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Firm R&D and financial analysis: How do they interact?[☆]

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ABSTRACT

This paper demonstrates, theoretically and empirically, that firms' research and development (R&D) efforts and investors' analyses of their prospects are mutually reinforcing. Entrepreneurs attempt more research when financiers are better informed about projects' profitability because they expect financiers to provide more funding to successful projects. Conversely, financiers collect more information about projects when entrepreneurs undertake more R&D because the opportunity cost of missing out on successful projects is then higher. Two natural experiments confirm that this interaction occurs and suggest that it contributes to about one third of the total effect of a policy designed to stimulate R&D. Overall, the analysis suggests that policies aimed at promoting R&D – such as research subsidies or tax breaks – have a multiplier effect owing to the induced improvement in capital efficiency. As a result, those policies can be rendered more effective by coupling them with other policies designed to increase capital efficiency. The feedback effect that we document also helps explaining why innovative ecosystems such as that in the Silicon Valley are challenging to set up.

1. Introduction

It is well known that technological innovation is a powerful engine of economic growth. It is also established that finance stimulates innovation (e.g., Levine, 1997, 2005; Levine and Zervos, 1998; Beck et al., 2000). However, it has been noted that there is a research and development (R&D) "funding gap" in the sense that there is underinvestment in R&D (e.g. Griliches, 1992; Hall, 1996; Hall and Lerner, 2010). Most research attributes this funding gap to informational frictions related to inadequate investor information about R&D payoffs and the riskiness and large size of R&D investments (e.g. Hall and Lerner, 2010; Jørring et al., 2022). While this is undeniably true, it is also possible that the information that investors have about R&D is not exogenously given but affected by investors' incentives to become informed, incentives that may themselves be influenced by the nature of the R&D project (e.g. Boot and Thakor, 1997). That is, the innovation-finance nexus is complex, with "feedback effects" from innovation to finance. Understanding the interplay between innovation and finance is essential not only to get to the sources of economic growth, but also to guide the design of economic policies. In particular, accounting for feedback effects can improve the effectiveness of policies aimed at promoting innovation and closing the funding gap, such as research subsidies or tax breaks. In many of these cases, it is also important to quantify direct and feedback effects. The research questions raised by these observations are: How is the firm's incentive to invest in R&D influenced by the information possessed by financial market investors, and conversely, how is investors' information affected by the firm's R&D? What are the magnitudes of these effects? This paper addresses these questions theoretically and empirically.

Conceptually, this interplay between firms' R&D efforts and investors' analyses of their prospects 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

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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 (we convey the intuition of our model with a simplified version that we present in Section 2 ; the full model and its extensions are presented in the Online Appendix).

The model highlights the ingredients needed to generate our effect and structures the empirical 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 a complementarity between capital and productivity. Expressing output as the product of a standard production function $Y = AK^{\alpha}$ 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).

We evaluate empirically the model's main predictions in a sample of publicly listed US firms that report non-zero R&D expenditures. 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, as well as potential omitted variable biases in each equation. 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 (see Section 3.2 and the references therein for evidence that analysts produce information that is important to corporate financing, in particular for R&D-intensive firms). To address the endogeneity of these relationships, we instrument each variable using shocks from two quasi-natural experiments: one that shifts firms' research effort plausibly without affecting learning other than through the research channel we investigate—the staggered implementation of R&D tax credits by US states between 1990 and 2006 (Wilson, 2009); and another that shifts learning by the financial sector plausibly without affecting firms' research other than through the learning channel we focus on—mergers between and closures of brokerage houses that resulted in the dismissal of analysts that is plausibly exogenous to firms' policies (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; Derrien and Kecskés, 2013). The estimations explicitly include controls for changes in corporate investments other than R&D, institutional ownership and asymmetric information to ensure that our evidence is not driven by alternative channels (e.g., a change in investments at large, in manager monitoring, or in asymmetric information).

The empirical evidence supports the notion that the interaction between learning and research truly occurs, and 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 37% of the size of that tax credit's total effect. A 10% increase in R&D expenditures triggered by an R&D tax credit has the effect of increasing coverage by 12%, which in turn is responsible for 3.7% (i.e., $12\% \times 0.31$) of the total 10% increase in R&D expenditures. Auxiliary predictions of the model in terms of the dispersion of new financing proceeds and risk taken by entrepreneurs are also supported empirically.

The analysis yields important insights on the effectiveness of policies aimed at promoting R&D (e.g., research subsidies or tax breaks). First, our analysis 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 two-thirds due to the credit's direct effect and about one third (37%) 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. More generally, the complementarity between innovating and learning also helps explain why governments have found it so challenging to set up an innovative ecosystem such as that in the Silicon Valley.

Related literature. Our study contributes to the literature on financing and innovation under imperfect information. In the theories of Bhattacharya and Chiesa (1995), de La Fuente and Marin (1996), Acemoglu and Zilibotti (1999), and Acemoglu et al. (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 et al. (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, as a natural consequence of the complementarity of capital and productivity in production. 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 breakthrough potential.

Empirical research to date has focused mainly on the beneficial effect of the financial sector on corporate innovation (for the effect of venture capital and private equity see Kortum and Lerner, 2000 and Lerner et al., 2011, for the effect of banks see Amore et al., 2013). Several studies (Chava et al., 2013; Hombert and Matray, 2017; Cornaggia et al., 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 firms studied (small vs. large, opaque vs. transparent, private vs. public).

Other scholars examine the specific role of financial analysts in innovative activity. Derrien and Kecskés (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. Our focus on innovative firms (for which innovation is most relevant to growth) sets our empirical work apart from both Derrien and Kecskés (2013) and He and Tian (2013). Indeed, as Clarke et al. (2015) show (and as we confirm in our setting ; see Online Appendix), high-quality innovators file fewer patents when they lose analysts – because they innovate less, as our model predicts – whereas their low-quality counterparts file more patents (as He and Tian, 2013 report)—presumably to signal to investors that they are innovative. Much less attention has been given to the reverse relationship: the effect of firms' innovation on financial sector activities.[1] Our paper is the first to describe, empirically, a two-way causal linkage between the financial sector and corporate innovation. We show that shocks to the financial sector affect firms' innovation and vice versa.

[1] For example, Barth et al. (2001) report a positive correlation (but no evidence of a causal link) between analyst coverage and firm R&D expenditures.

Our paper also contributes to the growing literature on the feedback from asset markets to real outcomes, through the information asset prices convey (see Bond et al., 2012 for a review of this literature). While, in our model, there is no explicit stock market, and no stock prices to learn from, the financier can be interpreted as an equityholder, and a feedback effect works through, what Bond et al. (2012) label, the "incentive channel". Specifically, the entrepreneur is incentivized to innovate, not by learning what the financier knows, but by the knowledge that the financier is well-informed. The link to the feedback literature is straightforward for our empirical analysis which focuses on publicly listed firms losing or gaining equity analysts. In contrast to our theoretical understanding of these phenomena which has improved rapidly, progress on the empirical front has been slower, hampered by identification issues. We offer a tight empirical setup in which the direct and feedback (i.e., indirect) effects are measured jointly on a single set of firms, through two distinct quasi-natural experiments. This setting allows us to not only establish the existence of a feedback channel influencing R&D activities (a type of investment central to economic growth), but also to assess its economic importance relative to the direct channel.

2. Hypotheses development

We develop the hypotheses that we will subsequently test. These hypotheses are derived from a general equilibrium model, presented in Online Appendix B, which describes the interaction between firms' research efforts and investors' information about them. We display here a simplified version of that model.

2.1. Setup

The simplified model features two periods and two agents. An entrepreneur ("she") can conceive a technology and a financier ("he") can fund it. Both are risk neutral and consume only in period 2.

A safe technology with constant returns to scale yields a certain return $\frac{\overline{A}}{2}$ in period 2 where $\overline{A}$ is a positive parameter. A risky technology can be created by the entrepreneur at a cost e_A (dubbed the "research effort"), who is then said to "innovate". Its output in period 2 is $Y \equiv \widetilde{A}K$ where K is the amount of capital invested in the technology in period 1, and $\widetilde{A}$ is its random productivity (which can be learned in period 1, as we shall describe). The technology succeeds (resp. fails) with a 0.5 probability, in which case, its productivity is $\widetilde{A} = \overline{A}$ (resp. zero), as Fig. 1a illustrates. We assume that the entrepreneur has no influence on the probability of success but we demonstrate in Online Appendix B.2 that the results of the model obtain for high-risk projects when the entrepreneur controls, not productivity, but rather the probability of success.

The entrepreneur raises the capital required to operate her technology from the financier. The financier is endowed with wealth w, which he invests either in the safe technology or in the risky technology (provided the entrepreneur innovated). At the time of investment, the financier can acquire, for a cost e_q (dubbed the "learning effort"), a signal that perfectly reveals whether the technology is successful. This notation is motivated by the full model in which q represents the precision of the financier's signal, chosen from a continuum that nests a perfect signal and no signal. Unlike research, learning does not affect technological productivity; instead, it enables a more efficient matching of capital to technologies.

Effort levels in both research and learning are assumed contractible. Accordingly, the objective of the entrepreneur and the financier is to maximize the ex ante total surplus (the first-best), defined as the expected output minus the research and learning efforts, e_A and e_q. This assumption of contractible efforts implies that multiple equilibria do not arise. Moreover, there are no information asymmetries in the model: at the time they choose their efforts, the entrepreneur and the financier are equally ignorant about whether the risky technology will be successful. The model is agnostic about how the surplus is shared between the entrepreneur and the financier, but the model's implications do not depend on the sharing rule.

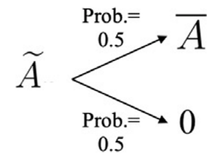

Fig. 1a. Entrepreneur's choice of project payoffs.

The timing is as follows. At the start of period 1, the entrepreneur and the financier determine cooperatively their research and learning efforts. Then the financier observes his signal (should he acquire one) and distributes his wealth across the safe and risky technologies (provided the entrepreneur innovated). In period 2, the risky technology's productivity is revealed, goods are produced, and agents consume their share of the profits.

2.2. Equilibrium characterization and properties

Let us consider in turn the different possible outcomes, as displayed in Fig. 1b. Suppose first that the entrepreneur innovates and the financier learns. The financier allocates all his wealth to the risky (resp. safe) technology if he discovers that the risky technology is a success (resp. failure). Hence, total surplus equals $w(\overline{A} - 1) - e_A - e_q$.

Suppose next that the entrepreneur does not innovate. Then the financier has no choice but to invest in the safe technology (yielding $w(\frac{\overline{A}}{2} - 1)$), in which case there is no point in learning. Conversely, suppose that the financier does not learn. Then the expected output from investing in the risky technology, $w(\frac{\overline{A}}{2} - 1)$, leads to a smaller surplus, net of the research effort, than does the safe technology; hence innovating is not optimal. Thus, if one agent does not exert effort, then the other does not either and the total surplus equals $w(\frac{\overline{A}}{2} - 1)$. To summarize, either both agents exert effort (the entrepreneur innovates and the financier learns), yielding a surplus of $w(\overline{A} - 1) - e_A - e_q$, or none does, in which case the surplus equals $w(\frac{\overline{A}}{2} - 1)$. The former case is optimal if and only if $w\frac{\overline{A}}{2} > e_A + e_q$, that is, if capital allocated (w) or productivity ($\overline{A}$) are large relative to the research and learning costs. The equilibrium is characterized by our first proposition, as follows.

Proposition 1. *If $w\frac{\overline{A}}{2} > e_A + e_q$, then the entrepreneur innovates and the financier learns. The financier allocates all his wealth to the risky (resp. safe) technology if he learns that the risky technology is a success (resp. failure). Total surplus equals $w(\overline{A} - 1) - e_A - e_q$. If instead $w\frac{\overline{A}}{2} < e_A + e_q$, then the entrepreneur does not innovate and the financier does not learn. The financier allocates all his wealth to the safe technology. Total surplus equals $w(\frac{\overline{A}}{2} - 1)$.*

The next proposition states the key insight of the model regarding how learning and research interact in equilibrium.

Proposition 2. *Learning and research are strategic complements: either both the entrepreneur and the financier exert effort (resp., innovate and learn), or neither does.*

The value of innovating is larger if the financier learns (compare the bottom row across Columns 1 and 2 in Fig. 1b). Intuitively, research is stimulated when the financier is better informed, because then the entrepreneur knows that her technology will be well funded should it succeed. Likewise, the value of learning is larger if the entrepreneur innovates (compare the last column across Rows 1 and 2). Indeed, the return differential between a successful and failed risky technology

	Surplus:	1 Financier learns	2 Financier doesn't learn	3 Value of learning (=Column 1 - Column 2)
1	Entrepreneur innovates	$w(\bar{A}-1)-e_A-e_q$	$w(\bar{A}/2-1)-e_A$	$w\bar{A}/2-e_q$
2	Entrepreneur doesn't innovate	$w(\bar{A}/2-1)-e_q$	$w(\bar{A}/2-1)$	$-e_q$
3	Value of research (=Row 1 - Row 2)	$w\bar{A}/2-e_A$	$-e_A$	$w\bar{A}/2$

Fig. 1b. Surplus as a function of the agent's actions.

creates an opportunity cost to mis-investing which encourages the financier to learn.

Combining both legs implies that knowledge about technologies and technological knowledge are mutually reinforcing. The bottom right cell of Fig. 1b encapsulates this complementary: it shows a positive effect (equal to $w\frac{\bar{A}}{2}$) of learning (resp., innovating) on the value of innovating (resp., learning). The positive feedback effect between research and learning follows from the complementarity of productivity and capital in production. Writing $Y = \widetilde{A}K$, the return on the financier's capital K increases with productivity $\widetilde{A}$, (because the larger is this term, the more productive is every unit of capital). Similarly, the reward for innovating increases with K because then the invention is applied on a larger scale. Thus the complementarity between $\widetilde{A}$ and K leads to the complementarity between learning and research. To see this in our simplified model, suppose that we make multiple i.i.d. draws of the economy. Expected output ($E[\widetilde{A}K]$) can be broken down into the contributions of expected productivity ($E[\widetilde{A}] = \frac{\bar{A}}{2}$), of capital ($E[K] = w$), and of the quality of the match between technologies and capital, i.e., the extent to which the risky technology is funded when, and only when, it is successful, as captured by $cov(\widetilde{A};K)$: $E[\widetilde{A}K] = E[\widetilde{A}]E[K] + cov(\widetilde{A};K)$. If the financier learns, then $cov(\widetilde{A};K) = \frac{\bar{A}w}{2}$ and $E[\widetilde{A}K] = \frac{1}{2}(w\bar{A}) + \frac{1}{2}(\frac{w\bar{A}}{2}) = \frac{3}{4}w\bar{A}$; otherwise, $cov(\widetilde{A};K) = 0$ and $E[\widetilde{A}K] = \frac{1}{2}w\bar{A}$.

We emphasize that, since learning and research affect each other in our model, both make direct and indirect contributions to output. This means that capturing the total effect of learning requires that one accounts also for its positive influence on entrepreneurs' incentive to innovate. Likewise, the full benefit of research consists of its direct effect plus its indirect positive effect on financier' incentive to learn. 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.

The following proposition characterizes the distribution of capital across projects.

Proposition 3. *Suppose that we make multiple i.i.d. draws of the productivity of the risky technology. Capital tracks productivity more closely and is more unequally distributed across draws when the financier learns than when he does not.*

Specifically, the correlation between capital and productivity is perfect (resp., zero) when the financier learns (resp., does not learn). Moreover when he does learn, a technology deemed a success (resp., failure) receives more (resp., less) capital than does the safe technology, leading to a distribution of capital that is more dispersed across technologies (specifically, across draws of the risky technologies as well as between the risky and safe technologies).

The full model in Online Appendix B.1 extends the results of Propositions 2 and 3 to a more general setting with the following features: (i) the model is cast in general equilibrium; (ii) the safe and risky technologies are endogenized with the entrepreneur selecting the payoffs of the risky technology; (iii) the financier chooses any precision for his signal; (iv) the technologies display constant or decreasing returns to scale; (v) there is a large number of risky technologies in which the financier invests. That model has three key parameters: the share of capital in total income, and the two cost elasticities, namely, the elasticity of the cost of a developing a technology with respect to its payoffs and the elasticity of the cost of acquiring a signal with respect to its precision. Importantly, the full model demonstrates that Propositions 1–3 apply not only at the extensive margin but also at the intensive margin. In that model indeed, agents choose their efforts from a continuum (which nests the cases analyzed in the simplified model). It predicts that the research effort is increasing in the learning effort and vice versa (see Proposition 5 in Online Appendix B.1 which generalizes Proposition 2). The model also yields additional insights regarding the dispersion of returns; specifically, that their distribution is more dispersed across technologies when either the learning or research efforts are higher (Proposition 7 in Online Appendix B.1).

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 hypotheses that follow from Propositions 2 and 3 of the simplified model (and their counterparts in the full model in Online Appendix B.1, namely Propositions 5 and 6). 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.

Proposition 3 allows us to formulate an auxiliary test of the model, as stated in the next hypothesis.

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.

The full model in Online Appendix B.1 yields an additional prediction, namely that returns are more dispersed when the learning effort is larger. 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 that model predicts.

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

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. To see why, let us appeal to a stylized version of the equilibrium conditions of the full model in Online Appendix B.1 (Eqs. (5) and (6)):

$$\ln(\overline{A}) = c_1[\ln(q) + \ln(w)] + c_2,$$
$$\ln(q) = c_1'[\ln(\overline{A}) + \ln(w)] + c_2',$$

where q denotes the precision of the financier's signal (the learning effort) and c_1, c_2, c_1', and c_2' represent constant terms.

The first bias is an omitted variable one. Indeed, any shock to capital (w in the model) will stimulate learning and research independently, thereby generating a spurious correlation between them. The second is an endogeneity bias generated by that two-way relationship. For example, a least-squares regression of learning on research (bottom equation) yields inconsistent estimates because the regression's residual is correlated with the regressor (i.e., research) through the top equation. Similarly, in the top equation, we see that the regressor (i.e., learning) is correlated with the residual through the bottom equation. 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 test our predictions on a sample of publicly-listed firms for which we have detailed data on firms' innovation efforts and on the information produced by financial market participants. We point out that, while our model features new firms raising financing for the first time, its logic and predictions also apply to existing firms issuing fresh capital (e.g., seasoned equity offerings) to fund new projects. 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, that their reports influence stock prices and firms' financing, and that this influence increases in the number of analysts following a firm.[2] That information is highly valuable for R&D-intensive firms given the complexity and uncertainty associated with innovations. As a matter of fact, analysts' recommendations are more profitable (in that they lead to higher abnormal trading profits) for these firms (Palmon and Yezegel, 2012).

While the evidence supports our theory, we see two caveats to using our estimates for quantifying the mechanisms at work and calibrating our model. First, research is carried out not only by public firms but also by private firms, and these firms are followed by other information producers, such as venture capitalists, corporate incubators, wealthy individual investors, and government agencies. Second, equity analysts aside, information about public firms is also produced by bankers, bondholders, rating agencies, large shareholders and other stakeholders. Thus, 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 between public and private firms, and across information producers.

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.[3] These policy changes provide a source of variation in firms' research activities—a source that is plausibly exogenous to firms' analyst coverage.

Table 1
R&D tax credits rate changes implemented by US states between 1990 and 2006.

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

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, not the actual level.

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.[4]

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, and controlling for economic conditions in the state in which the firm is located, 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. 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 et al., 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 introduced, the size of the credits, and subsequent changes.

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

[2] Many studies document that the larger the number of analysts covering a firm, the better its information environment (e.g., Brennan et al., 1993; Hong et al., 2000; Hou and Moskowitz, 2005; Badrinath et al., 2015).

[3] We 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).

[4] See 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.

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, conditional on control variables, the 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, our difference-in-differences procedure provides an estimate of the causal effect of firms' research effort on such coverage. In Section 5.3, we then perform the instrumental variable estimation – where we use the passage of state R&D tax credits as an instrument for firms' R&D expenditures – to quantify the sensitivity of analyst coverage to R&D expenditures in a single step.

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.[5] 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). We 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). Like Heider and Ljungqvist (2015) and Mukherjee et al. (2017), we estimate our main regression in first differences to control for firm time-invariant characteristics. All regressions include year dummies, and standard errors are clustered at the 3-digit industry level. The main specifications also feature contemporaneous and lagged time-varying controls, which include return on assets, the logarithm of total assets, capital expenditures over assets, acquisition expenditures over assets, fraction of institutional ownership, the probability of informed trading (PIN), the logarithm of lagged sales, a dummy variable indicating whether the firm reported an accounting loss the year before a shock (which affects the firm's tax liability and hence possibly the benefit of a tax credit), as well as state gross domestic product and state unemployment rate. These variables control, respectively, for possible changes in non-R&D investment, manager monitoring, asymmetric information, or state economic conditions that may be correlated with changes in coverage or R&D following the shocks. The baseline regression takes the following form:

$$\Delta \ln(Coverage_{i,s,t}) = \beta \mathrm{TC}^{+}_{s,t} + \eta_t + \sum_j \gamma_j \Delta X^j_{i,t} + \varepsilon_{it};$$

here $\mathrm{TC}^{+}_{s,t}$ 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 $X^j_{i,t}$ 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. As noted above, we also control for time-varying changes in firm characteristics by including these 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 (2013) 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 due to such events is largely exogenous to any policies implemented by the covered firms. Many closures and mergers of brokerage houses, indeed, are driven by changes in regulation or threats to the profitability of brokers' equity businesses (reduction in trading commissions and in income from market-making activities), so that coverage terminations are unlikely to be related to firms' future prospects or innovation policy. Further, in line with Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013), we do not find that firms losing analysts due to broker events have more pessimistic prospects (as measured by the median earnings forecast before or at the time of the event, over various horizons) than other firms.[6]

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. Merkley et al. (2017) extend those findings to industries.

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 stock returns that lead those of few-analyst firms (Brennan et al., 1993), and

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

[6] Kelly and Ljungqvist (2012) find that coverage terminations due to broker events are not associated with subsequent earnings surprises—in contrast to "endogenous terminations" whereby an analyst chooses to stop following a stock. Likewise, Derrien and Kecskés (2013) conclude that earnings estimates and investment recommendations are not more pessimistic for affected firms compared to other firms. See Table A1 in the Online Appendix for our analysis of earnings forecasts of affected firms.

exhibit less price momentum, indicating that stock prices of firms covered by more analysts adjust to public information faster (Hong et al., 2000; see also Brennan and Subrahmanyam, 1995, Hou, 2007, Menzly and Ozbas, 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. Two aspects of exploiting broker events to test our theory are noteworthy. First, the theory makes no distinction between public and private information. So the outcome of the test does not depend on whether one interprets analyst information as private (i.e., shared with a select group of clients) or public (i.e., communicated to the public at large). Second, it is possible that other types of information substitute for the lost analyst information. For instance, money managers might hire buy-side analysts. However, the substitution is unlikely to be perfect, which is what matters to the experiment.[7]

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. For 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 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". Unlike 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:

$$\Delta \ln(R\&D_{i,t}) = \beta \mathrm{AN}^{-}_{i,t} + \eta_t + \sum_j \gamma_j \Delta X^j_{i,t} + \varepsilon_{it};$$

here $\mathrm{AN}^{-}_{i,t}$ is a dummy variable that takes the value 1 only if a firm i is subject to a broker event in year $t-1$ (specifically, in the first full fiscal year following the shock), the η_t are year dummies, and $X^j_{i,t}$ are the firm controls described previously. 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. In addition, in Section 5.3, we perform the instrumental variable estimation – where we use the brokerage events as an instrument for firms' analyst coverage – to estimate the sensitivity of R&D expenditures to analyst coverage in one step.

A potential concern with our setting 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. Therefore, in our main regressions we isolate the direct effect of analyst coverage on R&D expenditures by controlling for possible changes in investment (assets, capital expenditures, acquisition expenditures) after broker events. We also ensure that our results are not driven by changes in firm monitoring or in asymmetric information by explicitly controlling for the change in institutional ownership and the probability of informed trading (PIN) around the shock.[8] The magnitude and statistical significance of the coefficient estimate remain unchanged.

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 firm in Compustat. When covariates (such as size) do not exhibit sufficient overlap between treatment and control groups, the result can be imprecise estimates (Crump et al., 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, by way of logit regression, 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. 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.

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 et al., 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.[9]

[7] Indeed, Merkley et al. (2017) document that the stock price reaction to earnings announcements (measured as the absolute cumulative abnormal returns within a three-day window around the earnings announcement) is higher in an industry that loses analysts following broker closures and mergers, indicating that these disclosures are more informative now that less of their information is pre-empted by analysts. This finding suggests that, on net, information decreases. We confirm this interpretation in our own sample of events and stocks. In Online Appendix Table A2, we find that analyst forecast errors increase following broker events. The coefficients imply that the loss of an analyst increase the average forecast error by about 10% of a standard deviation. Finally, the fact that we find a significant effect of analyst losses on R&D activities despite the possibility of substitution implies that it is not perfect.

[8] Institutional ownership can affect firms' innovation through various governance channels, such as more intense monitoring and a larger tolerance for failure (Aghion et al., 2013). PIN measures the likelihood that trades are initiated by informed traders (e.g., firm managers) (e.g., Easley et al., 2002); in other words, it reflects the severity of adverse selection. While informed traders include traders other than managers, Bharath et al. (2008), in their analysis of the determinant of firms' capital structure choices, report that PIN is correlated with managers' information advantage vis-a-vis the market.

[9] Howells (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 et al. (2014).

Table 2
Summary statistics.

	Mean	S.D.	25th	50th	75th	N
Coverage	11.06	9.05	4.36	8.33	14.92	851
R&D ($m)	81.51	290.46	6.54	15.01	37.63	851
R&D/assets (%)	6.95	7.34	1.81	4.40	10.35	851
Sales ($m)	3384.05	12021.69	195.31	577.61	1960.07	851
RoA (%)	8.62	11.02	5.36	9.58	13.79	851
Loss	0.16	0.26	0.00	0.00	0.24	851
Assets ($m)	4096.71	20458.16	205.83	597.67	1975.55	851
Capital expenditures/assets	0.06	0.03	0.03	0.05	0.07	851
Acquisition exp./assets	0.03	0.04	0.00	0.02	0.04	851
Institution ownership	0.55	0.21	0.41	0.58	0.70	851
PIN	1.20	0.48	0.88	1.12	1.43	851
Q	2.38	1.71	1.42	1.87	2.67	851
State GDP ($th)	45.03	7.89	39.95	44.23	49.61	851
State unemployment rate	5.59	1.03	4.86	5.51	6.14	851
TC+	0.07	0.10	0.00	0.00	0.12	851
AN−	0.03	0.05	0.00	0.00	0.00	851
New financing proceeds (%)	5.26	12.09	0.70	2.73	6.52	851
Patent values ($m)	759.66	3149.48	4.32	20.76	152.99	766
Patent forward citations	494.58	2068.61	22.09	62.74	223.1	766

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). Coverage measures the number of analysts following a firm as reported in I/B/E/S. Accounting variables are from Compustat. RoA denotes the return on assets and is defined as the ratio of EBIT to total assets. Loss is a dummy that equals one if the firm reports negative earnings before interests and taxes. 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. Institutional ownership is the fraction of common shares outstanding held by institutional investors and comes from Thomson Reuters. PIN is the probability of informed trading (obtained from Brown and Hillegeist, 2007 and available from 1993 onwards). State GDP is the firm's headquarter state real gross domestic product per capita from the Bureau of Economic Analysis. State unemployment rate is from the Bureau of Labor Statistics. TC+ is a dummy variable that takes the value 1 if the firm's headquarter state implemented or increased an R&D tax credit in the previous year. AN− is a dummy variable that takes the value of 1 if a firm is subject to a broker event in the previous year. Patent values are a function of the firm's share price reaction upon patent acceptance (collected from Kogan et al., 2017, available at https://iu.app.box.com/v/patents). Forward citations measure the number of citations received from the date a patent was accepted until 2011.

We use (the logarithm of) R&D expenditures to measure firms' research effort. As the input into the innovation process, this variable is a good proxy for the model's research effort A. 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). All firms in our sample are followed by at least one analyst in all years and we require firms to have at least four consecutive observations of analyst coverage and R&D expenditures. We deflate all accounting variables, which are taken from Compustat, using the Consumer Price Index. Data on analysts, institutional ownership and probability of informed trading (PIN) come from I/B/E/S, Thomson Reuters and Brown and Hillegeist (2007), respectively.

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.

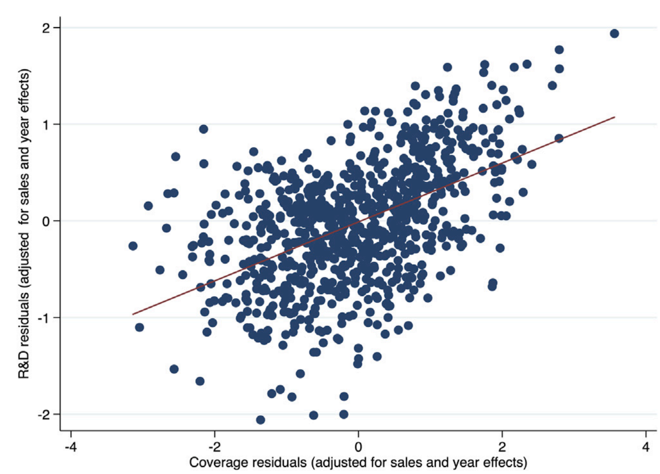

Fig. 2. Analyst coverage and R&D expenditures.
The figure shows the average log number of analyst (coverage) and log R&D expenditures (R&D) for each firm over the sample period. Average coverage and R&D are adjusted for size and time effects by extracting the residuals of a regression of each variable on log sales and year fixed effects. The residuals are then averaged by firm. Therefore, each dot represents a firm. The correlation between the adjusted variables is 0.51 (p-value<0.0001).

5. Empirical results

Fig. 2 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. 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 two-way causal relationship.

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 Columns (1) to (3) of 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

Table 3
State R&D tax credits: Effect on firm R&D expenditures and analyst coverage.

	Δln(R&D)$_t$			Δln(Coverage)$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
TC+$_{t+1}$			−0.015			−0.016
			(0.016)			(0.019)
TC+$_t$	0.039**	0.034**	0.033**	0.043**	0.041**	0.046***
	(0.016)	(0.016)	(0.015)	(0.019)	(0.017)	(0.016)
TC+$_{t-1}$			−0.003			−0.007
			(0.011)			(0.017)
Δln(Sales)$_{t-2}$		0.063***	0.073***		0.033*	0.028
		(0.018)	(0.020)		(0.018)	(0.023)
ΔLoss$_{t-2}$		−0.030***	−0.034***		−0.030**	−0.046***
		(0.010)	(0.010)		(0.014)	(0.016)
ΔRoA$_t$		−0.250***	−0.224***		−0.100	−0.167**
		(0.035)	(0.031)		(0.072)	(0.080)
Δln(Assets)$_t$		0.396***	0.405***		0.278***	0.278***
		(0.034)	(0.038)		(0.021)	(0.023)
ΔCapx$_t$		0.265***	0.239***		0.367**	0.372**
		(0.086)	(0.076)		(0.166)	(0.176)
ΔAcquisition$_t$		0.027	−0.003		−0.082**	−0.065
		(0.049)	(0.057)		(0.033)	(0.040)
ΔInstit. ownership$_t$		−0.145**	−0.176***		0.234***	0.185**
		(0.057)	(0.050)		(0.077)	(0.085)
ΔPIN$_t$		−0.015*	−0.012		−0.102***	−0.081***
		(0.009)	(0.010)		(0.028)	(0.029)
ΔQ$_t$		−0.007***	−0.009***		−0.009***	−0.007*
		(0.002)	(0.002)		(0.003)	(0.004)
Δln(State GDP)$_{t-1}$		0.047	0.035		0.473**	0.563***
		(0.073)	(0.076)		(0.195)	(0.197)
ΔState unempl. rate$_{t-1}$		−0.007	−0.009		0.015*	0.006
		(0.005)	(0.006)		(0.009)	(0.009)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff	Diff	Diff	Diff
N	8593	6047	5140	8593	6047	5140
R2	0.021	0.190	0.208	0.012	0.067	0.060

The table presents the results of the difference-in-differences estimation for the effect of R&D tax credit on firms' R&D expenditures (in Columns (1) to (3)) and analyst coverage (in Columns (4) to (6)). TC+$_t$ 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. Capx and Acquisition represent, respectively, the firm's capital and acquisition expenditures, scaled by total assets. Instit. ownership measures the fraction of the firm's common shares that are held by institutional investors. PIN is the probability of informed trading as calculated by Brown and Hillegeist (2007). These PIN data are available at http://scholar.rhsmith.umd.edu/sbrown/pin-data from 1993 onwards. Thus, the regressions that control for PIN exclude years 1990 to 1992. Q is the ratio of the market value of assets to the book value of assets. State GDP and state unemployment rate are the firm's headquarter state real gross domestic product per capita and unemployment rate, respectively. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firm 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.

***Significance at 1%.

**Significance at 5%.

*Significance at 10%.

expenditures by 3.4% relative to control firms (p-value = 0.034).[10] The change takes 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.

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 Columns (4) to (6) of Table 3 are consistent with this hypothesis because they show that, after passage of state R&D tax credits, firms in treated states are covered by 4.1% more analysts than are firms located in other states (p-value = 0.015). Column (6) confirms that this increase in analyst coverage is concentrated in the year following passage of the tax credit. Panel A of Fig. 3 depicts the dynamics for the growth in analyst coverage around R&D tax credits shocks and confirms the absence of pretrends.

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. Columns (1) to (3) of Table 4 confirm 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), which represents the loss of about 1 analyst for the average firm. This is the magnitude we would expect given the construction of the broker experiment.

Columns (4) to (6) of Table 4 present the main results regarding firms' research effort. We find that the R&D expenditures of treated

[10] The effect ranges from 3.3% to 3.9%. To facilitate comparison with the two-stage least-squares instrumental variables estimation of Section 5.3, 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.

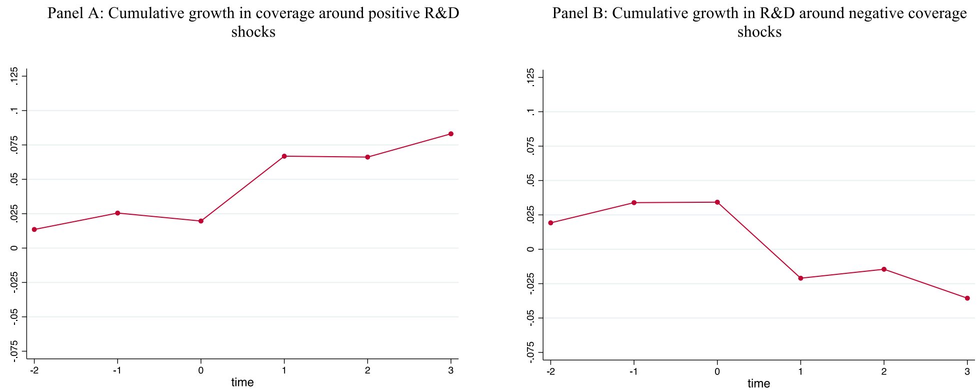

Fig. 3. Analyst Coverage and R&D expenditures around R&D and coverage shocks.
The figure displays the cumulative coefficients of the difference-in-differences regressions in first-differences assessing the differential effect of a shock on treated and control firms in the 6 years around the shock. Panel A shows the dynamic effects of R&D tax credit shocks on analyst coverage for the regression in Column 4 of Table 3. Panel B shows the dynamic effects of analyst coverage shocks on R&D for the regression in Column 4 of Table 4.

Table 4
Brokerage events: Effect on analyst coverage and R&D expenditures.

	Δln(Coverage)$_t$			Δln(R&D)$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
AN−$_{t+1}$			0.023			−0.012
			(0.019)			(0.017)
AN−$_t$	−0.113***	−0.101***	−0.079***	−0.042***	−0.031***	−0.039***
	(0.024)	(0.024)	(0.020)	(0.016)	(0.010)	(0.011)
AN−$_{t-1}$			−0.017			−0.004
			(0.017)			(0.016)
Δln(Sales)$_{t-2}$		0.032*	0.025		0.062***	0.072***
		(0.018)	(0.023)		(0.018)	(0.020)
ΔLoss$_{t-2}$		−0.028**	−0.044***		−0.029***	−0.033***
		(0.014)	(0.016)		(0.010)	(0.010)
ΔRoA$_t$		−0.105	−0.171**		−0.254***	−0.229***
		(0.071)	(0.079)		(0.034)	(0.030)
Δln(Assets)$_t$		0.279***	0.279***		0.397***	0.404***
		(0.021)	(0.023)		(0.033)	(0.037)
ΔCapx$_t$		0.370**	0.377**		0.266***	0.243***
		(0.165)	(0.177)		(0.087)	(0.077)
ΔAcquisition$_t$		−0.083**	−0.066*		0.028	−0.002
		(0.033)	(0.039)		(0.049)	(0.056)
ΔInstit. ownership$_t$		0.232***	0.183**		−0.145**	−0.178***
		(0.077)	(0.086)		(0.057)	(0.050)
ΔPIN$_t$		−0.103***	−0.083***		−0.016*	−0.013
		(0.028)	(0.030)		(0.009)	(0.010)
ΔQ$_t$		−0.010***	−0.008**		−0.008***	−0.009***
		(0.003)	(0.004)		(0.002)	(0.002)
Δln(State GDP)$_{t-1}$		0.518**	0.605***		0.078	0.062
		(0.199)	(0.203)		(0.074)	(0.075)
ΔState unempl. rate$_{t-1}$		0.013	0.006		−0.008	−0.009
		(0.009)	(0.010)		(0.005)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff	Diff	Diff	Diff
N	8593	6047	5140	8593	6047	5140
R2	0.014	0.069	0.061	0.021	0.189	0.208

The table presents the results of the difference-in-differences estimation for the effect of brokerage houses closures and mergers on firms' analyst coverage (in Columns (1) to (3)) and R&D expenditures (in Columns (4) to (6)). AN−$_t$ is a dummy variable that equals one in the year following the loss an analyst due to a brokerage house merger or closure. Loss is a dummy that equals one if the firm reports negative earnings before interests and taxes. Capx and Acquisition represent, respectively, the firm's capital and acquisition expenditures, scaled by total assets. Instit. ownership measures the fraction of the firm's common shares that are held by institutional investors. PIN is the probability of informed trading as calculated by Brown and Hillegeist (2007). These PIN data are available at http://scholar.rhsmith.umd.edu/sbrown/pin-data from 1993 onwards. Thus, the regressions that control for PIN exclude years 1990 to 1992. Q is the ratio of the market value of assets to the book value of assets. State GDP and state unemployment rate are the firm's headquarter state real gross domestic product per capita and unemployment rate, respectively. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firm 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.

***Significance at 1%.

**Significance at 5%.

*Significance at 10%.

Table 5
Instrumental variable estimation.

	2SLS				3SLS	
	Δln(Coverage)$_t$		Δln(R&D)$_t$		Δln(Cov.)$_t$	Δln(R&D)$_t$
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(R&D)$_t$	1.100***	1.208**			1.162*	
	(0.290)	(0.525)			(0.616)	
Δln(Coverage)$_t$			0.374***	0.306***		0.297**
			(0.117)	(0.096)		(0.151)
Δln(Sales)$_{t-2}$		−0.042		0.052***	−0.040	0.053***
		(0.040)		(0.017)	(0.045)	(0.014)
ΔLoss$_{t-2}$		0.007		−0.020*	0.006	−0.021*
		(0.018)		(0.012)	(0.026)	(0.012)
ΔRoA$_t$		0.202		−0.222***	0.191	−0.220***
		(0.184)		(0.037)	(0.168)	(0.037)
Δln(Assets)$_t$		−0.201		0.312***	−0.182	0.314***
		(0.218)		(0.040)	(0.246)	(0.044)
ΔCapx$_t$		0.047		0.153	0.062	0.156
		(0.158)		(0.103)	(0.215)	(0.096)
ΔAcquisition$_t$		−0.115		0.053	−0.115***	0.052**
		(0.073)		(0.052)	(0.042)	(0.025)
ΔInstit. ownership$_t$		0.409***		−0.216***	0.401***	−0.214***
		(0.120)		(0.055)	(0.105)	(0.047)
ΔPIN$_t$		−0.083***		0.015	−0.084***	0.015
		(0.026)		(0.016)	(0.019)	(0.018)
ΔQ$_t$		−0.001		−0.005***	−0.001	−0.005**
		(0.004)		(0.001)	(0.005)	(0.002)
Δln(State GDP)$_{t-1}$		0.417*		−0.080	0.427**	−0.093
		(0.241)		(0.119)	(0.206)	(0.133)
ΔState unempl. rate$_{t-1}$		0.023**		−0.012**	0.022	−0.011
		(0.011)		(0.006)	(0.013)	(0.007)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Diff	Diff	Diff	Diff	Diff	Diff
N	8593	6047	8593	6047	6047	6047

The table presents the results of the instrumental variable estimation 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+$_t$) and analyst coverage with the brokerage house events (AN−$_t$). TC+$_t$ 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. AN−$_t$ is a dummy variable that equals one in the year following the loss an analyst due to a brokerage house merger or closure. Loss is a dummy that equals one if the firm reports negative earnings before interests and taxes. Capx and Acquisition represent, respectively, the firm's capital and acquisition expenditures, scaled by total assets. Instit. ownership measures the fraction of the firm's common shares that are held by institutional investors. PIN is the probability of informed trading as calculated by Brown and Hillegeist (2007). These PIN data are available at http://scholar.rhsmith.umd.edu/sbrown/pin-data from 1993 onwards. Thus, the regressions that control for PIN exclude years 1990 to 1992. Q is the ratio of the market value of assets to the book value of assets. State GDP and state unemployment rate are the firm's headquarter state real gross domestic product per capita and unemployment rate, respectively. The regressions are estimated in first differences, which control for firms' time invariant characteristics (firm fixed effects). Columns (1) to (4) are estimated by two-stage least squares. Columns (5) and (6) estimate the joint system of equations by three-stage least squares. Column (5) also directly includes the AN− variable and Column (6) the TC+ variable. All regressions include year dummies to control for aggregate shocks in each year. Standard errors (displayed in brackets) are clustered at the industry level.

***Significance at 1%.

**Significance at 5%.

*Significance at 10%.

firms fall by 3.1%, relative to control firms, after losing an analyst (p-value = 0.003). 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. Column (3) confirms that this decline in R&D expenditures is concentrated in the year following passage of the tax credit. Panel B of Fig. 3 presents the evolution of the growth in R&D expenditures around broker shocks and confirms the absence of pretrends.

In Online Appendix Table A4, we assess the outcome of our experiments on other types of investments (capital expenditures and M&A incidence) and find statistically insignificant coefficients that are smaller than the ones we estimate for R&D expenditures. These additional results further support the notion that, in line with our theory, our results are specific R&D expenditures, a particularly risky type of investment for innovative firms.[11]

In summary, our results provide support for our second hypothesis—namely, that a higher learning effort by the financial sector encourages innovative firms to innovate. Collectively, 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.

[11] In the case of the analyst experiment, the differences in our results for capital and acquisition expenditures relative to Derrien and Kecskés (2013)'s can be attributed to differences in the sample of firms (we exclusively focus on innovative firms).

5.3. 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 and three-stage least squares:

$$\Delta \ln(Coverage_{i,t}) = \beta_1 \Delta \ln(\mathrm{RD}_{i,t}) + \eta_{1,t} + \sum_j \gamma_{1,j} \Delta X^j_{i,t} + \varepsilon_{1,it}, \tag{1}$$

$$\Delta \ln(\mathrm{RD}_{i,t}) = \beta_2 \Delta \ln(Coverage_{i,t}) + \eta_{2,t} + \sum_j \gamma_{2,j} \Delta X^j_{i,t} + \varepsilon_{2,it}. \tag{2}$$

In (1), we instrument R&D expenditures with the tax credit shocks, and in (2), we instrument analyst coverage with the broker events.

Table 5 displays the results of these two-stage and three-stage regressions (Columns (1) to (3) of Tables 3 and 4 presented the first stages). The instrumental variables procedure yields an estimate of the sensitivity of analyst coverage to R&D expenditures of between 1.10 and 1.21; that is, a 10% increase in R&D expenditures induces an 11.0% to 12.1% increase in analyst coverage (a gain of about one new analyst). In Columns (3) and (4) of Table 5 we see that the sensitivity of R&D expenditures to analyst coverage is between 0.31 and 0.37; in other words, a 10% increase in analyst coverage (a gain of about one analyst) induces a 3.1% to 3.7% increase in R&D expenditures.[12] In Columns (5) and (6) we estimate the join system of equations by three-stage least square to take account of the possible correlation of residuals across equations (i.e., a combination of seemingly unrelated regressions and two-stage least squares), and we find similar results.

The values reported in Table 3 (Column (5)) show that the passage of a tax credit increases analyst coverage by 4.1% on average. Hence the indirect effect of the tax credit – operating through analysts' response and denoted $\Delta \ln(\mathrm{RD})^*$ – equals approximately $0.31 \times 4.1\% = 1.27\%$. To put this number in perspective, we compare it to the total effect of the tax credit on $\Delta \ln(\mathrm{RD})$, which equals 3.4% according to Table 3 (Column (2)). Thus the indirect effect of the tax credit, through the response of analysts, is slightly more than a third ($37\% = 1.27\%/3.4\%$) 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 3.7% 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.

Online Appendix C features a dynamic extension of the model which is calibrated to evaluate the importance – to long-term growth – of the interplay between financial analysis and firms' research effort. It indicates that the interplay's contribution to income growth represents about a third of the total contributions of information collection and R&D.

5.4. Additional tests

Here, we report the results of auxiliary empirical investigations on the specific mechanism outlined in our theory. For that purpose, we evaluate Hypotheses 3 and 4.

[12] Recent papers (e.g., Almeida et al., 2012; Cingano et al., 2016; Degryse et al., 2019) document that firms cut investments in crisis periods. We confirm this finding for R&D in our sample and show further that this effect is unrelated to the one we study, namely the influence of learning on R&D. Indeed, Table A5 in the Online Appendix shows that the sensitivity of R&D to analyst shocks is no different in crisis periods compared to non-crisis.

5.4.1. 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 around the passage of R&D tax credits the dispersion of firms' capital proceeds using data on firms long-term financing. The result (presented along methodological details of the test) in Row (i) of Table A6 of the Online Appendix shows that the F-test for the equality of variances of firm's proceeds 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.

We then assess whether financing proceeds also track firm quality (proxied as a firm's value purged from any effect of firm size) more closely following the R&D shock, as predicted by Hypothesis 3. We find that not only better firms attract more capital (as one would expect), but also that the association between capital raising and firm quality is larger after the passage of R&D tax credits compared to before (see Row (ii) of Table A6).

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.

5.4.2. 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. 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). As predicted by the model, the results reported in Row (iii) of Table A6 indicate that the standard deviation of RoA significantly decreases following the shock.

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 (as inferred from the stock market by Kogan et al., 2017) and of its patent forward citations. 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 thus assess how the standard deviations of patent values and citation numbers change around the broker events. We find, in Row (iv) of Table A6, that both standard deviations significantly decrease after the loss of analysts. 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.

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.

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 third 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 1.2%, 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 model and 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.

CRediT authorship contribution statement

Jim Goldman: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Joel Peress:** Conceptualization, Methodology, Formal Analysis, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2022.101002.

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