stimulates R&D investments, and R&D increases TFP. Carlin and Mayer (2003) examine a sample of advanced OECD countries. These authors show that industries dependent on equity finance invest more in R&D and grow faster in countries with better accounting standards. They do not find a similar increase for investment in fixed assets. The implications are that finance is associated with the funding of new technologies and that informational problems are a serious impediment to providing capital. Brown, Fazzari, and Petersen (2009) also establish a link between equity financing and R&D by analyzing US high-tech firms. They estimate that improved access to finance explains most of the 1990's R&D boom in the United States. Credit (Maria Herrera and Minetti 2007) and venture capital (Hellmann and Puri 2000; Kortum and Lerner 2000; Ueda and Hirukawa 2003) are also essential to the funding of innovations. There also exists abundant evidence that R&D is an important determinant of productivity (e.g., Griliches 1988; Coe and Helpman 1995).

Financial development improves allocative efficiency, and allocative efficiency improves TFP. Countries whose financial sectors are more developed tend to allocate their capital more efficiently. In a cross-country study, Wurgler (2000) documents that such countries increase

investments more in their growing industries—and reduce investments more in their declining industries—than do countries with less developed markets.³¹ Event studies report similar findings. According to Bekaert, Harvey, and Lundblad (2001, 2005), Bertrand, Schoar, and Thesmar (2007), Galindo, Schiantarelli, and Weiss (2007), and Chari and Henry (2008), countries that liberalize their financial sector also allocate capital more efficiently. Henry (2003) and Henry and Sasson (2008) also document a rise in total factor productivity. This is not surprising when one considers that allocative efficiency is a key driver of TFP (Caballero and Hammour 2000; Jeong and Townsend 2007; Restuccia and Rogerson 2008; Hsieh and Klenow 2009). For example, Hsieh and Klenow find that TFP would double in China and India if capital and labor were reallocated to equalize their marginal products across plants.

Financial development alleviates information imperfections. Rajan and Zingales (1998) and others have shown that the quality of information disclosure, as proxied by accounting standards, encourages the growth of industries that depend on external finance. Carlin and Mayer (2003) report that (a) information disclosure is associated with more intense R&D in industries dependent on equity finance and (b) industry growth and R&D are more strongly related to information disclosure than to the size of the financial sector. Wurgler (2000) finds a positive cross-country relation between the efficiency of investments and the informativeness of stock prices. Maria Herrera and Minetti (2007) show that the quality of banks' information has a positive influence on the likelihood that Italian manufacturing firms innovate.³²

B Model Proofs

B.1 Proof of Proposition 1

We start with the financier's investment decision. Guided by the signals he receives, the financier allocates his wage w across the continuum of projects conceived by the entrepreneur.

³¹Hartmann, Heider, Papaioannou, and Lo Duca (2007) find that the same pattern holds among OECD countries.

³²Wurgler (2000) uses a proxy for informativeness developed by Morck, Yeung, and Yu (2000). They measure the extent to which stocks move together and argue that prices move in a less synchronized manner when they incorporate more firm-specific information. Examining a cross section of US firms, Durnev, Morck, and Yeung (2004) and Chen, Goldstein, and Jiang (2007) document that firms make more efficient capital budgeting decisions when their stock price is more informative. Maria Herrera and Minetti (2007) use the credit relationship's duration to proxy for the quality of a bank's information about a firm.

At this stage he takes as given the price of intermediate goods (ρ), the projects' returns in case of success and failure (\bar{A} and \underline{A} , respectively), and the precision of his signal (q). We denote by K^+ (resp. K^-) the amount of capital allocated to a project that the signal deemed successful (resp. unsuccessful). There are $1/2$ projects in each category. For example, projects deemed successful include not only the $q/2$ projects that are truly successful and correctly identified but also the $(1 - q)/2$ projects that are unsuccessful but incorrectly identified—a total of $q/2 + (1 - q)/2 = 1/2$ projects. The budget constraint imposes that $K^+/2 + K^-/2 = w$. Output equals

$$Y = \frac{q}{2}\bar{A}(K^+)^\alpha + \left(\frac{1-q}{2}\right)\bar{A}(K^-)^\alpha + \frac{q}{2}\underline{A}(K^-)^\alpha + \left(\frac{1-q}{2}\right)\underline{A}(K^+)^\alpha,$$

where the four terms correspond to (respectively) the production of successful projects correctly and incorrectly identified and the production of unsuccessful projects correctly and incorrectly identified. A more compact expression for output is $Y = \frac{1}{2}[v^+(K^+)^\alpha + v^-(K^-)^\alpha]$, where $v^+ \equiv q\bar{A} + (1 - q)\underline{A}$ and $v^- \equiv (1 - q)\bar{A} + q\underline{A}$. Profits can now be written as

$$\pi = \rho Y \frac{\rho}{2}[v^+(K^+)^\alpha + v^-(K^-)^\alpha] = \frac{\rho}{2}[v^+(K^+)^\alpha + v^-(2w - K^+)^\alpha]$$

after substituting in the budget constraint. Maximizing this expression with respect to K^+ yields $K^+ = 2w(v^+/v)^{1/(1-\alpha)}$ and $K^- = 2w(v^-/v)^{1/(1-\alpha)}$, where $v^{1/(1-\alpha)} \equiv (v^+)^{1/(1-\alpha)} + (v^-)^{1/(1-\alpha)}$ (provided that the signal is informative; i.e., that $q > 1/2$). The expected profit then simplifies to

$$\pi = \rho 2^{\alpha-1} w^\alpha v \tag{15}$$

once the optimal investment plan is set. The price of intermediate goods follows from their output:

$$\rho = \beta(Y)^{\beta-1} = \beta 2^{(1-\alpha)(1-\beta)} w^{\alpha(\beta-1)} v^{\beta-1}. \tag{16}$$

We turn now to determination of the learning and research efforts. The financier and the entrepreneur who exert efforts \bar{A} , \underline{A} , and q expect a surplus of $\pi - e_q(q) - e_A(\bar{A} + \underline{A})$. They maximize this expression with respect to \bar{A} , \underline{A} , and q while taking ρ , the price of intermediate

goods, as given. The first-order conditions with respect to \bar{A} , \underline{A} , and q are respectively:

$$\begin{aligned}\frac{\partial \pi}{\partial \bar{A}} &= 2^{\alpha-1} \rho w^\alpha \left[q \left(\frac{v^+}{v} \right)^{\frac{\alpha}{1-\alpha}} + (1-q) \left(\frac{v^-}{v} \right)^{\frac{\alpha}{1-\alpha}} \right] = e'_A(\bar{A} + \underline{A}); \\ \frac{\partial \pi}{\partial \underline{A}} &= 2^{\alpha-1} \rho w^\alpha \left[(1-q) \left(\frac{v^+}{v} \right)^{\frac{\alpha}{1-\alpha}} + q \left(\frac{v^-}{v} \right)^{\frac{\alpha}{1-\alpha}} \right] = e'_A(\bar{A} + \underline{A}); \\ \frac{\partial \pi}{\partial q} &= 2^{\alpha-1} \rho w^\alpha (\bar{A} - \underline{A}) \left[\left(\frac{v^+}{v} \right)^{\frac{\alpha}{1-\alpha}} - \left(\frac{v^-}{v} \right)^{\frac{\alpha}{1-\alpha}} \right] = e'_q(q).\end{aligned}$$

Observe that the marginal benefit of \bar{A} always exceeds that of \underline{A} . Formally, $\partial \pi / \partial \bar{A} > \partial \pi / \partial \underline{A}$ for all \bar{A} , \underline{A} , and $q > 1/2$, where these two terms correspond to the left-hand side (LHS) of the first-order conditions given previously with respect to \bar{A} and \underline{A} . Since \bar{A} and \underline{A} are perfect substitutes in the cost of research (i.e., e_A is a function of the sum $\bar{A} + \underline{A}$), it follows that the optimum with respect to \underline{A} is the corner solution $\underline{A} = 0$ as long as $q > 1/2$. That is, if the financier is informed then the entrepreneur is better-off concentrating her effort on improving returns in the event of success. The function v is equal to $\bar{A}V$; it captures the effects of research and learning efforts on output through the terms \bar{A} and $V(q)$, respectively. The first-order conditions with respect to the research and learning efforts, \bar{A} and q , simplify to

$$\begin{aligned}2^{\alpha-1} \rho w^\alpha [q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]^{1-\alpha} &= e'_A(\bar{A}), \\ 2^{\alpha-1} \rho w^\alpha \bar{A} \frac{q^{\alpha/(1-\alpha)} - (1-q)^{\alpha/(1-\alpha)}}{[q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]^\alpha} &= e'_q(q).\end{aligned}$$

In equilibrium, the price ρ of intermediate goods is given by equation (16). Substituting this expression into the first-order conditions for \bar{A} and q yields:

$$\frac{\beta w^{\alpha\beta} [q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]^{\beta(1-\alpha)}}{2^{\beta(1-\alpha)} \bar{A}^{1-\beta}} = e'_A(\bar{A}); \quad (17)$$

$$\frac{\beta w^{\alpha\beta} \bar{A}^\beta}{2^{\beta(1-\alpha)}} \frac{q^{\alpha/(1-\alpha)} - (1-q)^{\alpha/(1-\alpha)}}{[q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]^{1-\beta(1-\alpha)}} = e'_q(q). \quad (18)$$

Rearranging these expressions leads to equations (3) and (4), which characterize the equilibrium effort levels. Our assumptions on the cost functions (e_A and e_q) guarantee the existence and unicity of an interior equilibrium. Specifically, the equilibrium research effort \bar{A} equates the

marginal benefit of research in equilibrium ($\partial\pi/\partial\bar{A}$ on the LHS of equation (17)) to its marginal cost ($e'_A(\bar{A})$ on the right-hand side (RHS)). Since the former decreases with \bar{A} and since the latter increases ($e''_A > 0$) and spans the entire real line ($e'_A(0) = 0$ and $e'_A(+\infty) = +\infty$), it follows that there exists a unique solution and it is interior. Similarly, the equilibrium learning effort q is uniquely defined by equation (18), which equates the marginal benefit of research in equilibrium ($\partial\pi/\partial q$ on the LHS) to its marginal cost ($e'_q(q)$ on the RHS). The marginal benefit equals 0 when $q = 1/2$ or equals $\beta w^{\alpha\beta} \bar{A}^\beta / 2^{\beta(1-\alpha)}$ when $q = 1$. Its derivative with respect to q equals $\frac{\alpha}{1-\alpha} \beta w^{\alpha\beta} \bar{A}^\beta 2^{2-\beta}$ when $q = 1/2$; when $q = 1$, that derivative is equal to $\beta - 1 < 0$ if $\alpha > 1/2$, to β if $\alpha = 1/2$, or to $+\infty$ if $\alpha < 1/2$. Here the existence of an interior solution is obtained by assuming that $e'_q(1/2) = e''_q(1/2) = 0$, that $e'_q(1) = +\infty$, and that $e''_q > 0$; unicity is obtained by assuming $e'''_q > 0$. These are sufficient but not necessary conditions.

B.2 Proof of Proposition 2

The first part of the proposition follows from noting that the function V (defined in Proposition 1) increases with the learning effort q . Formally, we have $\partial V/\partial q = V^{-\alpha/(1-\alpha)}((v^+)^{\alpha/(1-\alpha)} - (v^-)^{\frac{\alpha}{1-\alpha}}) \geq 0$ for any $q > 1/2$. Equations (3) then imply that the research effort \bar{A} increases with q when wealth is held fixed. The proposition's second part follows from equation (4), which shows that the learning effort q increases with the research effort \bar{A} while holding wealth fixed. Note also that greater wealth w stimulates learning and research because it expands revenues without affecting costs (i.e., greater wealth implies larger investments).

B.3 Proof of Proposition 3

We start with the distribution of capital. It is bimodal: half of the projects are labeled as successes and receive K^+ units of capital; the other half, labeled as failures, receive K^- units. The expressions given in Proposition 1 for K^+ and K^- imply that $K^+/K^- = (q/(1-q))^{1/(1-\alpha)}$. This ratio, and hence the dispersion of capital, is increasing in q but is unrelated to \bar{A} .

We turn to the correlation between capital and productivity, $\text{Corr}(\tilde{A}_n, K_n)$. It is straightforward to show that $\text{Var}(\tilde{A}_n) = \bar{A}^2/4$. We compute next the variance of capital,

$\text{Var}(K_n) = E(K_n^2) - E(K_n)^2 = (K^+)^2/2 + (K^-)^2/2 - w^2$. Substituting in the expressions for K^+ and K^- (given in Proposition 1) yields $\sqrt{\text{Var}(K_n)} = w[q^{1/(1-\alpha)} - (1 -$

$q)^{1/(1-\alpha)}/[q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]$. Note that this expression is increasing in q and converges to w as α converges to 1. Finally, we compute the covariance between capital and productivity, $Cov(\tilde{A}_n, K_n) = E(\tilde{A}_n K_n) - E(\tilde{A}_n)E(K_n)$, where $E(\tilde{A}_n) = \bar{A}/2$ and $E(K_n) = w$. The variable $\tilde{A}_n K_n$ can take any one of four possible values: $\bar{A}K^+$ for a successful project identified as such, which happens with probability $q/2$; $\bar{A}K^-$ for a successful project mislabeled as a failure, which happens with probability $(1-q)/2$; $\underline{A}K^+ = 0$ for an unsuccessful project mislabeled as a success, which happens with a probability $(1-q)/2$; or $\underline{A}K^- = 0$ for a correctly identified unsuccessful project, which happens with probability $q/2$. It follows that $Cov(\tilde{A}_n, K_n) = q\bar{A}K^+/2 + (1-q)\bar{A}K^-/2 - w\bar{A}/2$. Substituting in the expressions for K^+ and K^- yields $Cov(\tilde{A}_n, K_n) = w\bar{A}(q-1/2)[q^{1/(1-\alpha)} - (1-q)^{1/(1-\alpha)}]/[q^{1/(1-\alpha)} + (1-q)^{1/(1-\alpha)}]$. Note that this expression is increasing in q and converges to $w\bar{A}(q-1/2)$ as α converges to 1. It follows that $Corr(\tilde{A}_n, K_n) = Cov(\tilde{A}_n, K_n)/\sqrt{Var(K_n)}/\sqrt{Var(\tilde{A}_n)} = 2q - 1$, which increases with q but is independent of \bar{A} .

B.4 Proof of Proposition 4

The return on capital is equal to $\tilde{A}_n(K_n)^{\alpha-1}$. In the case of constant returns to scale (i.e., if $\alpha = 1$), the return is independent of capital and equals \tilde{A}_n . In that case, $Var[\tilde{A}_n(K_n)^{\alpha-1}] = \bar{A}^2/4$. We assume next that $\alpha < 1$. The return on capital can take any one of four possible values: $\bar{A}(K^+)^{\alpha-1}$ for a successful project identified as such, which happens with probability $q/2$; $\bar{A}(K^-)^{\alpha-1}$ for a successful project mislabeled as a failure, which happens with probability $(1-q)/2$; $\underline{A}(K^+)^{\alpha-1} = 0$ for an unsuccessful project mislabeled as a success, which happens with a probability $(1-q)/2$; or $\underline{A}(K^-)^{\alpha-1} = 0$ for a correctly identified unsuccessful project, which happens with probability $q/2$. It follows that

$$Var[\tilde{A}_n(K_n)^{\alpha-1}] = \frac{q(\bar{A}(K^+)^{\alpha-1})^2}{2} + (1-q)\frac{(\bar{A}(K^-)^{\alpha-1})^2}{2} - \left[\frac{q\bar{A}(K^+)^{\alpha-1}}{2} + (1-q)\frac{\bar{A}(K^-)^{\alpha-1}}{2} \right]^2.$$

Substituting in the expressions for K^+ and K^- (given in Proposition 1) yields $Var[\tilde{A}_n(K_n)^{\alpha-1}] = (2w)^{2(\alpha-1)}\bar{A}^2 h(q)V(q)^2$, where $h(q) \equiv (1/q - 1/2)/2 + [(1+q)/(1-q)]/4 - 1/2$. This expression increases with \bar{A} . It also increases in q because both h and V are increasing in q for $q > 1/2$.

B.5 Proof of Proposition 5

We first prove the existence of steady states, after which we describe the transition to those states. A steady-state equilibrium is characterized by the following system of equations; these equations are obtained by setting $w_{t+1} = w_t = w^*$ in, respectively, equations (8), (6), and (7):

$$\begin{aligned} w^* &= (1 - \beta)w^{*\beta}\bar{A}^{*\beta}q^{*\beta}, \\ \beta q^{*\beta}w^{*\beta} &= \bar{A}^{*(1-\beta)}e'_A(\bar{A}^*), \\ \beta\bar{A}^{*\beta}w^{*\beta} &= q^{*(1-\beta)}e'_q(q^*). \end{aligned} \tag{19}$$

A trivial solution is $w^* = \bar{A}^* = q^* - 1/2 = 0$. By assuming that w^* , \bar{A}^* , and $q^* - 1/2$ are each strictly positive, we can take logs and write the same system as

$$\begin{aligned} -\ln(w^*) + \frac{\beta}{1-\beta}\ln(q^*) + \frac{\beta}{1-\beta}\ln(\bar{A}^*) &= -\frac{1}{1-\beta}\ln(1 - \beta), \\ -\ln(w^*) - \ln(q^*) + \frac{1}{\beta}\ln[\bar{A}^{*(1-\beta)}e'_A(\bar{A}^*)] &= \frac{1}{\beta}\ln(\beta), \\ -\ln(w^*) + \frac{1}{\beta}\ln[q^{*(1-\beta)}e'_q(q^*)] - \ln(\bar{A}^*) &= \frac{1}{\beta}\ln(\beta). \end{aligned}$$

The system's Jacobian matrix, J , is defined as

$$J = \begin{pmatrix} -1 & \frac{\beta}{1-\beta} & \frac{\beta}{1-\beta} \\ -1 & -1 & \frac{1}{\beta}(\varepsilon_A - \beta) \\ -1 & \frac{1}{\beta}(\varepsilon_q - \beta) & -1 \end{pmatrix}, \tag{20}$$

where we have used that $\partial \ln[\bar{A}^{*(1-\beta)}e'_A(\bar{A}^*)]/\partial \ln(\bar{A}^*) = \varepsilon_A - \beta$ and $\partial \ln[q^{*(1-\beta)}e'_q(q^*)]/\partial \ln(q^*) = \varepsilon_q - \beta$. The determinant of J satisfies $\beta^2(1 - \beta)\varepsilon_A\varepsilon_q \det J = 1 - \beta - \beta(1/\varepsilon_A + 1/\varepsilon_q)$. Since we assume that $1/\varepsilon_A(\bar{A}) + 1/\varepsilon_q(q) - 1/\beta + 1$ never equals 0, it follows that $\det J \neq 0$ for all $\bar{A}^* > 0$ and $1 > q^* > 1/2$. Hence there exists a unique and nontrivial steady state.

To study the dynamics, we log-linearize the system around its steady state. Taylor-series expansions yield $\ln[e'_q(q_t)] \approx \ln[e'_q(q^*)] + (\varepsilon_q - 1)[\ln(q_t) - \ln(q^*)]$ and $\ln[e'_A(\bar{A}_t)] \approx \ln[e'_A(\bar{A}^*)] + (\varepsilon_A - 1)[\ln(\bar{A}_t) - \ln(\bar{A}^*)]$. We substitute these expressions into equations (4) and (3), after taking

logs and using the conditions (19) that characterize a steady state, to obtain:

$$\ln(\bar{A}_t/\bar{A}^*) \approx \frac{\beta}{\varepsilon_A - \beta} [\ln(q_t/q^*) + \ln(w_t/w^*)]; \quad (21)$$

$$\ln(q_t/q^*) \approx \frac{\beta}{\varepsilon_q - \beta} [\ln(\bar{A}_t/\bar{A}^*) + \ln(w_t/w^*)]. \quad (22)$$

Solving for $\ln(\bar{A}_t/\bar{A}^*)$ and $\ln(q_t/q^*)$ yields

$$\ln(q_t/q^*) \approx \frac{\gamma + 1}{\varepsilon_q} \ln(w_t/w^*) \quad \text{and} \quad \ln(\bar{A}_t/\bar{A}^*) \approx \frac{\gamma + 1}{\varepsilon_A} \ln(w_t/w^*). \quad (23)$$

Finally, we take the log of equation (5) and use conditions (19) to write

$$\ln(w_{t+1}/w^*) \approx \beta \ln(q_t/q^*) + \beta \ln(\bar{A}_t/\bar{A}^*) + \beta \ln(w_t/w^*). \quad (24)$$

Substituting the expressions for $\ln(\bar{A}_t/\bar{A}^*)$ and $\ln(q_t/q^*)$ back into (24) leads to

$$\ln(w_{t+1}/w^*) \approx (\gamma + 1) \ln(w_t/w^*), \quad (25)$$

where γ is as defined in Proposition 2. Income grows if $\gamma > -1$ (i.e., $1/\varepsilon_A + 1/\varepsilon_q < 1/\beta$)—at a declining rate if $\gamma < 0$ or at an expanding rate if $\gamma > 0$. The former occurs if $1/\varepsilon_A + 1/\varepsilon_q < 1/\beta - 1$; the latter occurs if $1/\varepsilon_A + 1/\varepsilon_q > 1/\beta - 1$. If instead $\gamma < -1$ (i.e., if $1/\varepsilon_A + 1/\varepsilon_q > 1/\beta$), then income oscillates. The cycles are unstable because $\gamma < -1$ implies that $\gamma < -2$.

B.6 Proof of Corollary 6

We shall demonstrate how to compute $\bar{\gamma}$, or income's speed of convergence in an economy with no interplay between learning and research. This economy is governed by the following system of equations:

$$\begin{aligned} \beta q^\beta w_t^\beta &= \bar{A}_t^{1-\beta} e'_A(\bar{A}_t), \\ \beta \bar{A}^\beta w_t^\beta &= q_t^{1-\beta} e'_q(q_t), \\ w_{t+1} &= (1 - \beta) \times w_t^\beta \times q_t^\beta \times \bar{A}_t^\beta. \end{aligned}$$

Observe that q and \bar{A} are *arbitrary* constants in, respectively, the first and second of these equations (where the terms carry no time subscript).³³ Thus, q_t and \bar{A}_t both grow with income but do not influence each other directly. Computations similar to those performed when proving Proposition 5 yield $\bar{\gamma} = \frac{\beta \varepsilon_A \varepsilon_q - \beta^2}{(\varepsilon_A - \beta)(\varepsilon_q - \beta)}$. The effect on income of the interplay between learning and research is captured by the growth rate differential between the two economies: $\gamma - \bar{\gamma} = \frac{\beta^2(\beta + \gamma + 1)}{(\varepsilon_A - \beta)(\varepsilon_q - \beta)}$. This expression is positive if $\gamma + 1 > 0$ (i.e., if income grows).

B.7 Model Calibration

In this section we show how to relate the parameters of the cost functions—in particular, the elasticities ε_A and ε_q —to the estimates derived from our R&D tax credit and broker closure experiments. We assume that the economy is initially in a steady state and that it is perturbed in period T by a shock to the cost of either learning or research. Specifically, we assume that these functions are scaled by positive multiplicative parameters, c_A and c_q , as follows: $c_A \times e_A(\bar{A} + \underline{A})$ and $c_q \times e_q(q)$. An increase in R&D tax credits is interpreted as a decline in c_A , or as a reduction in the cost of research (but with no effect on the cost of learning). Conversely, broker closures are interpreted as an increase in c_q , or as an increase in the cost of learning (but with no effect on the cost of research). Once perturbed, the economy converges toward a new steady state (denoted $*$). In period T , before the shock, the economy is fully described by the system of equations (19) characterizing the initial steady state. The economy's evolution is then governed (approximately) by (10)–(12), from Proposition 5, under the parameters of the new steady state.

Next we compute the elasticity of R&D expenditures to analyst following—in the broker closure experiment—from period T (the initial steady state) to period $T + 1$ (the first period under the new dynamics); thus we compute $\ln(\bar{A}_{T+1}/\bar{A}_T) / \ln(q_{T+1}/q_T)$. We assume that the cost of learning increases (c_q rises) but that the cost of research does not (c_A is constant). The change in the learning intensity then triggers a change in the research intensity, a change that we express as $\ln(\bar{A}_{T+1}/\bar{A}_T) = \ln(\bar{A}_{T+1}/\bar{A}^*) - \ln(\bar{A}_T/\bar{A}^*)$. We start by evaluating the second term. After using the first equation of system (19) to eliminate income from the second equation and then taking logs, we obtain the following expression for the initial steady state (and a similar

³³These constants determine the steady-state level of income but have no bearing on its growth rate—even in the vicinity of the steady state.

one for the final steady state, with * replacing subscript T):

$$\left(\frac{1}{\beta} - \frac{1}{1-\beta}\right) \ln(\bar{A}_T) + \frac{1}{\beta} \ln(e'_A(\bar{A}_T)) = \ln(\beta^{1/\beta}(1-\beta)^{1/(1-\beta)}) + \frac{1}{1-\beta} \ln(q_T). \quad (26)$$

Substituting in the log-linearized expression for $\ln[e'_A(\bar{A}_T)]$ around the final steady state, $\ln[e'_A(\bar{A}^*)] + (\varepsilon_A - 1)[\ln(\bar{A}_T/\bar{A}^*)]$, yields:

$$\begin{aligned} \left(\frac{1}{\beta} - \frac{1}{1-\beta}\right) \ln(\bar{A}_T) + \frac{1}{\beta} \ln[e'_A(\bar{A}^*)] + \frac{1}{\beta} (\varepsilon_A - 1) [\ln(\bar{A}_T/\bar{A}^*)] \\ = \ln(\beta^{1/\beta}(1-\beta)^{1/(1-\beta)}) + \frac{1}{1-\beta} \ln(q_T). \end{aligned}$$

Subtracting equation (26) written for the final steady state, leads to

$$\ln(\bar{A}_T/\bar{A}^*) = \frac{\beta}{(1-\beta)\varepsilon_A - \beta} \ln(q_T/q^*). \quad (27)$$

Next we evaluate $\ln(\bar{A}_{T+1}/\bar{A}^*)$. From (23) it follows that

$$\ln(\bar{A}_{T+1}/\bar{A}^*) \approx \frac{\gamma+1}{\varepsilon_A} \ln(w_{T+1}/w^*) \approx \frac{(\gamma+1)^2}{\varepsilon_A} \ln(w_T/w^*),$$

where the first approximation is implied by (23) and the second by (12). Taking logs of system (19)'s first equation for the initial and final steady states and then taking the difference, we obtain $\ln(w_T/w^*) \approx \frac{\beta}{1-\beta} (\ln(q_T/q^*) + \ln(\bar{A}_T/\bar{A}^*))$. Equation (27) then implies that $\ln(w_T/w^*) \approx \beta\varepsilon_A / [(1-\beta)\varepsilon_A - \beta] \ln(q_T/q^*)$.³⁴ Substituting this approximation into the formula for $\ln(\bar{A}_{T+1}/\bar{A}^*)$ now yields

$$\ln(\bar{A}_{T+1}/\bar{A}^*) \approx \frac{\beta(\gamma+1)^2}{(1-\beta)\varepsilon_A - \beta} \ln(q_T/q^*). \quad (28)$$

Together, (27) and (28) imply the approximation

$$\ln(\bar{A}_{T+1}/\bar{A}_T) \approx \frac{\beta((\gamma+1)^2 - 1)}{(1-\beta)\varepsilon_A - \beta} \ln(q_T/q^*).$$

³⁴Here we cannot exploit (23) which relates deviations of w and q from the steady state because the cost of learning is not held constant in this experiment. The expression used here is derived from the first-order condition for q , which is displayed in the third equation of system (19).

We proceed in a similar way to evaluate $\ln(q_{T+1}/q_T)$:

$$\begin{aligned}
\ln(q_{T+1}/q_T) &= \ln(q_{T+1}/q^*) - \ln(q_T/q^*) \\
&\approx \frac{\gamma + 1}{\varepsilon_q} \ln(w_{T+1}/w^*) - \ln(q_T/q^*) \\
&\approx \frac{(\gamma + 1)^2}{\varepsilon_q} \ln(w_T/w^*) - \ln(q_T/q^*) \\
&\approx \frac{\beta\varepsilon_A(\gamma + 1)^2}{\varepsilon_q[(1 - \beta)\varepsilon_A - \beta]} \ln(q_T/q^*) - \ln(q_T/q^*) \\
&\approx \left(\frac{\beta\varepsilon_A(\gamma + 1)^2}{\varepsilon_q[(1 - \beta)\varepsilon_A - \beta]} - 1 \right) \ln(q_T/q^*).
\end{aligned}$$

So in our broker closure experiment, the elasticity of R&D expenditures to analyst following is given by

$$\frac{\ln(\bar{A}_{T+1}/\bar{A}_T)}{\ln(q_{T+1}/q_T)} \approx \frac{(\gamma + 1)^2 - 1}{\varepsilon_A(\gamma + 1)^2/\varepsilon_q - (1/\beta - 1)\varepsilon_A + 1}. \quad (29)$$

Analogously, in our R&D tax credit experiment we obtain the following formula for the elasticity of analyst following to R&D expenditures:

$$\frac{\ln(q_{T+1}/q_T)}{\ln(\bar{A}_{T+1}/\bar{A}_T)} \approx \frac{(\gamma + 1)^2 - 1}{\varepsilon_q(\gamma + 1)^2/\varepsilon_A - (1/\beta - 1)\varepsilon_q + 1}. \quad (30)$$

Given γ as defined in (12), the expressions (29) and (30) form a system of two equations with two unknowns, ε_A and ε_q . We assume here that ε_A and ε_q do not change much across the two experiments; hence we can treat them as the same unknowns in these equations.

C Model Extension: Controlling Projects' Probability of Success

Here we describe and solve a version of the model in which the entrepreneur controls projects' *probability* of success—rather than their return—while assuming constant returns to scale in the intermediary sector (i.e., $\alpha = 1$). Projects' returns are exogenously set to 1 in case of success and to 0 in case of failure. Creating projects with a success probability p requires a research effort $e_p(p)$. Here e_p is continuous, increasing, and convex; $e_p(0) = e'_p(0) = 0$, $e'_p(1) = +\infty$,

and $\varepsilon_p(p) \equiv 1 + pe_p''(p)/e_p'(p) > 0$.

The financier allocates K^+ units of capital to a project deemed successful by his signal and allocates K^- to a project deemed unsuccessful. The former consist of the pq successful projects correctly identified as well as the $(1-p)(1-q)$ unsuccessful projects incorrectly identified; hence there are $pq + (1-p)(1-q)$ projects in total. Similarly, the number of projects deemed unsuccessful equals $(1-p)q + p(1-q)$. The budget constraint imposes that $[pq + (1-p)(1-q)]K^+ + [(1-p)q + p(1-q)]K^- = w$. Output is $Y = pqK^+ + p(1-q)K^-$, where the first term represents the undertaking of correctly identified successful projects, and the second term that of incorrectly identified successful projects. Substituting in the budget constraint and maximizing this expression leads to $K^+ = w/[pq + (1-p)(1-q)]$, $K^- = 0$, $Y = w\varpi$, and $\pi(p, q, w) = \rho w\varpi$ for $\varpi \equiv pq/[pq + (1-p)(1-q)]$. These expressions match those obtained in the main model if $p = 1/2$ and $\bar{A} = 1$ (equations (15) and (16)).

By maximizing the surplus, $\pi(p, q, w) - e_q(q) - e_p(p)$, with respect to p and q and taking the price of intermediate goods (ρ) as given, we derive the first-order conditions:

$$\rho w(1 - \varpi)^2/(1 - p)^2 = e'_q(q) \quad \text{and} \quad \rho w(1 - \varpi)^2/(1 - q)^2 = e'_p(p). \quad (31)$$

Finally, substituting $\rho = \beta(\varpi w)^{\beta-1}$ into these equations yields the conditions that characterize the equilibrium:

$$\frac{\beta w^\beta (1 - \varpi)^2}{\varpi^{1-\beta} (1 - p)^2} = e'_q(q) \quad \text{and} \quad \frac{\beta w^\beta (1 - \varpi)^2}{\varpi^{1-\beta} (1 - q)^2} = e'_p(p). \quad (32)$$

We assume from now on that p is small—in other words, that projects are extremely risky (as when e_p is strongly convex). The existence of a unique interior solution to equations (31) is guaranteed for any ρ if e_q is sufficiently convex (i.e., if $\varepsilon_q(q) > (1+q)/(1-q)$ for $1 > q > 1/2$). Equations (32) simplify to

$$\beta w^\beta p^\beta = q^{1-\beta} (1 - q)^{1+\beta} e'_q(q) \quad \text{and} \quad \beta w^\beta q^\beta = p^{1-\beta} (1 - q)^\beta e'_p(p).$$

The equilibrium properties of learning and research are the same as in the main model (Proposition 2). Namely: the financier learns more when the entrepreneur carries out more research (so q increases with p when w is fixed); and the entrepreneur carries out more research

when the financier learns more (so p increases with q while holding w fixed).

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Table 1
R&D Tax Credits Rate Changes Implemented by US States between 1990 and 2006

Data on states R&D tax credit are obtained from Daniel Wilson's website (<http://www.frbsf.org/economic-research/economists/daniel-wilson/>). In this table, given our focus on high-tech firms, we report the statutory tax credit for the highest tier of R&D spending, though for most states the tax credit rate does not vary with the level of R&D spending. Our regressions are based on the direction of the change in tax credit only, not the actual level

State	Year	Tax Credit	Direction of Tax Credit Rate Change
AZ	1994	20.0%	+
AZ	2001	11.0%	-
CA	1997	11.0%	+
CA	1999	12.0%	+
CA	2000	15.0%	+
CT	1993	6.0%	+
DE	2000	10.0%	+
GA	1998	10.0%	+
HI	2000	20.0%	+
ID	2001	5.0%	+
IL	1990	7.0%	+
IL	2003	0.0%	-
IL	2004	7.0%	+
IN	2003	10.0%	+
LA	2003	8.0%	+
ME	1996	5.0%	+
MD	2000	10.0%	+
MA	1991	10.0%	+
MO	1994	7.0%	+
MT	1999	5.0%	+
NE	2006	3.0%	+
NH	1993	7.0%	+
NH	1994	15.0%	+
NH	1995	0.0%	-
NJ	1994	10.0%	+
NC	1996	5.0%	+
NC	2006	3.0%	-
OH	2004	7.0%	+
PA	1997	10.0%	+
RI	1994	5.0%	+
RI	1998	17.0%	+
SC	2001	3.0%	+
SC	2002	5.0%	+
TX	2001	4.0%	+
TX	2002	5.0%	+
UT	1999	6.0%	+
VT	2003	10.0%	+
WV	2003	3.0%	-

Table 2
Summary Statistics

This table presents the summary statistics on our sample. The sample includes listed US manufacturing firms reporting strictly positive R&D expenditures between 1990 and 2006. The statistics are computed on one observation per firm (the time average of the variable). The last column reports the median in the Compustat universe of manufacturing firms. Coverage measures the number of analysts following a firm. RoA denotes the return on asset and is defined as the ratio of EBIT to total assets. Q is the ratio of the market value of assets to the book value of assets. Net new financing proceeds is the highest of the sum of stock issues and long-term debt issues, and zero, scaled by total assets. Patent values are a function of the firm's share price reaction upon patent acceptance (collected from Kogan et al. 2017). Forward citations measure the number of citations received from the date a patent was accepted until 2011.

	Mean	S.D.	25th	50th	75th	N	Compustat 50 th
Coverage	11.08	9.05	4.39	8.41	14.93	844	1.70
R&D (\$m)	72.19	206.6	6.55	15.02	37.53	844	2.26
R&D/assets (%)	6.77	6.53	1.81	4.38	10.37	844	3.12
Sales (\$m)	2964.82	7875.05	196.75	578.53	1954.48	844	76.92
RoA (%)	8.54	10.7	5.35	9.54	13.8	844	4.01
Q	2.38	1.71	1.42	1.88	2.68	844	1.85
New financing proceeds (%)	5.29	12.13	0.70	2.76	6.53	844	4.02
Patent values (\$m)	755.92	3152.47	4.34	20.90	152.62	844	0.00
Patent forward citations	437.16	1972.86	6.35	42.77	174.52	844	0.00

Table 3
State R&D Tax Credits: Effect on Firm R&D Expenditures

The table presents the results of the difference-in-differences estimation for the effect of R&D tax credit on firms' R&D expenditures. TC_{t+1} is a dummy variable which equals one in the year following the passage or increase in an R&D tax credit in the state in which a firm is headquartered. $Loss$ is a dummy that equals one if the firm reports negative earnings before interests and taxes. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firms fixed effects). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(R\&D)_t$	$\Delta \ln(R\&D)_t$	$\Delta \ln(R\&D)_t$
	(1)	(2)	(3)
TC_{t+1}			0.008 (0.018)
TC_t	0.039** (0.016)	0.046** (0.018)	0.042** (0.019)
TC_{t-1}			-0.014 (0.012)
$\Delta \ln(Sales)_{t,2}$		0.123*** (0.033)	0.141*** (0.035)
$\Delta Loss_{t,2}$		-0.041*** (0.012)	-0.042*** (0.013)
Year FE	Yes	Yes	Yes
Firm FE	Diff.	Diff.	Diff.
N	8499	7191	6281
R2	0.021	0.039	0.049

Table 4
State R&D Tax Credits: Effect on Analyst Coverage

The table presents the results of the difference-in-differences estimation for the effect of R&D tax credit on firms' coverage by financial analysts. TC_{t+1} is a dummy variable which equals one in the year following the passage or increase in an R&D tax credit in the state in which a firm is headquartered. Loss is a dummy that equals one if the firm reports negative earnings before interests and taxes. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firms fixed effects). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$
	(1)	(2)	(3)
TC_{t+1}			-0.008 (0.018)
TC_t	0.044** (0.019)	0.051*** (0.018)	0.052*** (0.018)
TC_{t-1}			0.004 (0.016)
$\Delta \ln(\text{Sales})_{t,2}$		0.057** (0.023)	0.055** (0.027)
$\Delta \text{Loss}_{t,2}$		-0.046*** (0.010)	-0.056*** (0.011)
Year FE	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff
N	8499	7191	6281
R2	0.012	0.014	0.015

Table 5
Brokerage Events: Effect on Analyst Coverage

The table presents the results of the difference-in-differences estimation for the effect of brokerage houses closures and mergers on firms' analyst coverage. AN_{t+1} is a dummy variable that equals one in the year following the loss an analyst due to a brokerage house merger or closure. $Loss_t$ is a dummy that equals one if the firm reports negative earnings before interests and taxes. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firms fixed effects). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$
	(1)	(2)	(3)
AN_{t+1}			0.009 (0.019)
AN_t	-0.114*** (0.024)	-0.100*** (0.024)	-0.077*** (0.019)
AN_{t-1}			-0.018 (0.018)
$\Delta \ln(\text{Sales})_{t,2}$		0.057** (0.023)	0.054** (0.026)
$\Delta \text{Loss}_{t,2}$		-0.044*** (0.010)	-0.055*** (0.011)
Year FE	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff
N	8499	7191	6281
R2	0.013	0.016	0.016

Table 6
Brokerage Events: Effect on R&D Expenditures

The table presents the results of the difference-in-differences estimation for the effect of brokerage houses closures and mergers on firms' R&D expenditures. AN_{t+1} is a dummy variable that equals one in the year following the loss an analyst due to a brokerage house merge or closure. $Loss$ is a dummy that equals one if the firm reports negative earnings before interests and taxes. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firms fixed effects). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(R\&D)_t$	$\Delta \ln(R\&D)_t$	$\Delta \ln(R\&D)_t$
	(1)	(2)	(3)
AN_{t+1}			-0.016 (0.020)
AN_t	-0.037** (0.015)	-0.025** (0.012)	-0.034** (0.013)
AN_{t-1}			0.002 (0.015)
$\Delta \ln(Sales)_{t,2}$		0.122*** (0.033)	0.141*** (0.035)
$\Delta Loss_{t,2}$		-0.040*** (0.012)	-0.039*** (0.012)
Year FE	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff
N	8499	7191	6281
R2	0.020	0.037	0.047

Table 7
Robustness

The table presents the results of robustness tests of Tables 4 and 6. Column (1) shows the base regression of the tax credit experiment (Column (2) in Table 4). Column (2) adds industry fixed effects (which, given the first difference specification, are equivalent to industry-specific trends). Column (3) controls for the state economic conditions (gross state product and unemployment rate) in the year of the increase in R&D tax credit. Column (4) shows the base regression of the broker experiment (Column (2) in Table 6). Column (5) controls for contemporaneous capital expenditures. Column (6) controls for additional variables that may be affected by the broker experiment (Derrien and Kesckes 2013). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{R\&D})_t$	$\Delta \ln(\text{R\&D})_t$	$\Delta \ln(\text{R\&D})_t$
	(1)	(2)	(3)	(4)	(5)	(6)
TC_{+t}	0.051*** (0.018)	0.044** (0.017)	0.046** (0.018)			
AN_{-t}				-0.025** (0.012)	-0.026** (0.012)	-0.025** (0.012)
$\Delta \ln(\text{Sales})_{t,2}$	0.057** (0.023)	0.049** (0.024)	0.057** (0.023)	0.122*** (0.033)	0.130*** (0.033)	0.129*** (0.033)
$\Delta \text{Loss}_{t,2}$	-0.046*** (0.010)	-0.047*** (0.010)	-0.046*** (0.010)	-0.040*** (0.012)	-0.041*** (0.012)	-0.041*** (0.011)
$\Delta(\text{State GSP})_{t-1}$			0.007*** (0.002)			
$\Delta(\text{State unempl. rate})_{t-1}$			0.008 (0.007)			
ΔCapx_t					0.600*** (0.125)	0.602*** (0.122)
$\Delta \text{Acquisition}_t$						0.108** (0.047)
$\Delta \text{LT Debt}_t$						0.025 (0.021)
ΔCash_t						-0.036*** (0.013)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No
Firm FE	Diff	Diff	Diff	Diff	Diff	Diff
N	7191	7191	7191	7191	7191	7191
R2	0.014	0.022	0.016	0.037	0.048	0.056

Table 8
Instrumental Variable Estimation

The table presents the results of the instrumental variable estimation by two-stage least squares for the effect of analyst coverage on firm R&D and of firm R&D on analyst coverage. We instrument firm R&D with the tax credit shocks (TC+) and analyst coverage with the brokerage house events (AN-). The regressions are estimated in first differences, which control for firms' time invariant characteristics (firms fixed effects). All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{Coverage})_t$	$\Delta \ln(\text{R\&D})_t$	$\Delta \ln(\text{R\&D})_t$
	(1)	(2)	(3)	(4)
$\Delta \ln(\text{R\&D})_t$	1.120*** (0.288)	1.118*** (0.300)		
$\Delta \ln(\text{Coverage})_t$			0.323*** (0.108)	0.250** (0.106)
$\Delta \ln(\text{Sales})_{t,2}$		-0.080 (0.053)		0.108*** (0.029)
$\Delta \text{Loss}_{t,2}$		-0.000 (0.014)		-0.029** (0.014)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff	Diff
N	8499	7191	8499	7191
F	10.395	15.498	9.556	26.956

Table 9
Effects of Research on the Distribution of Financing, and of Learning on Risk

The table tests auxiliary predictions of our model on the effect of learning by the financial sector and firms' research. In Row (i) (resp. Row(iii)) we check whether the cross-sectional standard deviations of firms' net issues of long-term capital (resp. return on asset) decreases (resp. increases) after the passage of R&D tax credits (resp. broker events). In Row (ii), we test whether the slope of a regression of firms' net issues of long-term capital on Tobin's Q increases after the passage of R&D tax credits. In Row (iv), we check whether the within-firm standard deviation of patent values and forward citations decreases after broker events. The tests methodologies are adapted from Bertrand, Duflo, and Mullainathan (2004). For Row (i) and Row (iii), we retain firms that are never treated, as well as observations for treated firms from two years before to two years after the shock. In a first stage, we pool all observations and regress the variable of interest on year dummies, industry dummies, treatment dummies, and ln(Sales). We extract the residuals for treated firms, and, for each firm, time-average them over the two years before the shock and the two years after the shock (leaving two observations for each firm). We then compare the residuals' cross-sectional standard deviation before and after the shock. For Row (ii), we construct residuals in a similar way, but only consider Tobin's Q residuals at the end of each two-year period. We then compare, thanks to a Chow test, the slope of a regression of financing residuals on (end-of-period) Tobin's Q residuals before and after the shock. For Row (iv), we retain all patents for firms that are never treated, as well as observations for treated firms from two years before to two years after the shock. In a first stage, we pool all patent observations and regress their value or forward citations (i.e., the number of citations received from the date it was accepted until 2011) on technological class-year dummies, treatment dummies, and ln(Sales). We extract the residuals for treated firms and, for each firm, calculate the standard deviation of the residuals in the two years before the shock and in the two years after the shock (leaving two observations for each firm). We then compare the mean within-firm standard deviation before and after the shock. For each row, we consider the first shock that affects a firm in case it was shocked multiple times. ***, **, * denote significance at 1%, 5%, and 10%, respectively.

	Shock	Time	Measure	Mean	Statistic	p-value
(i) Long-term financing (equity + debt)	R&D	Before	S.D.	0.079	0.32***	0.000
		After		0.139		
(ii) Match between Long-term financing and Q	R&D	Before	Slope	0.026	15.38***	0.000
		After		0.079		
(iii) Return on assets	Learning	Before	S.D.	0.117	1.55***	0.003
		After		0.094		
(iv) Within-firm dispersion of patent metrics	Learning	Before	Mean	0.553	1.92*	0.056
		After	(value)	0.413		
		Before	Mean	0.890	1.97**	0.049
		After	(citations)	0.846		

Table 10
Model Calibration

This table displays the results of the model calibration. Column (1) displays β , the share of capital in total income. Columns (2) and (3) display the parameters of the costs of research and learning, ε_A and ε_q . They are derived from the estimates of the elasticity of R&D expenditures with respect to analyst following in the broker closure experiment (0.25), and from the estimates of the elasticity of analyst following with respect R&D expenditures in the R&D tax credit experiment (1.12), assuming that the economy, perturbed by a shock (changes in R&D tax credits or broker closures) transitions from one steady-state to another. In Column (4), γ measures the speed of convergence of income to its steady-state. Columns (5) to (7) display the first three components of γ , i.e., the contributions to income growth of, respectively, diminishing returns to capital, γ_K , research, γ_A , and learning, γ_q . Column (8) displays $\bar{\gamma}$, the growth rate of income in an economy with no interplay between learning and research. Column (9) displays the final component of γ , namely the contribution to income growth of the interaction between research and learning, γ_{Aq} (defined as $\gamma - \bar{\gamma}$). Column (10) displays γ_{Aq} in proportion of the total contribution of research and learning. Returns to scale in the intermediate goods sector are assumed constant ($\alpha = 1$). The top panel shows growth rates of income per period, and the bottom panel rates per annum assuming that one period lasts 30 years so the annual rate equals $(1 + \text{per period rate})^{1/30} - 1$.

Panel A: Rates per period									
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β	ε_A	ε_q	γ	γ_K	γ_A	γ_q	$\bar{\gamma}$	γ_{Aq}	$\frac{\gamma_{Aq}}{\gamma_A + \gamma_q + \gamma_{Aq}}$
0.10	0.54	0.21	-69.46%	-90.00%	2.27%	9.52%	-78.21%	8.75%	0.43
0.20	1.15	0.43	-45.34%	-80.00%	4.22%	17.04%	-58.75%	13.41%	0.39
0.30	1.81	0.68	-24.25%	-70.00%	5.97%	23.39%	-40.64%	16.40%	0.36
0.33	2.02	0.76	-18.31%	-67.00%	6.46%	25.13%	-35.41%	17.09%	0.35
0.40	2.52	0.95	-5.01%	-60.00%	7.56%	28.96%	-23.48%	18.47%	0.34
0.50	3.27	1.24	12.94%	-50.00%	9.03%	33.93%	-7.04%	19.98%	0.32
0.60	4.06	1.54	29.94%	-40.00%	10.41%	38.43%	8.84%	21.10%	0.30
0.66	4.55	1.72	39.78%	-34.00%	11.19%	40.95%	18.14%	21.64%	0.29
0.70	4.89	1.85	46.21%	-30.00%	11.69%	42.56%	24.25%	21.96%	0.29
0.80	5.76	2.18	61.88%	-20.00%	12.90%	46.37%	39.27%	22.61%	0.28
0.90	6.66	2.52	77.07%	-10.00%	14.05%	49.90%	53.95%	23.12%	0.27
1.00	7.61	2.88	91.85%	0.00%	15.14%	53.21%	68.34%	23.50%	0.26

Panel B: Rates per annum									
β			γ	γ_K	γ_A	γ_q	$\bar{\gamma}$	γ_{Aq}	$\frac{\gamma_{Aq}}{\gamma_A + \gamma_q + \gamma_{Aq}}$
0.10			-3.88%	-7.39%	0.07%	0.30%	-4.95%	0.28%	0.43
0.20			-1.99%	-5.22%	0.14%	0.53%	-2.91%	0.42%	0.39
0.30			-0.92%	-3.93%	0.19%	0.70%	-1.72%	0.51%	0.36
0.33			-0.67%	-3.63%	0.21%	0.75%	-1.45%	0.53%	0.35
0.40			-0.17%	-3.01%	0.24%	0.85%	-0.89%	0.57%	0.34
0.50			0.41%	-2.28%	0.29%	0.98%	-0.24%	0.61%	0.32
0.60			0.88%	-1.69%	0.33%	1.09%	0.28%	0.64%	0.31
0.66			1.12%	-1.38%	0.35%	1.15%	0.56%	0.66%	0.30
0.70			1.27%	-1.18%	0.37%	1.19%	0.73%	0.66%	0.30
0.80			1.62%	-0.74%	0.41%	1.28%	1.11%	0.68%	0.29
0.90			1.92%	-0.35%	0.44%	1.36%	1.45%	0.70%	0.28
1.00			2.20%	0.00%	0.47%	1.43%	1.75%	0.71%	0.27

Figure 1
Entrepreneur's Decision on Project Outcomes

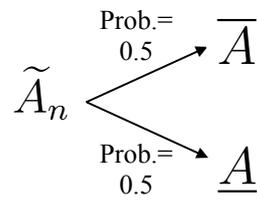


Figure 3
Analyst Coverage and R&D Expenditures

The figure shows the average log number of analyst (coverage) and log R&D expenditures (R&D) for each firm over the sample period. Average coverage and R&D are adjusted for size and time effects by extracting the residuals of a regression of each variable on log sales and year fixed effects. The residuals are then average by firm. The correlation between the adjusted variables is 0.51 (p-value<0.0001).

