

KNOWLEDGE SPILLOVERS, INNOVATION AND GROWTH*

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Cohen and Levinthal (1989) introduced the notion of absorptive capacity and demonstrated that knowledge spillovers can induce complementarities in R&D efforts. We show that this idea has rich implications when analysing important aspects of the growth process such as cross-country convergence and divergence, the international co-ordination of climate change policies, and the role of openness in the production of ideas. We also show that the notion of absorptive capacity sets an agenda for new empirical and theoretical analyses of the role of R&D spillovers in innovation and growth.

In the 99th issue of this JOURNAL, Cohen and Levinthal (1989, p. 569) wrote that:

Economists conventionally think of R&D as generating one product: new information. We suggest that R&D not only generates new information, but also enhances the firm's ability to assimilate and exploit existing information. [...] we show that, contrary to the traditional result, intra-industry spillovers may encourage equilibrium industry R&D investment.

Traditionally, economists have thought of technology spillovers as arising from the fact that technological knowledge is a public good (Arrow, 1962). Innovation pushes the technological frontier forward and facilitates future innovation, creating externalities and a rationale for the use of policy instruments such as the R&D tax credit to address this market failure. This traditional view suggests that knowledge spillovers diminish firms' incentives to invest in R&D as the returns to innovation cannot be fully appropriated. Cohen and Levinthal's critical insight is that R&D also plays an important role in learning: it increases a firm's 'absorptive capacity', its ability to assimilate knowledge from its environment. Consequently, knowledge spillovers induce complementarities in firms' R&D efforts and Cohen and Levinthal showed that knowledge spillovers may increase equilibrium R&D investment.¹ It is only through its own R&D that a firm can exploit the knowledge created by its competitors.

This is a far-reaching idea with numerous implications and applications in many research areas. The notion of absorptive capacity was particularly influential in the study of agglomeration economies (Anselin *et al.*, 1997; Audretsch, 1998; Agrawal and

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¹ This increase in equilibrium R&D investment is relative to a world without knowledge spillovers. As discussed in the remainder of this article, this observation does not mean that once absorptive capacity is taken into account there is no longer a wedge between the competitive equilibrium's solution and the social planner's solution.

Cockburn, 2003), of technology diffusion (Baptista, 2000; Keller, 2004), of the determinants of firm-level productivity (Jaffe and Adams, 1996; Cockburn and Henderson, 1998), of R&D co-operation between firms (Kamien and Zang, 2000; Branstetter and Sakakibara, 2002), of the outsourcing of R&D (Veugelers, 1997; Higgins and Rodriguez, 2006), of patterns of innovation across firms (Geroski *et al.*, 1997; Breschi *et al.*, 2000) and more generally for our understanding of economic growth (Griffith *et al.*, 2003, 2004). Absorptive capacity is still a prominent concept, influencing frontier research.

In this article, we focus on six issues where recent research has been particularly active and which relate directly or indirectly to Cohen and Levinthal's insights:

- (i) theoretical growth models where knowledge spillovers drive cross-country convergence and imply that optimal policies depend on a country's distance to the world technology frontier;
- (ii) models of growth and green innovation which emphasise strategic complementarities in (green) research across countries and explore their policy implications;
- (iii) new theoretical work examining the spillovers of R&D spending through general equilibrium effects;
- (iv) recent work on the role of openness in the discovery process;
- (v) new empirical work focusing on knowledge spillovers among individuals and offering a micro-foundation for absorptive capacity; and
- (vi) recent empirical research on R&D spillovers.

1. Knowledge Spillovers, Convergence and Growth Policies

The notion of absorptive capacity plays an important role in the debate on the sources of cross-country convergence or divergence as well as in the debate on appropriate growth policies. On the one hand, knowledge spillovers between advanced and less advanced countries are a strong force underlying cross-country convergence. On the other hand, the logic of absorptive capacity points to self-reinforcing feedback leading to divergence: for example, the educated tend to migrate to areas with already high concentration of skilled individuals.² Which of these counteracting effects dominates? In this Section, we discuss how the forces of convergence and the forces of divergence interact in the context of endogenous growth models.

Convergence is one of the most studied topics in the growth literature. A first approach explains convergence as a result of decreasing returns in physical or human capital accumulation. This is the neoclassical approach pioneered by Solow (1956) and subsequently developed by Barro and Sala-i-Martin (1991, 1995) and Mankiw *et al.* (1992). A second approach explains convergence as resulting primarily from cross-

² More generally, Griffith *et al.* (2004) show empirically that R&D affects both the rate of innovation and technology transfers and, therefore, that failing to take into account R&D-based absorptive capacity results in large underestimates of the social rate of return to R&D. From a more theoretical perspective, Griffith *et al.* (2003) develop a model featuring absorptive capacity that reconciles a wide array of empirical evidence on R&D-based innovation and productivity convergence.

country knowledge spillovers. Namely, innovations in one sector or one country often build on knowledge that was created by innovations in another sector or country. The process of diffusion, or technology spillover, is an important factor behind cross-country convergence. Howitt (2000) showed how this can lead to cross-country conditional convergence of growth rates in Schumpeterian growth models. Specifically, a country that starts far behind the world technology frontier can grow faster than one close to the frontier because the former country will make a larger technological advance every time one of its sectors catches up to the global frontier. In Gerschenkron's (1962) terms, countries far from the frontier enjoy an 'advantage of backwardness'. This advantage implies that in the long run a country with a low rate of innovation will fall behind the frontier but will grow at the same rate as the frontier; as they fall further behind, the advantage of backwardness eventually stabilises the gap that separates them from the frontier.

But there are also counteracting forces of divergence. Thus, as shown by Howitt and Mayer-Foulkes (2005) or by Aghion *et al.* (2005*b*), there may also be disadvantages of backwardness. In Howitt and Mayer-Foulkes (2005), the frequency of innovations in the catching-up country depends negatively upon the ratio between the distance to the technological frontier and the current stock of skilled workers: and the more backward the country, the more skilled workers are required for the country to catch up with the technological frontier. This is totally in line with Cohen and Levinthal's theory of absorptive capacity. Aghion *et al.* (2005*b*) instead explore the role of credit constraints to explain why the frequency of innovations might fall when a country falls further behind the frontier. In both cases, the combination between the advantages and disadvantages of backwardness explains not only why some countries converge while others stagnate but also why even countries with a positive long-run growth rate may diverge. This shows the role played by absorptive capacity in self-reinforcing feedback cycles that can result in either convergence or divergence.

These same considerations imply that there is a role for policies and institutions to help non-frontier countries catch up with the world technology frontier by building absorptive capacity up. These policies and institutions are distinct from those that favour frontier innovation in more advanced countries.

The idea of appropriate growth policy can be formalised in a simple discrete time model. Following Acemoglu *et al.* (2006), henceforth AAZ, and more remotely Nelson and Phelps (1966), let A_t denote the current average productivity in the domestic country, and $\bar{A}_t$ denote the current (world) frontier productivity. Then, think of innovation as multiplying productivity by a factor γ , and of imitation as catching-up with the frontier technology.

Then, if μ_n denotes the intensity of frontier innovation and μ_m denotes the intensity of imitation (or 'technological adaptation'), we have:

$$A_{t+1} - A_t = \mu_n(\gamma - 1)A_t + \mu_m(\bar{A}_t - A_t).$$

Both μ_n and μ_m are associated with research efforts, hence this framework shares with Cohen and Levinthal the view that imitation (or 'technological adaptation') is as much an investment as frontier R&D. Whether μ_m will increase or decrease with the technological gap ($\bar{A}_t - A_t$) depends upon the relative importance of the advantage and disadvantages of backwardness.

In any case productivity growth hinges upon the country's degree of 'frontierness', i.e. its 'proximity' $a_t = A_t/\bar{A}_t$ to the world frontier, namely:

$$g_t = \frac{A_{t+1} - A_t}{A_t} = \mu_n(\gamma - 1) + \mu_m(a_t^{-1} - 1).$$

This immediately generates the prediction that the closer to the frontier an economy is, that is, the closer to one the proximity variable a_t is, the more growth is driven by 'innovation-enhancing' rather than 'imitation-enhancing' policies or institutions.

While institutions or policies such as property right protection, contractual enforcement, the rule of law and macroeconomic stability are conducive to both frontier innovation and imitation, there are other institutional or policy features that tend to be more favourable to the former than to the latter.

Thus, more product market competition and more free entry encourage innovation in sectors or countries that are closer to the technological frontier but can have detrimental effects on innovations in laggard sectors or countries (see Aghion *et al.*, 2005*a*, 2009*a*).

Similarly, Aghion *et al.* (2009*b*) use cross-US-states panel data to look at how spending on various levels of education matter differently for growth across US states with different levels of 'frontierness', as measured by their average productivity compared to the frontier-state (Californian) productivity. They show that research education is always more growth-enhancing in states that are more frontier, whereas a bigger emphasis on two-year colleges is more growth-enhancing in US states that are farther below the productivity frontier.³ Moreover, in line with the feedback effect predicted by Cohen and Levinthal, they show that migration of skilled labour from less advanced to more advanced states accounts for a noticeable share (nearly 40%) of the total effect: the skilled tend to migrate to states where other skilled workers are located.

Therefore, the complementarity between absorptive capacity and external knowledge suggests that countries that are near the knowledge frontier will benefit from further advances in knowledge, while laggards with little absorptive capacity will be unable to capitalise on this new knowledge and will fall further behind. Without appropriate growth policies restoring absorptive capacity, for example in education and R&D, laggards may never be able to converge to the technology frontier, leading to a roughly bimodal distribution in the technological capabilities of countries. The role of policy is key because private investment in absorptive capacity has a self-reinforcing nature and the social returns to absorptive capacity (convergence) are not fully internalised by the private market. Thus, private market forces may fail to ensure convergence. Indeed, given the complementarity between absorptive capacity and external knowledge, at sufficiently low levels of absorptive capacity further increases in external knowledge may not increase marginal private incentives to build absorptive capacity and attempt to catch up. In addition, investment in absorptive capacity in one period may increase the marginal impact of

³ Vandenbussche *et al.* (2006) obtain similar conclusions using cross-country panel data, namely that tertiary education is more positively correlated with productivity growth in countries that are closer to the world technology frontier.

investment in absorptive capacity in a subsequent period, as argued in Cohen and Levinthal (1994).

2. Knowledge Spillovers and Green Innovation

At the heart of the current environmental debate is the issue of how to organise the international co-ordination of policy intervention. As the benefits of reductions in CO₂ emissions will be global, this sets the scene for countries engaging in classic free-riding, avoiding the costs of interventions. What if other countries are not intervening to support a switch to clean technologies? Does it still pay to intervene unilaterally? Is it good policy to make actions conditional on the level of other countries' commitments? As we will show, these issues are closely related to the broader question of the role of absorptive capacity in the diffusion of technologies.

Developing countries object to engage in costly environmental policies, as this will prevent them from catching up with more advanced countries. For instance, they are reluctant to introduce carbon emission reduction targets. Why subject them now to environmental criteria which developed countries did not follow when they were in comparable stages of development?

Factoring in directed technological change brings new light on how countries should debate and negotiate on the implementation of a global environmental policy. While some of the emerging countries, like China or Brazil, are also part of the global innovation machine, most of the 'South' at best can only imitate or adopt green technologies previously invented in the developed countries.

Acemoglu *et al.* (2014) appeal to complementarities between (green) research in developed and in less developed countries – much in the spirit of Cohen and Levinthal – to argue that by having the developed countries directing their own technical change towards clean technologies and by then facilitating the diffusion of new clean technologies, one can go a long way towards overcoming global climate change. In particular, it may not be necessary to tax dirty input production in the 'South' in order to avoid a global environmental disaster: unilateral government intervention in developed countries will turn on the green 'innovation' machine in the 'North', which then will set in motion the green 'imitation' machine in the 'South' to adopt cleaner technologies developed in the 'North'. The higher the spillovers from the developed green innovation machine to the developing green imitation machine, the more active the 'imitation' machine in the 'South' to implement clean technologies rather than dirty ones. This makes a case for unilateral policy intervention by the developed countries, even if the developing countries would not take any actions. It also makes a case to ease the technology transfers from the 'North' to the 'South' and to improve their capacity to effectively absorb Northern technology.

Note that, quite in line with Cohen and Levinthal's theory of absorptive capacity, Southern countries need to invest in (green) innovation in order to benefit from knowledge spillovers from the North. The point is that directing innovation in the North towards green innovation will encourage Southern countries to themselves direct their R&D efforts towards green innovation.

Factoring in trade, however, introduces a more cautious stance on unilateral climate change policies. In a free trade world, if a country or region adopts unilateral

environmental policies by taxing its dirty technologies, the other countries will automatically acquire a competitive advantage in producing with the dirty technology, and thus may decide to specialise in the production of dirty goods which they can subsequently export to the rest of the world. Similarly, multinational companies may decide to relocate dirty production activities and innovation to free-riding countries, and then re-export dirty goods and technologies to the region that has initiated environmental policies. This will not only create short-run environmental degradation but will also deter or slow down the adoption of clean technologies.

In order to avoid such perverse effects of unilateral environmental policies, it is important to make clean technologies available and affordable to poor countries. Carbon tariffs (or the threat of introducing them) may come into play if and only if clean technologies are available at an affordable cost, in order to prevent countries from reacting to unilateral environmental policies by specialising in large-scale production and export of dirty goods. If the threat of carbon tariffs is credible, any country or region could engage in unilateral environmental policy that could eventually be emulated by other countries and thereby solve the global environmental problem.

A particularly interesting insight of the notion of absorptive capacity in that context is that the diffusion of green technologies from the 'North' to the 'South' is not an entirely free lunch. In fact, less developed nations need to make a number of foundational investments in their own technological capabilities in order to subsequently be able to adopt the green technologies developed in the 'North' and adapt them to their particular settings. Whether investments in green innovation in the 'North' will strengthen the incentives of less developed nations sufficiently to lead them to invest in the required absorptive capacity is an open empirical question.

3. Knowledge Spillovers and General Equilibrium Effects

So far we have mostly focused on knowledge spillovers resulting from the law of motion of the technology frontier and their interaction with absorptive capacity. However, innovative activities in general and R&D spending in particular may have spillover effects on the rest of the economy of a different nature. Recent papers have shown the importance of general equilibrium effects that interact with knowledge spillovers from R&D spending and result in new recommendations for R&D policy, sometimes radically different from existing policies. The role of reallocation effects and the role of the business cycle are of particular interest and are explored in greater detail below. These papers show the importance of rethinking the nature of R&D spillovers. However, they do not incorporate the notion of absorptive capacity and we believe that a fruitful area for future research would be to study the interaction between general equilibrium effects and R&D investment in models in which R&D facilitates learning in addition to creating new knowledge.

In ongoing work, Acemoglu *et al.* (2014) find that R&D subsidies may impede growth by slowing down the reallocation process from incumbents to new entrants. They make the point that R&D spillovers exist not only through the law of motion of the research frontier but also through reallocation effects. The key dimension of reallocation in their model comes from the fact that skilled labour is used both for

R&D as well as to pay the fixed cost of operating a product line. As a result, in the competitive equilibrium, low productivity firms remain active too long relative to what the welfare-maximising social planner would choose. Indeed, the social planner would take into account that by freeing resources from the fixed cost of operations for low-productivity firms, he can increase R&D. This effect is not fully internalised by the market because the skilled wage is depressed relative to its social value for the usual reasons (innovators imperfectly appropriate the returns to innovation). Structurally estimating their model by the simulated method of moments using administrative data, they find that the optimal policy would combine a large tax on incumbent operations with a small incumbent R&D subsidy in order to speed up the movement of R&D resources from less efficient innovators (struggling incumbents) towards more efficient innovators (new firms). Crucially, they show that the conventional policy of R&D subsidies to incumbents results in a large welfare loss because it slows down reallocation. Introducing absorptive capacity in this model may have novel implications, as it creates another trade-off between incumbents (with a large stock of R&D and a high absorptive capacity) and new firms.

Another example of recent theory of R&D spillovers resulting in new policy recommendations is the work of Barlevy (2007). He points out the existence of a dynamic externality inherent in R&D, whose implications had not been fully understood so far. More specifically, he shows that the private incentives to innovate during a downturn are much lower than during a boom, because of short-run demand and productivity effects. However, the long-term social value of R&D (through the law of motion of the research frontier) is the same regardless of whether R&D investments take place in a boom or in a recession. As a result, the wedge between the private and social benefits of R&D varies over the business cycle. This effect, which results from dynamic knowledge spillovers, creates a rationale for countercyclical R&D policy. His calibration exercise using US data suggests that introducing countercyclical R&D tax credits may result in large welfare gains. Introducing absorptive capacity in this model would presumably strengthen the results by making the wedge between the private and social benefits of R&D even more countercyclical.

4. Openness in the Knowledge Production Process

Green and Scotchmer (1995) were first to model early-stage research as providing a set of tools which serve as inputs to later-stage work. In their framework, increased openness discourages basic research, the reason being that there is more scope for the outcome of basic research to be 'expropriated' by subsequent (or follow-on) research. However, as observed in Cohen and Levinthal (1989), a benefit of basic research is to build a firm's absorptive capacity. Therefore, by increasing the stock of publicly available knowledge, greater openness may stimulate firms' investments in basic research.

In contrast with Green and Scotchmer (1995), Aghion *et al.* (2008), henceforth ADS, have developed a framework in which openness can encourage basic research and in fact lead to an increase in the flow of discoveries. In ADS, research can be done either 'in academia', i.e. with the researcher having control rights on his research agenda; or it can be done in the private sector, with the employer determining what the research

agenda should be. One advantage of academic freedom is that the researcher is ready to accept lower wages in exchange for research freedom. One drawback of academia is that the researcher may end up pursuing research which does not lead to commercialisable innovations: in other words, researchers in academia may not focus on the pursuit of commercialisable innovations. ADS show that it is optimal to pursue the early stages of a research line in academia, whereas the later stages require focus and therefore are best pursued in private firms. The ADS framework also sheds new light on the role of openness in the discovery process, and in particular it introduces positive feedback similar to those emphasised by Cohen and Levinthal.

In particular, the ADS framework points to at least two reasons as to why more openness should have a positive impact on research and innovation. First, openness increases the scope for cross-fertilisation among free researchers. This in turn makes it possible for an individual researcher to build on the idea that another researcher started but then decided to abandon. Thus, overall more openness improves the matching between researchers and ideas and thereby reduces the costs associated with academic freedom. Thanks to openness, free researchers can improve upon other researchers' ideas when the latter lack the expertise or desire to do so. Openness therefore increases the number of research lines that end up being pursued collectively.

Second, to the extent that academic researchers are more likely to be credit-constrained than private firms, what openness does is to reduce the academic researchers' costs of accessing new tools and ideas. Murray *et al.* (2013) explore the implications of the NIH-Dupont agreements aimed at reducing the cost of accessing information on genetically engineered mice and they show that these agreements led to a higher flow of follow-on research, which was also more diversified.

The idea that openness should play an important role in the innovation process goes beyond the dichotomy between academic and private sector research. For example, the best-selling book *Wikinomics* shows how IBM took advantage of catering to the openness culture of Linux: this allowed IBM to obtain research input more cheaply, capitalising on the fact that Linux contributors accept working for nothing, much in the way that academic researchers accept working for lower wages: namely because they enjoy freedom and also openness, i.e. the ability to interact and exchange freely with other contributors.

Last but not least, the notion of absorptive capacity suggests that 'openness' in the knowledge production process does not mean that knowledge becomes free for everyone to use. Individuals and institutions need to have sufficiently invested in their absorptive capacity in order to be able to assimilate and exploit 'open' knowledge. Because of the role of absorptive capacity, as suggested above, knowledge in the public domain is not as much of a public good as conventionally thought.

5. Identifying Knowledge Spillovers from Individual-level Data

Considering the existence of spillovers at the micro level – among inventors, scientists and researchers – is an important new area for empirical work that has the potential to provide micro-foundations for absorptive capacity by identifying the role of individuals in the process of learning. In addition, such work might reveal a number of market

failures that have been neglected so far and could result in a new rational for innovation policy. For instance, inventors often work in networks that extend beyond the boundaries of the firm, such that their compensation may not fully internalise the effect they have on other inventors through knowledge creation and knowledge diffusion.

A series of recent papers have improved our understanding of knowledge spillovers in academia, for instance Azoulay *et al.* (2010), Borjas and Doran (2012) and Waldinger (2012). These papers creatively exploit various sources of quasi-experimental variation to estimate the magnitude of knowledge spillovers but the evidence is mixed.⁴ Azoulay *et al.* (2010) use the premature deaths of a number of 'academic superstars' in biomedical sciences as a source of exogenous variation in the structure of their collaborator's networks and find large spillovers. In contrast, Borjas and Doran (2012) find that the wave of immigration of Russian mathematicians to the US in the 1990s mainly had a 'crowding-out effect' on American mathematicians and no positive externalities. Lastly, Waldinger (2012) finds that the expulsion of Jewish scientists from their universities in the 1930s did not result in a decline in the productivity of their peers, except for their PhD students.

These studies all rely on citations as a proxy for productivity and their conflicting results suggest that knowledge spillovers might greatly vary across fields. Further empirical work is ongoing in the profession to improve our understanding of these issues, in particular with studies focusing on inventors in private firms instead of academics and using alternative measures of productivity such as compensation in addition to patent citations. This new empirical literature raises many new questions that are currently under-researched, such as, the extent to which knowledge spillovers between individuals are internalised by private firms and whether they reflect dynamic learning between individuals, match-specific human capital or bargaining effects within the firm.

Overall, empirical work using individual-level data has a lot to tell us about the nature of knowledge spillovers and whether knowledge flows are embodied in individuals or 'in the air'.

Identifying the magnitude of spillovers among individuals is a great contribution to the debate on innovation policy, because the impacts of any policy may depend greatly not just on a given inventor's behaviour but on a 'multiplier effect' at the individual level that affects the broader innovation process. In addition, research designs based on individuals can identify knowledge spillovers from exogenous shocks affecting individuals; they are thus robust to the 'reflection problem' (Manski, 1993). These new studies can thus make valuable contributions to an extensive and insightful literature on R&D spillovers across firms (see for instance Griliches, 1992 and Mairesse and Mulkey, 2007).

⁴ The absence of controls for absorptive capacity in these studies might be a factor, among others, explaining why the results are mixed. A given researcher's productivity will be less affected by this researcher's peers if he or she does not have sufficient absorptive capacity to learn from them.

6. More Evidence on Positive R&D Spillovers

Growth theory teaches us that innovation is fundamental, that it is endogenous to the economic environment and therefore open to potentially welfare-improving policy interventions. The general assumption is that there are positive externalities from knowledge and, hence, that there will be under-investment in R&D from a social point of view.

But demonstrating this empirically has proved to be challenging for a variety of reasons. First, if R&D decisions are endogenous, this must be dealt with econometrically by treating productivity and R&D investments as jointly determined. Second, since innovation markets will generally be imperfectly competitive, there will be business-stealing effects from innovation, which can lead to excessive incentives to invest in R&D from a social perspective. Third, since there is huge firm-level heterogeneity in R&D performance, a credible empirical investigation cannot rely solely on macro-economic variation as there will likely be too many confounding factors. In recent work, Bloom *et al.* (2013), henceforth BSVR, make headway on these long-standing issues by relying on US firm-level panel data over two decades covering the majority of private-sector R&D.

BSVR make several fundamental contributions to the existing literature on R&D spillovers. First, from a substantive, policy perspective they conclude that even after addressing all three of the above problems that have plagued the literature, the social returns to R&D are two to three times as large as the private returns. Second, BSVR identify the causal effects of R&D on firm performance using instrumental variables. They use idiosyncrasies of the state and federal US R&D tax credit system to develop an IV strategy. For example, they exploit the fact that firms will be differentially affected by the unexpected introduction of an R&D tax credit in (say) California, if a firm already has some R&D labs located in California prior to the introduction of the tax credit.

More specifically, BSVR set up a general model of oligopolistic competition between firms. They characterise the two offsetting effects of neighbours' R&D on a firm's value: first, a positive effect from knowledge spillovers (i.e. your research helps me through improving my ideas); second, a negative effect through business-stealing/product-market rivalry (i.e. your ideas leapfrog my ideas). BSVR demonstrate how the two offsetting sources of spillovers can be identified in the data by considering the distance between firms in different spaces. The technological spillover can be identified through patenting in similar fields, while the business stealing effect through overlaps in the product-market space (here the authors build on previous work by Jaffe, 1986). Using this methodology, BSVR can successfully identify both product market rivalry and technology spillover effects. And, despite the importance of product market rivalry effects of R&D (the focus of many IO models of R&D), they find that the positive knowledge spillover effects dominates quantitatively.

Incorporating the channel of absorptive capacity in a model in the spirit of BSVR, which could be estimated using firm-level data, is an important area left for future research. It appears to be a fruitful research effort for at least three reasons. First, taking into account the learning channel of R&D should increase the social rate of return to R&D relative to the estimate of BSVR and it would be instructive to compare

estimates from firm-level data with existing cross-country estimates of the learning effects of R&D. Second, the learning component of the social rate of return to R&D may vary considerably by firm size: for instance, a marginal increase in R&D may have larger learning effects in small firms compared to large firms (this effect would counterbalance the finding of BSVR, who show that the positive knowledge spillover effect of R&D is smaller in small firms, compared with large firms, because they tend to operate in technological niches, suggesting that the R&D tax credit should be increasing with firm size).

Third, comparing the results of such a study with the results of the ongoing studies based on individual-level data described in the previous Section would give us a better sense of the relative importance of organisational-level *versus* individual-level determinants of absorptive capacity.

7. Conclusion

Cohen and Levinthal pointed out that knowledge spillovers have implications that go beyond the familiar free-rider problem in R&D spending. They introduced the notion of absorptive capacity and showed that knowledge spillovers can induce complementarities in R&D efforts. Here, we showed that this idea has rich implications when analysing important aspects of the growth process such as cross-country (or cross-state) convergence and divergence, the international co-ordination of climate change policies, or, at a more basic level, the role of openness in the production of ideas.

At the same time, Cohen and Levinthal's notion of absorptive capacity set an agenda for new empirical and theoretical analyses of the role of R&D spillovers in innovation and growth. Here, we mentioned recent studies on reallocation effects and the dynamic aspect of R&D spillovers and recent attempts at estimating the magnitude and nature of knowledge spillovers and learning effects from individual-level and firm-level data.

Taken together, these theoretical and empirical studies should help improve our understanding of the innovation process and of the appropriate policies and institutions to enhance sustainable growth.

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Appendix A. Cohen, W.M. and Levinthal, D.A. (1989). 'Innovation and learning: the two faces of R & D', *ECONOMIC JOURNAL*, vol. 99(397), pp. 569–96.

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INNOVATION AND LEARNING: THE TWO FACES
OF R&D**Wesley M. Cohen and Daniel A. Levinthal*

Economists conventionally think of R&D as generating one product: new information. We suggest that R&D not only generates new information, but also enhances the firm's ability to assimilate and exploit existing information. In this paper we consider the implications of this dual role of R&D for the firm's incentive to invest in R&D. We argue that recognition of this second role of R&D suggests that the ease and character of learning within an industry will both affect R&D spending and condition the influence of appropriability and technological opportunity conditions on R&D. For example, we show that, contrary to the traditional result, intra-industry spillovers may encourage equilibrium industry R&D investment.

Scholars of technological change have observed that firms invest in own R&D to be able to utilise information which is available externally (e.g., Tilton, 1971; Allen, 1977; Mowery, 1983).¹ Tilton, for example, states that one of the main reasons firms invested in R&D in the semiconductor industry was that, '... an R & D effort provided an in-house technical capability that could keep these firms abreast of the latest semi-conductor developments and facilitate the assimilation of new technology developed elsewhere' (1971, p. 71). Accordingly, we argue that while R&D obviously generates innovations, it also develops the firm's ability to identify, assimilate, and exploit knowledge from the environment—what we call a firm's 'learning' or 'absorptive' capacity. While encompassing a firm's ability to imitate new process or product innovations, absorptive capacity also includes the firm's ability to exploit outside knowledge of a more intermediate sort, such as basic research findings

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¹ In a different context, Evenson and Kislev (1973) make a similar point when they observe that the international transfer of agricultural technology depends, in part, upon the recipients' own research efforts.

that provide the basis for subsequent applied research and development. Also, in light of the dependence of industrial innovation upon extramural knowledge,² absorptive capacity represents an important part of a firm's ability to create new knowledge. In this regard, the exercise of absorptive capacity represents a sort of learning that differs from learning-by-doing, the focus of industrial economists' work on firm learning in recent years (e.g., Spence, 1981; Lieberman, 1984). Learning-by-doing typically refers to the automatic process by which the firm becomes more practiced, and, hence, more efficient at doing what it is already doing. In contrast, with absorptive capacity a firm may acquire outside knowledge that will permit it to do something quite different.

The role that R&D plays in learning has received little attention in the past because, following Arrow (1962) and Nelson (1959), economists have assumed that technological knowledge which is in the public domain is a public good. Like a radio signal or smoke pollution, its effects are thought to be costlessly realised by all firms located within the neighbourhood of the emission. When economists do think about the costs of knowledge transfer, they typically identify them with immediate information processing or imitation costs. In suggesting technological knowledge is a public good, Arrow and others do not deny the existence of such costs, but argue that they are typically small relative to the cost of creating new knowledge. This argument, however, raises the question of what determines these immediate costs of assimilating technological knowledge. We suggest that if these costs are relatively small, it is by virtue of the considerable R&D already conducted by the firms in the vicinity of the 'emission'; the firm has already invested in the development of its absorptive capacity in the relevant field.³

Thus, we are suggesting that the long-run cost of learning may be substantial. Second, most of this cost is borne via the development of a stock of prior knowledge that constitutes the firm's absorptive capacity. Third, a significant benefit of R&D is its contribution to this knowledge base. Therefore, the incentives to learn should influence R&D spending. Those incentives will be shaped by the quantity of knowledge to be assimilated and the ease with which learning may occur. The ease of learning, in turn, depends upon the characteristics of the underlying technological and scientific knowledge upon which innovation depends in a given industry.

To explore the implications of the dual role of R&D for R&D investment, we construct a simple theoretical model of the generation of a firm's

² According to Brock (1975) most of the computer industry's innovations originated with developments outside the industry, particularly in semiconductors. In his study of the aluminium industry, Peck (1962) makes the same point. In a study of twenty-seven major inventions made between 1946 and 1955, Hamberg (1963) showed that twenty came from sources outside industrial R&D laboratories. In his study of twenty-five major discoveries introduced into the United States by DuPont, Mueller (1962) indicated that, despite the company's reputation for path-breaking research, fifteen originated with work done outside the company. In their study of information usage in technological innovation, Johnston and Gibbons (1975) even concluded that information obtained from outside the company contributes significantly more to the solution to technical problems than does internally available information.

³ For example, compare a firm's immediate costs of reverse engineering a product versus the considerable costs, incurred over time, of acquiring the experience and background necessary to execute the task.

technological knowledge. Our model considers the basic sources of technological knowledge utilised by a firm: the firm's own R&D, knowledge which originates with its competitors' R&D spillovers,⁴ and knowledge which originates outside the industry. Section I of the paper develops the model structure. In Section II, we explore the determinants of industry equilibrium R&D, focusing on the effect of the ease of learning. In Section III, we test hypotheses suggested by our framework with survey data on technological opportunity and appropriability conditions recently collected by Levin *et al.* (1983, 1987), and data on business unit R&D expenditures from the Federal Trade Commission's Line of Business Programme. In this section, we examine how the ease of learning shapes the influence on R&D spending of appropriability and technological opportunity conditions.

I. MODEL STRUCTURE

Central to our model is the determination of the firm's stock of knowledge. We represent additions to firm i 's stock of technological and scientific knowledge by z_i , and assume that z_i increases the firm's gross earnings, Π^i (i.e., $\Pi^i_{z_i} > 0$), but at a diminishing rate (i.e., $\Pi^i_{z_i z_i} < 0$). We characterise the determination of z_i such that,

$$z_i = M_i + \gamma_i (\theta \sum_{j \neq i} M_j + T), \quad (I)$$

where M_i is a firm's investment in R&D; γ_i is the fraction of knowledge in the public domain that the firm is able to assimilate and exploit, and represents the firm's absorptive capacity; θ is the degree of intra-industry spillovers; and T is the level of extra-industry knowledge. Other firms' investments in research and development, represented by M_j for $j \neq i$, also contribute to z_i . The degree to which the research effort of one firm may spill over to a pool of knowledge potentially available to all other firms is characterised by θ where $0 \leq \theta \leq 1$. A value of θ of one means that the R&D effort of one firm increases the pool of knowledge available to other firms by the total amount of the firm's R&D. A value of zero means that the benefits of research are exclusively appropriated by the firm conducting the research. Exogenous factors such as patent policy shape θ .

Our model postulates that a firm's capacity to absorb externally generated knowledge depends on its R&D effort. We assume that $0 \leq \gamma_i \leq 1$. When $\gamma_i = 1$, the firm absorbs all knowledge that is in the public domain. Alternatively, when $\gamma_i = 0$, the firm absorbs none. We assume that the firm's own R&D increases absorptive capacity, $\gamma_M > 0$, though at a decreasing rate, $\gamma_{MM} < 0$. Although not formally captured by our static model, we think of γ as being cumulatively built through past as well as current R&D effort.

We consider γ_i to be a function not only of M_i , but also of a variable β (i.e.,

⁴ We define spillovers to include any original, valuable knowledge generated in the research process which becomes publicly accessible, whether it be knowledge fully characterising an innovation, or knowledge of a more intermediate sort.

$\gamma_i \equiv \gamma(M_i, \beta)$ that is determined by the characteristics of the underlying scientific and technological knowledge that affect the ease of learning from the environment. The variable, β , reflects the characteristics of outside knowledge that make R&D more or less critical to the maintenance and development of absorptive capacity. Although difficult to specify all the relevant characteristics *a priori*, we suggest they would include the complexity of the knowledge to be assimilated, and the degree to which the outside knowledge is targeted to the needs and concerns of the firm. When outside knowledge is less targeted to the firm's particular needs and concerns, a firm's own R&D becomes more important in permitting it to recognise, assimilate and exploit valuable knowledge. Sources that produce less targeted knowledge include, for example, university laboratories involved in basic research, while more targeted knowledge may be generated by contract research laboratories or input suppliers. In addition, the degree to which a field is cumulative, or a field's pace of advance should also affect how critical R&D is to the development of absorptive capacity. To the extent that findings in a field build upon prior findings, an understanding of prior research is necessary to the assimilation of subsequent findings. The pace of advance of a field affects the importance of R&D to developing absorptive capacity because, the faster is the pace of knowledge generation, the larger will be the staff required to keep abreast of developments.⁵

We define β such that a higher level indicates that the firm's ability to assimilate external knowledge is more dependent on the firm's own R&D. This dependence is reflected in two effects. We assume that the larger is β , the larger is the marginal impact of own R&D on absorptive capacity such that $\gamma_{M\beta} \equiv \gamma_{M\beta}(M_i, \beta) > 0$. In addition, for a given level of M , absorptive capacity decreases with β (i.e., $\gamma_\beta(M_i, \beta) < 0$).⁶ Thus, we are assuming that increasing β increases the marginal effect of R&D on absorptive capacity, but diminishes the level of absorptive capacity. This second effect indicates that when external knowledge becomes more difficult to assimilate, the firm will assimilate less of it for a given R&D effort.

Equation (1) reflects the assumption that the appropriation of other firms' research is realised through the interaction of θ and γ , indicating that the firm cannot assimilate what is not spilled out. Also, the firm cannot passively assimilate externally available knowledge. It must invest in its own R&D to absorb any of the R&D output of its competitors. In this sense, not only is absorptive capacity endogenous, but the appropriability of rents due to inventive activity is endogenous as well.

Another critical determinant of R&D is technological opportunity, which may be thought of as how costly it is for the firm to achieve technical advance in a given industry. We incorporate two determinants of technological

⁵ Pavitt (1987), in an analysis of policies affecting the utilisation of technology, focuses on some of the same characteristics of knowledge as considered here, including complexity and cumulativeness.

⁶ Therefore, as β approaches zero, absorptive capacity is less responsive to the level of own R&D and γ_i approaches 1. Thus, a β of zero is equivalent to the setting in which absorptive capacity is not endogenous and $\gamma \equiv 1$.

opportunity in our model. One is the quantity of extra-industry technological knowledge, represented by the variable T . Examples of T include the output of government or university laboratories, or the knowledge provided by equipment suppliers. Like its assimilation of competitors' R&D output, a firm's assimilation of outside knowledge is constrained by its absorptive capacity.⁷ Another dimension of technological opportunity, represented by the variable f , is the degree to which new knowledge, z , improves the technological performance of the firm's manufacturing processes or products. We assume that the more that knowledge contributes to technological performance, the more it increases profit (i.e., $\Pi_{zif}^i > 0$).⁸

We assume that there are n firms in the industry with symmetric R&D policies. Each firm chooses its level of R&D to maximise profits, taking the R&D levels of the other firms as given. Thus, we model a symmetric Nash equilibrium in R&D levels. Accordingly, the firms anticipate the effect of changes in their R&D investments on their competitors' knowledge levels and, in turn, the effects of these changes on the firms' own profits. As a result, the firm's profit is a function not only of its own knowledge, z_i , but the technological knowledge of all firms in the industry. To reflect the effect of rivalry, we assume that an increase in a competitor's knowledge diminishes both firm i 's profits and firm i 's marginal benefit from increasing its knowledge level so that $\Pi_{z_j}^i < 0$, and $\Pi_{z_i z_j}^i < 0$, where z_j represents the change in a competitor's knowledge level. When knowledge has a large impact on technological performance, increases in competitors' knowledge levels are more damaging to own profits (i.e., $\Pi_{z_j f}^i < 0$). In addition to being a function of increments to firms' knowledge levels, we assume that profit due to R&D is also a function of demand conditions.

Differentiating Π^i with respect to M_i yields,

$$R \equiv \Pi_{z_i}^i [1 + \gamma_{M_i} (\theta \sum_{j \neq i} M_j + T)] + \theta \sum_{j \neq i} \gamma_j \Pi_{z_j}^i. \quad (2)$$

The function R is the marginal return to own R&D. Deriving this expression for each firm and setting it equal to one (the per unit cost of R&D) generates a set of equations characterising the firm's optimal R&D policy given its competitors' R&D levels. When solved simultaneously, these equations yield the equilibrium value of each firm's R&D, which we represent as M^* .

II. ANALYSIS

We will consider the direct effect of the ease of learning on R&D, as well as its impact on the influence of spillovers and technological opportunity on R&D spending. In this latter regard, we will show that as learning becomes more dependent on own R&D, increasing technological opportunity or spillovers

⁷ For simplicity, we assume that all extra-industry research findings are made public, implying that the spillover parameter applicable to extra-industry knowledge equals unity.

⁸ See Cohen and Levin (1989) for a discussion of the two dimensions of technological opportunity represented here as T and f .

will tend to elicit more R&D effort, *ceteris paribus*. Indeed, the presence of an endogenous absorptive capacity may change the qualitative effect of these traditionally considered determinants of inventive activity. Most notably, spillovers may encourage R&D under some conditions.

In the context of our n -firm symmetric equilibrium, we can show that for any arbitrary parameter, k , that influences M^* , the sign of $(\partial M^*/\partial k)$ equals the sign of R_k , where R is defined by equation (2) above.⁹ Therefore, to simplify the presentation of our results, we only present the analogues of R_k , including R_β , R_θ , R_T , and R_f to establish the signs of, respectively, $(\partial M^*/\partial \beta)$, $(\partial M^*/\partial \theta)$, $(\partial M^*/\partial T)$ and $(\partial M^*/\partial f)$.¹⁰ In addition to analysing the direct effect of β on R&D spending, we also examine how the ease of learning affects the influence of spillovers and technological opportunity on R&D; that is, the effect of β on $(\partial M^*/\partial \theta)$, $(\partial M^*/\partial T)$ and $(\partial M^*/\partial f)$. Exploring these effects analytically is, however, quite complex. Thus, to provide an intuitive sense of the basic forces at work, we simplify the analysis by considering only the first-order effects of knowledge on firm profit and assume the second-order condition to be constant. Since we therefore cannot claim the analysis to be general, we have confirmed the intuition developed here with numerical analysis.¹¹ Given our assumption of a constant second-order condition, we can show that the signs of the cross-partial derivatives, $(\partial^2 M^*/\partial \theta \partial \beta)$, $(\partial^2 M^*/\partial T \partial \beta)$ and $(\partial^2 M^*/\partial f \partial \beta)$ are identical to the signs of, respectively, $R_{\theta\beta}$, $R_{T\beta}$, and $R_{f\beta}$. Therefore, to simplify further the presentation of our results, we only present $R_{\theta\beta}$, $R_{T\beta}$, and $R_{f\beta}$.

II.1 Direct Effect of the Ease of Learning

As β increases, reflecting, for example, an increase in the complexity or a diminution in the targeted quality of outside knowledge, own R&D becomes more critical to absorptive capacity. However, that also means that the cost per unit of knowledge, z , increases. Despite these seemingly countervailing effects of β , differentiating equation (2) by β reveals that equilibrium R&D increases with β (i.e., $(\partial M^*/\partial \beta) > 0$).¹² We can see the main forces at work if we focus on the first-order effects.¹³ Deriving R_β and constraining the second-order terms of

⁹ This assumes that the Nash equilibrium is stable. The proof is available in a technical appendix available from the authors.

¹⁰ The complete derivative, $\partial M^*/\partial k$, equals $R_k/[a + (n-1)b]$, where $a \equiv \partial^2 \Pi^i/\partial M_i \partial M_i$ and $b \equiv \partial^2 \Pi^i/\partial M_i \partial M_j$.

¹¹ Results of the numerical analysis are contained in the technical appendix available from the authors.

¹² This result holds if we assume that the sufficient condition for the reaction function to be downward sloping applies when $\gamma_M = 0$. The reaction function is downward sloping when $\Pi^i_{M_i M_j} < 0$. A sufficient condition for this to hold is that $\Pi^i_{z_j z_j} + \Pi^i_{z_i z_j} + (n-2) \Pi^i_{z_j z_k} < 0$, where $k \neq j \neq i$.

¹³ The complete characterisation of R_β is:

$$\begin{aligned} R_\beta = & \Pi^i_{z_i} \gamma_{M\beta} [\theta(n-1) M + T] + \theta(n-1) \gamma_\beta \Pi^i_{z_i} \\ & + \gamma_\beta [\theta(n-1) M + T] \{ [\Pi^i_{z_i z_i} + (n-1) \Pi^i_{z_i z_j}] \{ 1 + \gamma_M [\theta(n-1) M + T] \} \\ & + \theta(n-1) \gamma [\Pi^i_{z_j z_j} + \Pi^i_{z_j z_i} + (n-2) \Pi^i_{z_j z_k}] \}. \end{aligned}$$

Π^i with respect to knowledge to equal zero allow us to characterise the effect of β on R&D spending as

$$\text{sign}\left(\frac{\partial M^*}{\partial \beta}\right) = \text{sign}\left(\Pi_{z_i}^i \{\gamma_M \beta [\theta(n-1) M + T]\} + \theta(n-1) \frac{\partial \gamma}{\partial \beta} \Pi_{z_j}^i\right). \quad (3)$$

The first expression, $\Pi_{z_i}^i(\cdot)$, indicates that with a higher β the firm has greater incentive to conduct R&D because its own R&D has become more critical to assimilating both its competitors' spillovers, $\theta(n-1) M$, and extra-industry knowledge, T . At the same time, the second expression, $\theta(n-1) (\partial \gamma / \partial \beta) \Pi_{z_j}^i$, indicates that competitors' levels of absorptive capacity, $(n-1) \gamma$, decline with β . As a consequence, competitors are less able to exploit the firm's spillovers. Due to both of these effects, the payoff to the firm's R&D increases and, *ceteris paribus*, more R&D is conducted.

II.2. Intraindustry Spillovers

Economists (e.g., Nelson, 1959; Arrow, 1962) have long argued that research spillovers diminish firms' incentives to invest in R&D by undermining the appropriability of returns to inventive activity. The contribution of R&D to a firm's absorptive capacity implies, however, that there is an offsetting incentive associated with spillovers, because only through its own R&D may a firm exploit the knowledge generated by its competitors.

To explore the relationship between spillovers and equilibrium R&D, we differentiate equation (2) with respect to θ . In the absence of an endogenous absorptive capacity, we can verify the traditional claim that higher levels of spillovers reduce R&D investment.¹⁴ With an endogenous absorptive capacity, the result changes. In addition to a negative appropriability incentive, we now also observe a positive absorption incentive. These countervailing forces may be clearly seen if we eliminate the effect of diminishing returns to knowledge (represented by the second-order terms of firm profits with respect to knowledge).¹⁵ In this case, deriving R_θ permits us to sign $(\partial M^* / \partial \theta)$ where,

$$\text{sign}\left(\frac{\partial M^*}{\partial \theta}\right) = \text{sign}[\Pi_{z_i}^i \gamma_M (n-1) M + (n-1) \gamma \Pi_{z_j}^i]. \quad (4)$$

Contrary to the standard proposition that increasing spillovers reduces the incentive to invest in R&D, the sign of $(\partial M^* / \partial \theta)$ is ambiguous. This ambiguity is due to two offsetting effects: the benefit to the firm of increasing its absorptive capacity, represented by $\Pi_{z_i}^i \gamma_M (n-1) M$, and the loss associated with the diminished appropriability of rents as spillovers increase, represented by

¹⁴ As with the comparative static result with respect to β , we need to assume that the sufficient condition for the reaction function to be downward sloping holds.

¹⁵ The complete characterisation of R_θ is:

$$R_\theta = \Pi_{z_i}^i \gamma_M (n-1) M + (n-1) \gamma \Pi_{z_j}^i + \gamma(n-1) M \{[\Pi_{z_i}^i + (n-1) \Pi_{z_j}^i] \{1 + \gamma_M [\theta(n-1) M + T]\} + \theta(n-1) \gamma [\Pi_{z_i}^i + \Pi_{z_j}^i + (n-2) \Pi_{z_k}^i]\}.$$

$(n-1)\gamma\Pi_{z_j}^i$. The former expression indicates that with an endogenous absorptive capacity, a higher spillover rate provides a positive incentive to conduct R&D by increasing the pool of available knowledge. Thus, our introduction of absorptive capacity changes the traditional result in two ways. Most importantly, the desire to assimilate the knowledge generated by other firms provides a positive incentive to invest in R&D as θ increases.¹⁶ Second, the disincentive associated with other firms' assimilation of the firm's R&D output is dampened because other firms' absorptive capacities are less than unity.¹⁷

Equation (4) also suggests that the positive impact of θ is typically greater the larger is β , the impact of own R&D on absorptive capacity. To examine this formally we evaluate the sign of the cross-partial derivative, $(\partial^2 M^*/\partial\beta\partial\theta)$, by deriving $R_{\beta\theta}$. If we focus only on first-order effects of z on profit and assume that $\gamma_{MM} = 0$, then we can show that $R_{\beta\theta}$ is positive.¹⁸ There are three distinct effects. First, a higher β enhances the positive absorption incentive to invest in R&D. Second, by reducing competitors' absorptive capacities, a higher β encourages R&D by mitigating the negative appropriability effect of spillovers, *ceteris paribus*. Finally, since a higher β increases the optimal level of R&D, β increases the optimal M_j which, while increasing the pool of knowledge available to firm i , also increases firm j 's absorptive capacity to firm i 's detriment. However, as long as the magnitude of the marginal return to own knowledge exceeds the marginal effect on profits of a change in a competitor's knowledge level (i.e., $|\Pi_{z_i}^i| > |\Pi_{z_i}^j|$), this last effect is positive.¹⁹

In light of the importance of spillovers in economists' analysis of R&D incentives, we examine how demand conditions and market structure interact with β to determine the qualitative effect of spillovers on R&D spending. In order to do this, we develop a model of cost-reducing technological change.²⁰ We specify a cost function with a constant marginal cost of production that is a decreasing exponential function of z_i , the firm's knowledge level. We also assume that the demand curve and the absorptive capacity function have constant elasticities with respect to price and R&D spending, respectively.

¹⁶ While Levin and Reiss (1988) show that high spillovers and high R&D investment may coincide when the productivity of spillovers (i.e., their impact on cost reduction) is high, they do not show, as we do in our theoretical analysis and as the empirical results below suggest, that increasing the extent of spillovers may have a direct positive effect on R&D investment incentives.

¹⁷ Suppose that the appropriability disincentive effect outweighs the absorption incentive effect such that we obtain the standard result that equilibrium R&D diminishes with θ . If R&D declines, the level of absorptive capacity will also decline in equilibrium given our assumption that $\gamma_M > 0$. This decline will, in turn, diminish competitors' abilities to exploit the firm's spillovers, and thus dampens the negative incentive effect with which spillovers are associated. Thus, the interaction of an endogenous absorptive capacity and θ means that even where the negative appropriability effect dominates, its effect is attenuated relative to a world where firm's absorptive capacity is not a function of its own R&D.

¹⁸ Under these conditions,

$$R_{\beta\theta} = (n-1) \left[M_j \gamma_{M\beta} \Pi_{z_i}^i + \gamma_{\beta} \Pi_{z_j}^i + \gamma_M \frac{\partial M^*}{\partial \beta} (\Pi_{z_i}^i + \Pi_{z_j}^i) \right].$$

¹⁹ We can show that $|\Pi_{z_i}^i| > |\Pi_{z_i}^j|$ in the context of the specialised model discussed below.

²⁰ The development of this model and its analysis is contained in the technical appendix available from the authors. As Spence (1984) suggests, such a model may be interpreted to consider product as well as process innovation if we think of products as delivering services to customers, and product innovation as simply increasing the quantity of service per unit of output.

Again, we analyse Nash equilibria in which the firms' R&D policies are assumed to be symmetric.

In this specialisation of our model, spillovers are more likely to cause an increase in industry equilibrium R&D where β is high, which is indicated as well by the general analysis above. We also find that the higher is the price elasticity of demand or the less concentrated is the industry, the more likely it is that equilibrium R&D investment will rise with spillovers, *ceteris paribus*. Thus, as firms face a more competitive environment, in the sense that they are less inter-dependent due to either an increase in demand elasticity or a lower concentration level, spillovers are more likely to encourage R&D investment. The intuition is that as an industry becomes more competitive, the private loss associated with the public good character of R&D spillovers diminishes relative to the private benefit of being able to exploit competitors' spillovers.

II.3. *Technological Opportunity*

Our model suggests that increased levels of extra-industry knowledge will only substitute for own R&D unless absorptive capacity is endogenous. With an endogenous absorptive capacity, there is also a positive incentive for the firm to conduct R&D in order to exploit the pool of external knowledge. To formalise this intuition, we characterise the sign of $(\partial M^*/\partial T)$ by deriving R_T , and assume $\theta = 0$ to highlight the role of T :²¹

$$\text{sign}\left(\frac{\partial M^*}{\partial T}\right) = \text{sign}[\gamma_M \Pi_{z_i}^i + (\Pi_{z_i z_i}^i + (n-1) \Pi_{z_i z_j}^i) \gamma(1 + \gamma_M T)]. \quad (5)$$

In the absence of an endogenous absorptive capacity (i.e., $\gamma_M \equiv 0$), this expression is negative. A higher T merely substitutes for the firm's own R&D. However, with an endogenous absorptive capacity, a higher T also provides an incentive to enhance the firm's absorptive capacity, as reflected in the first expression on the right hand side.

To examine the impact of the second dimension of technological opportunity, f , which reflects the degree to which new knowledge, z , improves technological performance, we derive R_f to sign $(\partial M^*/\partial f)$:

$$\text{sign}\left(\frac{\partial M^*}{\partial f}\right) = \text{sign}(\Pi_{z_i f}^i \{1 + \gamma_M [T + \theta(n-1) M]\} + \theta(n-1) \Pi_{z_j f}^i). \quad (6)$$

The net effect of f is ambiguous. There is a positive effect of increasing the payoff to the firm's own knowledge level, and a negative effect of spillovers being more damaging to the firm. Thus, both components of technological opportunity, f and T , have ambiguous effects on optimal R&D spending, although for different reasons. The countervailing negative effect of T results from diminishing returns to knowledge, and that of f reflects the negative appropriability incentive associated with spillovers.

²¹ We can derive the same qualitative result as below with a positive θ under the assumption invoked and motivated before, that $\Pi_{z_i z_i}^i + \Pi_{z_j z_j}^i + (n-2) \Pi_{z_i z_j}^i < 0$. The complete characterisation of R_T is:

$$R_T = \Pi_{z_i}^i \gamma_M + \gamma \{[\Pi_{z_i z_i}^i + (n-1) \Pi_{z_i z_j}^i] \{1 + \gamma_M [\theta(n-1) M + T]\} + \theta(n-1) \gamma^2 [\Pi_{z_i z_j}^i + \Pi_{z_j z_j}^i + (n-2) \Pi_{z_i z_i}^i]\}.$$

We are interested not only in the direct effect of technological opportunity on the firm's R&D level, but, particularly for the empirical analysis, how this effect is mediated by the ease of learning. We find that increasing β has the same qualitative effect on the influence of both T and f . Increasing β causes increases in T or f to call forth higher levels of R&D spending, notwithstanding the sign of their direct effects. If we again focus exclusively on the first-order effects of knowledge on firm profits and assume $\gamma_{MM} = 0$, we sign $(\partial^2 M^* / \partial T \partial \beta)$ by deriving $R_{T\beta}$, which equals $\gamma_{M\beta} \Pi_{z_i}^i$. A higher level of β increases the incentive to build absorptive capacity in order to assimilate the greater level of outside knowledge. Thus, the first-order effect suggests that increasing β causes R&D to increase more (or decline less) with increases in external knowledge.

The analysis of the effect of β on $(\partial M^* / \partial f)$ resembles that of β on $(\partial M^* / \partial \theta)$, involving three similar incentives.²² The first represents an enhancement of the absorption incentive effect. The second is that increasing β diminishes competitors' absorptive capacities, and thereby reduces the negative appropriability incentive. Finally, as firm j 's optimal R&D increases with β , increases in the pool of knowledge are all the more valuable as f increases. However, to the firm's detriment, the competitor's absorptive capacity also increases with M_j . If the positive marginal effect of f on the contribution of own knowledge to profits is greater than the magnitude of its negative marginal effect on the influence of competitors' knowledge on firm i 's profits (i.e., $|\Pi_{z_i f}^i| > |\Pi_{z_j f}^j|$), then this latter incentive is positive. Given this assumption, the first-order effects suggest that higher levels of β should cause R&D to increase (or decrease less) as f increases.

III. EMPIRICAL ANALYSIS

Our theoretical analysis suggests that the determinants of the ease of learning (i.e., β), including the targeted quality of knowledge and the characteristics of scientific fields (such as pace of advance and cumulativeness), should have a direct effect on R&D intensity. We also hypothesise that these variables condition the influence on R&D of technological opportunity and appropriability conditions. The Levin *et al.* survey data on technological opportunity and appropriability conditions do not permit construction of direct measures of the ease of learning or its determinants, and thus do not allow analysis of their direct effects. These survey data do, however, permit an examination of the ways in which the effects of technological opportunity and appropriability on R&D intensity are influenced by the ease of learning.

In Section III.1, we describe the data. In Section III.2, we operationalise the

²² Deriving $R_{\beta f}$ and again focusing on the first-order effects, we have

$$R_{\beta f} = \gamma_{M\beta} [T + \theta(n-1)M] \Pi_{z_i f}^i + \theta(n-1) \gamma_{\beta} \Pi_{z_j f}^j + \theta(n-1) \gamma_M (\Pi_{z_i f}^i + \Pi_{z_j f}^j) \frac{\partial M^*}{\partial \beta}.$$

Consistent with our assumption above that $|\Pi_{z_i}^i| > |\Pi_{z_j}^j|$, we assume that $|\Pi_{z_i f}^i| > |\Pi_{z_j f}^j|$. Again, this property can be shown to hold in the context of the example developed in the technical appendix available from the authors.

hypotheses and discuss the empirical specification. In Section III.3, estimation issues are considered, and in Section III.4, the results are presented.

III.1. Data

Our dependent variable is company-financed business unit research and development expenditures, expressed as a percentage of business unit sales and transfers over the period 1975–7. The variable was averaged to control for possible differences in the impact and timing of business cycles across industries. Business unit level data on firms' R&D expenditures and sales were obtained from the Federal Trade Commission's Line of Business Programme. Data on inter-industry differences in technological opportunity and appropriability conditions were drawn from the survey data collected by Levin *et al.* (1983, 1987).²³ The survey-based variables are defined at the FTC's line of business level, which is between the SIC's three and four digit levels of aggregation. All the survey-based variables are industry (line of business) mean scores computed as an average over all respondents within a given industry.²⁴

We used two samples in our analysis. The larger sample includes both R&D performing and non-performing business units, and consists of 1,719 business units representing 318 firms in 151 lines of business. The smaller sample includes only R&D performing business units, and consists of 1,302 business units representing 297 firms in 151 lines of business. Table 1 presents the mean, median, and minimum and maximum values for, respectively, R&D intensity, business unit sales, and firm sales for each of the two samples. As Table 1 suggests, business units performing R&D are on average larger than those that do none, and tend to be operated by larger parent firms. We should note that even our more inclusive sample is not quite representative of the manufacturing sector as a whole, because the sample is restricted to only those lines of business covered by the Levin *et al.* survey.²⁵

III.2. Specification

Our hypotheses are tested in the context of a simple empirical model of business unit R&D intensity which considers technological opportunity, appropriability, and demand conditions as principal industry-level determinants.

²³ We wish to thank Professors Levin, Klevorick, Nelson, and Winter for permitting us to use these data.

²⁴ Respondents were R&D laboratory managers.

²⁵ Both samples are drawn from a larger sample, constructed from the FTC's Line of Business Programme dataset, that consists of 2,494 business units, representing 345 firms operating in 244 manufacturing lines of business. This larger dataset, developed by Cohen and Mowery (1984), excludes all firms in the FTC database that operate mainly in regulated industries, and firms with obvious inter-temporal inconsistencies in reporting methods or other obvious reporting errors. All business units operating outside the manufacturing sector, and those that were not continuously active during the period 1974–7, were excluded as well. See Cohen and Mowery (1984, Appendix V) for a discussion of the screening procedures used to check the validity of the FTC's Line of Business Programme R&D data. Relative to the full sample of 2,494 business units, the firms and business units covered by the Levin *et al.* survey tend to be somewhat larger, and R&D intensity is somewhat higher. For example, in the sample of 2,494 business units, the mean R&D intensity is 1.59%, the mean business unit sales is 0.20 billion dollars, and the mean sales of the parent firm 2.31 billion dollars. In comparison, Table 1 indicates that for our sample of 1,719 business units, the mean R&D intensity is 1.81%, the mean business unit sales is 0.25 billion dollars, and the mean sales of the parent firm is 2.46 billion dollars.

Table 1
Descriptive statistics on R&D intensity, business unit sales and firm sales by sample

	R&D intensity* (%)		Business unit sales (\$billion)		Firm sales (\$billion)	
	All business units (<i>N</i> = 1,719)	R&D performers only (<i>N</i> = 1,302)	All business units (<i>N</i> = 1,719)	R&D performers only (<i>N</i> = 1,302)	All firms (<i>N</i> = 318)	R&D performers only (<i>N</i> = 297)
Mean	1.81	2.31	0.25	0.30	2.46	2.57
Median	0.81	1.30	0.07	0.08	1.23	1.31
Minimum†	0.00	0.00	0.00	0.01	0.11	0.12
Maximum†	22.35	22.35	16.04	16.04	34.13	34.13

* Business unit R&D spending as a percentage of business unit sales and transfers.

† To preserve the confidentiality of responding firms, we report the mean values of the four smallest and largest business units of firms, respectively.

Technological Opportunity

In assessing the importance for technological progress of what are considered to be two sources of technological opportunity – the relevance of science and the importance of extra-industry sources of knowledge – the Levin *et al.* survey data permit us to examine the effects of the determinants of the ease of learning on the influence of technological opportunity. The survey provides a measure of the relevance to an industry's R&D of each of eleven basic and applied scientific fields for each line of business (Levin *et al.*, 1983, Question III.A). The basic sciences include biology, chemistry, geology, mathematics, and physics. The applied sciences include agricultural science, applied mathematics/operations research, computer science, materials science, medical science, and metallurgy. In the survey questionnaire, relevance is assessed on a seven-point Likert scale in which a score of one indicates no relevance and a seven indicates the field is very relevant.²⁶ 'Relevance' may be interpreted to reflect either of the two dimensions of technological opportunity represented in our model, *T* or *f*. If by the relevance of a field of science, the respondent means the quantity of the research findings of, say, physics that applies to its business, then *T*, the quantity of outside knowledge, is the appropriate representation. If, alternatively, relevance refers to the impact on profit of the technical advance

²⁶ As indicated in Cohen *et al.* (1987), there are several statistical problems associated with the use of Likert-scale survey responses as independent variables in regressions. The most important is whether responses along a semantic continuum can be treated as if they were interval data. In the absence of adequate alternative measures, we assume that such treatment is reasonable. Given this assumption, there remain other potential sources of measurement error. First, individual respondents may differ in their use of the seven-point scale. After conducting a preliminary examination of the importance of inter-rater differences in mean responses and in the variance of responses, Levin concluded that the ranking of industry mean responses to particular questions is reasonably insensitive to correction for these individual effects. Another form of measurement error is introduced by using industry means instead of individual responses. We attempt to control for this type of error by including the number of survey responses per industry among the variables used to correct regression results for heteroscedasticity.

generated by using some quantity of research output from a particular field, then f is the appropriate representation.

The survey questionnaire also asks respondents to evaluate the importance (on a seven-point scale) of the contributions of various external sources of knowledge to technical progress within each line of business (Levin *et al.*, 1983, Question III.E). Five sources of outside knowledge are considered: upstream suppliers of raw materials and equipment (*MATERIALTECH* and *EQUIP-TECH*, respectively), downstream users of the industry's products (*USER-TECH*), government agencies and research laboratories (*GOVTECH*), and universities (*UNIVTECH*). Like our interpretation of the 'relevance' of scientific fields, we interpret the 'importance of the contribution to technical progress' of the external sources of knowledge to refer to either T or f . If 'importance of the contribution' reflects T , it represents how much knowledge from each source is of use. If it reflects f , it represents the impact of a given quantity of knowledge from that source on technical advance and profit.

In our empirical analysis, we are able to approach the ambiguity of the terms 'relevance' and 'importance' with equanimity because, whether these notions represent T or f , our model predicts that β should condition their influence on R&D intensity in the same qualitative fashion. Specifically, for a given change in either T or f , the effect of that change on R&D should be more positive the higher is β .

The question is how do we observe the mediating effect of β on the influence of technological opportunity (i.e., f or T) given no direct measure of β or its determinants. Recall that we have eleven variables indicating the technological opportunity associated with each of eleven scientific fields for each line of business,²⁷ and five variables indicating the technological opportunity associated with each of five sources of external knowledge. These two sets of variables allow us to test for the influence of β if one assumes that β varies across the elements of each set. Determinants of β , such as cumulativeness, pace of advance, or the targeted quality of knowledge, are all field-specific to some degree. Therefore, one test of the influence of β is to see whether the effect on R&D spending of technological opportunity differs across the field variables. However, we can go beyond this relatively weak proposition.

Our theory suggests that as β increases, the effect of either f or T on R&D spending becomes more positive. Therefore, if we can ordinaly rank the value of β across either the field variables or the knowledge sources variables, then we can predict the ordinal rank of the effects of these variables on R&D intensity. We suggest that there are categorical differences across the elements of each set

²⁷ One might argue that it is not the relevance of every field of science that represents the dimension of technological opportunity associated with an industry's closeness to science. Rather, it may be the relevance of the most relevant field. To represent this notion of technological opportunity, we examined the effect of a variable that represents the maximum of the relevance scores received by the fields of science for each line of business. Given the close conceptual and operational relationship between this variable and the vector of variables representing the relevance of each of the scientific fields, it is not surprising that the coefficient of the variable is never significant when the field vector is included, while it is always positive and significant when the field relevance variables are dropped. Also, when this variable alone is dropped, none of the qualitative results change. We therefore omit it from our specifications.

of variables that roughly correspond to differences in one determinant of β . A characteristic that distinguishes the basic from the applied sciences is the extent to which findings are targeted to the needs and concerns of firms, where the knowledge associated with basic science is less targeted than that associated with applied science. Accordingly, the β value associated with basic science is higher than that associated with applied science. Our analysis of the influence of β then suggests that for a given change in the technological opportunity associated with less targeted basic science, firms will conduct relatively more R&D. Thus, the coefficient values of the technological opportunity variables associated with the basic sciences should exceed those of the applied sciences.

The targeted quality of knowledge not only distinguishes fields; it also distinguishes the knowledge originating from external sources. By distinguishing the five extra-industry sources of knowledge on the basis of how targeted to a firm's needs the knowledge is, we can predict the ordinal ranking of the associated effects on R&D spending. Although we cannot distinguish all five sources of knowledge on the basis of how targeted they are to a firm's needs, we can approximately rank four of the five. First, we would expect suppliers' knowledge to be most targeted since such knowledge is often conveyed to stimulate sales. Between equipment and materials suppliers, the knowledge provided by equipment suppliers is typically more targeted since suppliers tend to differentiate their products more via support service and point-of-sale information. On the other end of the spectrum, we suggest that the knowledge generated by university laboratories is the least targeted because it tends to be the most oriented toward basic science and is typically conducted with little regard for its exploitation by manufacturing firms. The knowledge generated by government laboratories also tends to be basic scientific, although many government laboratories also concern themselves with applied problems. In addition, some government laboratories work quite closely with, and are often managed by, large manufacturing firms. Thus, as the knowledge from each of these four sources is scored as 'more important' to a given industry, the magnitude of their respective effects should be ranked in ascending order as follows: 1. *EQUIPTECH*; 2. *MATERIALTECH*; 3. *GOVTECH*; 4. *UNIVTECH*.

It is difficult to predict the ordinal rank of *USERTECH*, the importance of knowledge from users, for two reasons. First, as von Hippel (1978) suggests, users will often provide a product idea to potential suppliers, but the informativeness of the 'solution concept' is quite variable. Therefore, the targeted quality of the information is variable as well. Second, *USERTECH* may actually reflect something other than technological opportunity because this particular source of knowledge, users, is also an important source of information on market demand. *USERTECH* may, therefore, represent some dimension of demand conditions.

Appropriability

Having considered how the ease of learning affects the influence of technological opportunity on R&D spending, we now consider how an endogenous absorptive capacity shapes the way in which appropriability conditions influence R&D spending. To represent the level of intra-industry

spillovers, θ , we use a measure drawn from the Levin *et al.* survey. Respondents were asked to rate (on a seven-point scale) the effectiveness of six mechanisms used by firms to capture and protect the competitive advantages of new processes and new products.²⁸ For a line of business, *APPROPRIABILITY* is the maximum score received by any one of these mechanisms for either process or product innovations. Thus, if *APPROPRIABILITY* increases, the spillover level declines.²⁹

Our general model predicts that as β increases, the negative appropriability incentive associated with spillovers diminishes relative to the positive absorption incentive, implying that the coefficient of *APPROPRIABILITY* should decline. Our more specialised model predicts that the coefficient of *APPROPRIABILITY* should also decline as the price elasticity of demand and the number of firms in the industry increase. To test these hypotheses, we interact measures of each of these three variables with *APPROPRIABILITY*. We should, however, be cautious in interpreting our results, since our prediction of the effects of industry structure and the demand elasticity emerge from our specialised model that, while directly considering process R&D, may be interpreted to also consider product R&D only under restrictive assumptions.

As an index of the number of firms in an industry, we employ four-firm concentration ratios (C_4) taken from the 1977 Census of Manufactures. When necessary, these concentration ratios are aggregated to the FTC's line of business level using the value of shipments as weights. Since C_4 will tend to diminish as the number of firms in the industry increases, we hypothesise a positive coefficient on the interaction of C_4 and *APPROPRIABILITY*. To represent the price elasticity of demand, we employ price elasticities (*PELAS*) developed by Levin (1981), and predict a negative effect of the interaction of *APPROPRIABILITY* and *PELAS*.

The representation of β is a more difficult matter. We distinguish categorically among industries on the basis of whether basic science or applied science is, on average, more relevant, and assume that the targeted quality of extramural knowledge is less in the former case. Two dummy variables, *DUMAPP* and *DUMBAS*, denote those industries for which the applied or the basic sciences are, respectively, the more relevant. Thus *DUMAPP* designates those industries for which β is relatively low, and *DUMBAS* designates those for which β is relatively high. Our analysis therefore suggests that the coefficient of *APPROPRIABILITY* $\times$ *DUMAPP* will exceed that of *APPROPRIABILITY* $\times$ *DUMBAS*.

Other determinants

To evaluate the role played by our featured variables, we control for other conventionally considered determinants of R&D intensity. Another variable which may reflect a dimension of technological opportunity is industry

²⁸ These mechanisms are patents to prevent duplication, patents to secure royalty income, secrecy, lead time, moving quickly down the learning curve, and complementary sales and service efforts (Levin *et al.*, 1983, Questions I.A and I.B).

²⁹ In terms of our theory, *APPROPRIABILITY* represents $(1 - \theta)$. The reader should note that while spillover effects, reflecting the interaction of θ and γ in our model, are endogenous, $(1 - \theta)$, or *APPROPRIABILITY* in the empirical model, is not.

maturity. We employ *NEWPLANT* to reflect the relative maturity of an industry's technology. It measures the percentage of an industry's property, plant, and equipment installed within the five years preceding 1977, as reported to the FTC's Line of Business Programme.

To represent industry demand conditions, we use industry estimates, previously developed by Levin (1981), of price elasticity (*PELAS*) and income elasticity (*INCELAS*), and a time shift parameter (*DGROWTH*). We expect demand growth and income elasticity to be positively associated with R&D intensity, but the expected effect of the price elasticity of demand is ambiguous. Elastic demand should provide a positive incentive to invest in process R&D, while an inelastic demand may encourage product R&D by magnifying the returns from a rightward shift in the demand curve.³⁰

III.3 *Estimation Issues*

To estimate our specifications, three problems are addressed. First, using a Breusch-Pagan statistic to test for heteroscedasticity, we could not always accept the null hypothesis of homoscedasticity. Where heteroscedasticity was evident, we found the error structure to be one of 'multiplicative heteroscedasticity,' in which the logarithm of the error variance is a linear function of the exogenous variables and the number of respondents to the Levin *et al.* survey question in the associated line of business. In these instances we followed the procedure suggested by Harvey (1976) to obtain asymptotically efficient GLS estimates of the parameters. Breusch-Pagan statistics were then calculated for each transformed specification, and in no case can we reject the null hypothesis of homoscedasticity at the 0.05 level.

In addition to heteroscedasticity, there is a second estimation problem. Of the business unit observations in our sample, 24 % perform no R&D. If the independent variables in our model affect both the probability of conducting R&D and the amount of R&D spending, then estimating our specification on a sample that includes only R&D performing business units will bias the resulting parameter estimates due to truncation of the error term. The Tobit model addresses this problem, but at the cost of the possible specification error introduced by restricting the way in which the explanatory variables simultaneously determine the probability of performing R&D and the amount of R&D spending. Indeed, it may be the case that the variables reflecting the ease of learning may not affect the probability of engaging in R&D, but only affect R&D performance given that a firm is already conducting R&D. The reason is that a firm may require some initial level of absorptive capacity before it can recognise the characteristics of the information environment relevant to its R&D decision. For example, the findings of university labs may have no effect on a firm's propensity to conduct R&D if, without the requisite

³⁰ One may think that another variable, industry concentration, should also be considered as an independent determinant of R&D intensity. However, we omit industry concentration because it has been shown (Levin *et al.*, 1985) that once more fundamental determinants, such as appropriability and technological opportunity conditions, are controlled for, industry concentration appears to exercise no influence on R&D intensity. Indeed, when concentration is added to our benchmark specification presented in Table 2 below, we find the same result.

absorptive capacity, it cannot recognise their value. Thus, the firm must already be an R&D performer for such factors to have any effect. In this event, the sample should be confined to only the R&D performers, and OLS (or, if required, GLS), rather than Tobit, is preferred assuming that any unobserved variables affecting the likelihood of performing R&D are not correlated with the error term. In light of the uncertainty with respect to the appropriate estimation model, we explore the robustness of our results by presenting the OLS and GLS coefficient estimates for the R&D performing business units only, and the Tobit coefficient estimates for the full sample which also includes non-performers.³¹

The third estimation problem is posed by the likely endogeneity of market concentration with respect to R&D spending.³² Although concentration *per se* is not featured, we do examine the role of the interaction of the four-firm concentration ratio (C_4) with *APPROPRIABILITY*. Expecting this interactive variable to be endogenous, we employ a two stage least squares procedure. We construct an instrument by regressing *APPROPRIABILITY* $\times$ C_4 on the right-hand-side variables plus other variables thought to affect concentration.³³ Based on Lee (1981), we also use the predicted value from this regression as an instrument in our Tobit estimation.

III.4 Results

Table 2 presents the OLS, GLS, and Tobit estimates of the effects of the nature of knowledge inputs and other industry characteristics on business unit R&D intensity. In general, the results confirm our hypotheses.

Technological Opportunity

First, the coefficients (α_8 – α_{18}) of the eleven variables representing the technological opportunity associated with the scientific fields are jointly significant at the 0.01 level across all three estimation methods.³⁴ With regard to the role of learning, we can reject across all three estimation methods the hypothesis that the effects on R&D spending of the eleven applied and basic science variables are equal. This finding is consistent with our hypothesis that there exist differences in characteristics of the fields, such as pace of advance, cumulativeness, and targetedness, that affect the ease of learning, and, in turn, the influence of technological opportunity on R&D spending.

The results also confirm the related hypothesis that increasing the technological opportunity associated with the relatively less targeted basic

³¹ The OLS/GLS coefficients and the Tobit coefficients are not directly comparable because the latter should be interpreted in our model as a weighted average of two effects: (1) the effect of an increase in an independent variable on the probability that the dependent variable, R&D intensity, is greater than zero and (2) the effect on the expected value of R&D intensity given that it is above zero. If one assumes that Tobit is the correct estimation procedure, then the OLS coefficients should provide a biased estimate of the second effect. However, we are making no such assumption here.

³² Suggested by Schumpeter's (1942) notion of creative destruction, the endogeneity of market concentration is also highlighted by Phillips (1971), and Levin and Reiss (1988), among others.

³³ These include minimum efficient scale and capital intensity.

³⁴ For the relevant F, Chi-square, and Wald statistics, see the bottom of the table under discussion. In this case, see Table 2.

Table 2
Effects of knowledge and industry characteristics on R&D intensity

Parameter	Variable/hypothesis	Regression coefficient (standard error)		
		OLS (1)	GLS (2)	Tobit (3)
α_1	<i>INTERCEPT</i>	-4.226** (1.348)	-2.016* (0.945)	-3.391** (1.261)
α_2	<i>APPROPRIABILITY</i>	0.396* (0.156)	0.360** (0.104)	0.260 (0.161)
α_3	<i>USERTECH</i>	0.387** (0.099)	0.409** (0.070)	0.510** (0.106)
α_4	<i>UNIVTECH</i>	0.346** (0.128)	0.245** (0.089)	0.321* (0.147)
α_5	<i>GOVTECH</i>	0.252* (0.100)	0.170* (0.076)	0.200* (0.100)
α_6	<i>MATERIALTECH</i>	-0.315** (0.096)	-0.198** (0.070)	-0.369** (0.097)
α_7	<i>EQUIPTECH</i>	-0.392** (0.111)	-0.462** (0.079)	-0.570** (0.115)
α_8	<i>BIOLOGY</i>	0.176 (0.096)	0.042 (0.057)	0.159 (0.116)
α_9	<i>CHEMISTRY</i>	0.195** (0.071)	0.095 (0.050)	0.149 (0.078)
α_{10}	<i>MATH</i>	0.146 (0.117)	0.131 (0.093)	0.091 (0.122)
α_{11}	<i>PHYSICS</i>	0.189 (0.109)	0.037 (0.082)	0.156 (0.109)
α_{12}	<i>AGRICULTURAL SCIENCE</i>	-0.373** (0.084)	-0.253** (0.055)	-0.259* (0.101)
α_{13}	<i>APPLIED MATH/OPERATIONS RESEARCH</i>	-0.220 (0.135)	-0.001 (0.099)	-0.325* (0.136)
α_{14}	<i>COMPUTER SCIENCE</i>	0.336** (0.123)	0.157 (0.093)	0.446** (0.121)
α_{15}	<i>GEOLOGY</i>	-0.301** (0.082)	-0.228** (0.058)	-0.327** (0.095)
α_{16}	<i>MATERIALS SCIENCE</i>	-0.005 (0.121)	-0.028 (0.089)	0.231* (0.116)
α_{17}	<i>MEDICAL SCIENCE</i>	-0.076 (0.089)	-0.042 (0.062)	-0.036 (0.106)
α_{18}	<i>METALLURGY</i>	-0.244** (0.075)	-0.169** (0.052)	-0.322** (0.085)
α_{19}	<i>NEWPLANT</i>	0.055** (0.008)	0.041** (0.006)	0.042** (0.007)
α_{20}	<i>PELAS</i>	-0.180** (0.061)	-0.071 (0.044)	-0.147* (0.060)
α_{21}	<i>INCELAS</i>	1.062** (0.170)	0.638** (0.136)	1.145** (0.180)
α_{22}	<i>DGROWTH</i>	0.060 (0.090)	-0.059 (0.052)	-0.018 (0.106)
	$H_0: \text{FIELDS} = 0$	F(11, 1280)	χ^2 (11)	χ^2 (11)
	$(\alpha_8, \alpha_9, \alpha_{10}, \dots, \alpha_{18} = 0)$	9.341**	8.575**	99.059**
	$H_0: \alpha_8 = \alpha_9 = \alpha_{10} = \dots = \alpha_{18}$	F(10, 1280)	χ^2 (10)	χ^2 (10)
		9.987**	9.287**	98.839**

Table 2 (cont.)

Variable/hypothesis	OLS (1)	GLS (2)	Tobit (3)
H_0 : <i>EXTRA-INDUSTRY</i> <i>KNOWLEDGE</i> = 0 ($\alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7 = 0$)	F(5, 1280) 17.433**	χ^2 (5) 25.615**	χ^2 (5) 90.988**
H_0 : $\alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7$	F(4, 1280) 19.912**	χ^2 (4) 29.194**	χ^2 (4) 89.782**
H_0 : $\alpha_3 = \alpha_4$	F(1, 1280) 0.054	χ^2 (1) 1.894	χ^2 (1) 0.948
H_0 : $\alpha_4 = \alpha_5$	F(1, 1280) 0.230	χ^2 (1) 0.291	χ^2 (1) 0.322
H_0 : $\alpha_5 = \alpha_6$	F(1, 1280) 19.844**	χ^2 (1) 14.403**	χ^2 (1) 20.32**
H_0 : $\alpha_6 = \alpha_7$	F(1, 1280) 0.200	χ^2 (1) 4.856*	χ^2 (1) 1.335
R^2	0.278		
n	1,302	1,302	1,719

* Significant at the 0.05 level.
** Significant at the 0.01 level.

sciences elicits more R&D spending than does increasing the technological opportunity associated with the applied sciences. A comparison of the coefficient magnitudes of the basic ($\alpha_8, \alpha_9, \alpha_{10}, \alpha_{11}, \alpha_{15}$) versus the applied ($\alpha_{12}, \alpha_{13}, \alpha_{14}, \alpha_{16}, \alpha_{17}, \alpha_{18}$) sciences in Table 2 reveals that, with the sole exceptions of the coefficient of *GEOLOGY* (α_{15}) among the basic sciences and *COMPUTER SCIENCE* (α_{14}) among the applied sciences, the coefficients are uniformly greater for the basic sciences.³⁵ Furthermore, one could readily argue that, although classed as a basic science by the Levin *et al.* survey, geology is as targeted as the applied fields considering its inductive methodology and intensive use by firms in the extractive sector. The other major exception to the predicted pattern, *COMPUTER SCIENCE*, reminds us that an implicit premise of this hypothesised pattern is that field characteristics affecting β other than their targeted quality do not vary. However, casual empiricism suggests that relative to the other applied fields, the pace of advance of computer science has been rapid. Thus, it is not surprising that computer science is the major exception to the postulated pattern of coefficient values if a field's pace of advance also affects β , as suggested above.

To probe further our observation that the coefficient values of the less targeted, basic science field variables exceed those of the applied fields, we estimated a specification, otherwise identical to that of Table 2, in which we constrained the coefficients of the basic sciences, excluding geology, to be the same, and the coefficients of the applied sciences, including geology, to be the same. Thus, we are examining the effect on R&D spending as the overall technological opportunity associated with basic science and applied science, respectively, change. The constrained GLS coefficient estimate of the effect of

³⁵ In column (3) presenting the Tobit results, we find one additional exception to this pattern, *MATERIALS SCIENCE*.

the technological opportunity associated with the basic sciences equals 0.130, and that of the applied sciences equals -0.049.³⁶ The Tobit coefficient estimates are 0.182 and -0.115, respectively. We can always reject the null hypothesis of the equality of these coefficients, confirming that, relative to the effect of an increase in the technological opportunity associated with applied science, an increase in that associated with basic science elicits more R&D.

Our predicted ranking of the coefficient magnitudes associated with the extra-industry sources of knowledge (*UNIVTECH*, *GOVTECH*, *MATERIALTECH*, and *EQUIPTECH*) is largely confirmed. Table 2 shows that, across all estimation methods, the coefficient estimate for *UNIVTECH* is greater than that of *GOVTECH*, which exceeds that of *MATERIALTECH*, which, in turn, exceeds that of *EQUIPTECH*. The appropriate F, Chi-square, and Wald test statistics, presented at the bottom of Table 2, indicate whether the coefficients differ significantly from one another. The coefficients of *UNIVTECH* and *GOVTECH* do not differ significantly. The coefficient estimate of *GOVTECH* is, however, significantly higher than that of *MATERIALTECH* across all estimation methods. In the GLS results the coefficient estimate of *MATERIALTECH* is significantly greater than that of *EQUIPTECH*.

Although we had no priors with respect to the ordinal rank of the coefficient of *USERTECH*, its coefficient estimates are nonetheless surprising. For all three sets of results, *USERTECH* had the highest coefficient estimate, and was always significantly different from zero. *USERTECH* may, however, be representing some dimension of demand conditions, as suggested above. For example, a high score for *USERTECH* may indicate that information from buyers is important when product differentiation is a critical dimension of competition, and that, as Comanor (1967) suggests, when product differentiation is important, firms tend to do more R&D.³⁷

The coefficient patterns for both the scientific field variables and the extra-industry knowledge source variables are predicted by our hypothesis that an increase in technological opportunity (i.e., f or T) elicits greater R&D spending the higher is β . Is there, however, another explanation? If we assume that the values of the relevance scores for a given field of science or knowledge source have little effect on own R&D productivity, and the main effect occurs across the technological opportunity variables, perhaps the results simply indicate that the marginal productivity of R&D is greater as the underlying

³⁶ The OLS estimates yield the identical qualitative results. Also, constraining the basic science variables and the applied science variables to have the same coefficient values raises the question whether, beyond this simple distinction, do individual field characteristics add any explanatory power. To address this, we tested whether the coefficient values across the applied science variables equal one another, and the coefficient values across the basic science variables equal one another. With geology considered as a basic science, we can reject both null hypotheses at the 0.05 confidence level. Treating geology as an applied science changes the result. We then cannot reject the null hypothesis that the coefficients of the basic science variables are equal, but can reject, at the 0.01 level, the null hypothesis that the applied science variables exercise the same effect.

³⁷ To probe the relationship between *USERTECH* and product differentiation, we computed the correlation coefficient between it and two variables, also drawn from the Levin *et al.* survey, that measure on a seven-point Likert scale the importance in each line of business of, respectively, 'improving the physical properties of the product,' and 'improving the performance characteristics of the product.' The correlation coefficients are, respectively, 0.23 and 0.28, and each is significant at the 0.01 level.

knowledge base is more basic scientific in character.³⁸ First, aside from the hazard of ignoring the variation in technological opportunity associated with each field or knowledge source, it is far from obvious that basic science will have a greater effect on R&D productivity at the margin than applied science. Second, even if this were so, the observed ordinal ranking of coefficients would not necessarily be the prediction. For example, if we equate outside knowledge's productivity impact with f , the theoretical analysis above indicates that the effect of f on own R&D is ambiguous, and consequently predicts no ordinal ranking of the sort observed. Alternatively, since the results indicate that outside applied science tends to substitute for internal R&D while basic science tends to complement it, perhaps they simply show that extramural basic research is more complementary to internal R&D than applied research.³⁹ We are left, however, with the question of why external applied research acts as a substitute while more basic research acts as a complement. We suggest that because basic science is less targeted to the needs and concerns of the firm, a firm must invest more to assimilate and exploit it.

Appropriability

In Table 2, the OLS and GLS estimate of the coefficient of *APPROPRIABILITY* is positive and significant, suggesting spillovers have a negative effect on R&D. Though also positive, the Tobit coefficient estimate is not significant. These results suggest a negative *net* effect of spillovers. They do not, however, disconfirm our hypothesis that spillovers generate countervailing appropriability and absorption incentives. We therefore consider whether, as predicted, the positive absorption incentive increases relative to the negative appropriability incentive as β , the price elasticity of demand, and the number of firms in the industry rise.

Table 3 presents the coefficient estimates of the interactions between *APPROPRIABILITY* and, respectively, market concentration (C_4), the price elasticity of demand (*PELAS*), and the two dummy variables representing β (*DUMAPP* and *DUMBAS*). The results largely confirm that the ease of learning conditions the effect of *APPROPRIABILITY* as hypothesised. First, the four interactions are jointly significant across all estimation methods. Second, the hypothesis that the coefficient of *APPROPRIABILITY* $\times$ *DUMAPP* should exceed that of *APPROPRIABILITY* $\times$ *DUMBAS* holds across all estimation methods, and the difference is always significant. Therefore, the

³⁸ More formally, this argument assumes that, for example, f varies across fields or knowledge sources, but not with the associated relevance scores, and that the results reflect the direct effect, $(\partial M^*/\partial f)$, not the cross partial, $(\partial^2 M^*/\partial f \partial \beta)$ and therefore do not reflect the influence of the ease of learning.

³⁹ Because our central hypotheses with respect to the technological opportunity variables concern the ordinal ranking of their coefficients, we have not considered their signs. We do observe, however, that the signs of the applied fields are generally negative and those of the basic fields are generally positive, and the signs of *MATERIALTECH* and *EQUIPTECH* are negative, while those of *UNIVTECH* and *GOVTECH* are positive. Consistent with these findings, our theoretical analysis suggests that the sign of the direct effect of technological opportunity (either f or T in this model) on R&D may vary. If we interpret the respective technological opportunity variables as representing f , then a negative effect may be realised if the negative appropriability incentive effect is relatively large while β is relatively small. Alternatively, if these variables represent T , then diminishing returns to knowledge may account for negative signs, again assuming that β is relatively small. In either case, a higher value of β will tend to be associated with a positive coefficient.

Table 3
*Effect of appropriability interactions and knowledge and industry characteristics on
 R&D intensity*

Parameter	Variable/ Hypothesis	Regression coefficient (standard error)		
		OLS (1)	GLS (2)	Tobit (3)
α_1	INTERCEPT	-5.184** (1.522)	-2.355* (1.037)	-4.086** (1.461)
α_2	APPROPRIABILITY $\times$ C ₄	0.213 (0.128)	0.342** (0.103)	0.368** (0.130)
α_3	APPROPRIABILITY $\times$ PELAS	-0.192 (0.106)	-0.200* (0.091)	-0.176 (0.103)
α_4	APPROPRIABILITY $\times$ DUMAPP	0.448* (0.202)	0.248 (0.143)	0.211 (0.194)
α_5	APPROPRIABILITY $\times$ DUMBAS	0.302 (0.208)	0.174 (0.144)	0.094 (0.206)
α_6	USERTECH	0.470** (0.104)	0.397** (0.069)	0.612** (0.107)
α_7	UNIVTECH	0.374** (0.131)	0.318** (0.091)	0.395** (0.147)
α_8	GOVTECH	0.221* (0.106)	0.069 (0.079)	0.137 (0.107)
α_9	MATERIALTECH	-0.258** (0.098)	-0.074 (0.070)	-0.303** (0.100)
α_{10}	EQUIPTECH	-0.401** (0.111)	-0.484** (0.077)	-0.574** (0.117)
α_{11}	BIOLOGY	0.314** (0.102)	0.185** (0.071)	0.276* (0.114)
α_{12}	CHEMISTRY	0.289** (0.084)	0.081 (0.062)	0.191* (0.088)
α_{13}	MATH	0.184 (0.131)	0.151 (0.097)	0.123 (0.143)
α_{14}	PHYSICS	0.373** (0.117)	0.323** (0.091)	0.310* (0.128)
α_{15}	AGRICULTURAL SCIENCE	-0.441** (0.088)	-0.273** (0.064)	-0.308** (0.099)
α_{16}	APPLIED MATH/OPERATIONS RESEARCH	-0.237 (0.148)	-0.117 (0.102)	-0.366* (0.152)
α_{17}	COMPUTER SCIENCE	0.294* (0.124)	0.116 (0.090)	0.433** (0.122)
α_{18}	GEOLOGY	-0.363** (0.084)	-0.240** (0.061)	-0.365** (0.097)
α_{19}	MATERIALS SCIENCE	-0.110 (0.125)	-0.150 (0.095)	0.116 (0.118)
α_{20}	MEDICAL SCIENCE	-0.179 (0.093)	-0.133 (0.070)	-0.133 (0.103)
α_{21}	METALLURGY	-0.315** (0.077)	-0.195** (0.053)	-0.393** (0.089)
α_{22}	NEWPLANT	0.057** (0.008)	0.049** (0.006)	0.045** (0.007)
α_{23}	PELAS	0.936 (0.611)	1.082* (0.527)	0.892 (0.573)
α_{24}	INCELAS	1.077** (0.170)	0.587** (0.131)	1.112** (0.188)

Table 3 (*cont.*)

Parameter	Variable/ Hypothesis	Regression coefficient (standard error)		
		OLS (1)	GLS (2)	Tobit (3)
α_{25}	<i>DGROWTH</i>	0.068 (0.090)	-0.074 (0.053)	0.004 (0.105)
	$H_0: \alpha_2, \alpha_3, \alpha_4, \alpha_5 = 0$	$F(4, 1277)$	$\chi^2(4)$	$\chi^2(4)$
	$H_0: \alpha_4 = \alpha_5$	5.773** $F(1, 1277)$	7.367** $\chi^2(1)$	18.783** $\chi^2(1)$
	R^2	10.495** 0.287	5.169*	5.545*
	n	1,302	1,302	1,719

* Significant at the 0.05 level.

** Significant at the 0.01 level.

positive absorption incentive associated with spillovers appears to increase relative to the negative appropriability incentive in industries where β is higher. Third, as predicted, the effect of *APPROPRIABILITY* $\times$ *C4* is positive across all estimation methods, and is significant in the GLS and Tobit estimations. Finally, the coefficient of *APPROPRIABILITY* $\times$ *PELAS* is always negative as predicted, but is significant only in the GLS estimate.⁴⁰

As suggested above, the predictions on the effects of the interactions of *APPROPRIABILITY* with concentration and price elasticity are derived from a model of process innovation.⁴¹ The dependent variable in the Table 3 specification, however, is total business unit R&D intensity. Therefore, to explore the robustness of our results, we replace our dependent variable with an approximation of business unit process R&D intensity and re-estimate the equation.⁴² We do not feature this specification, however, because adjusting our dependent variable comes at the cost of introducing measurement error into the majority of our right-hand-side variables. While the Levin *et al.* survey permits us to measure *APPROPRIABILITY* for process innovations alone, none of the measures of technological opportunity distinguish between process and product innovation. This introduces measurement error if respondents' evaluations of technological opportunity are weighted largely by their views characterising product, rather than process innovation, which may be expected since most R&D in American manufacturing is product R&D.⁴³ Moreover, we

⁴⁰ It is, however, significant at the 0.10 level in both the Tobit and OLS results.

⁴¹ In contrast, the effect of the interaction of our proxy variable for β is derived from the general model.

⁴² To approximate business unit process R&D intensity, we multiply total business unit R&D intensity by the share of each industry's innovations represented by process innovations. The estimates of each industry's share of process innovations were developed by F. M. Scherer using patent data. Scherer (1982, 1984) classified all US patents granted within a 15 month period in the mid-1970's by industry of origin and industry of use, and assumed that process innovations are those represented by patents used in their industry of origin. We use this data to divide an industry's R&D expenditure between process and product R&D assuming that each industry devotes to process innovation a percentage of R&D equal to the percentage of its patents assigned to processes. As noted in Cohen and Levin (1989), this assumption is suspect, however, to the extent that process innovations are less likely to be patented than product innovations.

⁴³ Employing Scherer's measures of the shares of process and product innovation, we find that approximately 29% of the business unit R&D in our sample is dedicated to process innovation, and 71% is dedicated to product innovation.

cannot reasonably assume that the technological opportunity facing product innovation is the same as that facing process innovation within a line of business.

Despite these difficulties, using process R&D intensity as the dependent variable scarcely changes the qualitative results of interest. The coefficient of *APPROPRIABILITY* $\times$ *PELAS* remains negative, but is no longer significant. The coefficient of *APPROPRIABILITY* $\times$ *C*₄ becomes significantly positive across all three estimates. The coefficient of *DUMAPP* remains significantly greater than that of *DUMBAS* in the OLS and GLS specifications.⁴⁴ However, consistent with the expected introduction of measurement error into the technological opportunity measures, the F statistics testing the joint significance of the technological opportunity variables decline, and the variance explained by the equation drops by more than half.

As predicted, increases in β , the price elasticity of demand, and the number of firms in the industry appear to diminish the coefficient of *APPROPRIABILITY*, reflecting a relative increase in the positive absorption incentive associated with spillovers. The question remains, however, whether spillovers may, on balance, actually encourage R&D in some industries. To explore this possibility, we examine the effect of *APPROPRIABILITY* in the four two-digit SIC code level industries for which our sample contains enough lines of business to permit separate industry regressions.⁴⁵ These include SICs 20 (food processing), 28 (chemicals), 35 (machinery), and 36 (electrical equipment). The OLS and GLS estimates show that in SIC's 28 and 36, the effect of *APPROPRIABILITY* is negative and significant, implying that R&D intensity rises with spillovers.⁴⁶ It is interesting to note that SIC 36 is the two-digit industry group in which the semiconductor industry is found, the industry whose coincidence of high spillovers and high R&D perplexed Spence (1984).⁴⁷ Most importantly, we obtain these results after controlling for other industry-level variables conventionally thought to drive R&D spending, including technological opportunity and demand conditions. Although a negative effect of spillovers in these two industry groups does not represent a direct test of our model, it does suggest, particularly when considered with our Table 3 results, that the positive absorption incentive associated with spillovers may be

⁴⁴ In the Tobit estimation, the difference is significant at the 0.10 level.

⁴⁵ The technical appendix available from the authors provides a detailed discussion of the specification, the estimation procedure, and the results for these two-digit level industry regressions.

⁴⁶ In the Tobit results, the sign of *APPROPRIABILITY* is also negative for SIC's 28 and 36, but the coefficient estimates are not quite significant at the 0.05 level.

Our explanation for a negative coefficient on *APPROPRIABILITY* is that firms invest in R&D to build the absorptive capacity that permits them to assimilate and exploit spillovers. An alternative explanation is that the immediate R&D effort associated with the process of imitation in these industries is considerable, and we are simply observing a lot of costly imitation. However, if such immediate imitation costs are largely a negative function of prior investment in absorptive capacity, as we would suggest, this second argument is a corollary of our own. Also, this argument alone would not explain the interaction effects observed in Table 3.

⁴⁷ Bernstein (1988) also found a positive effect of spillovers on R&D intensity for the Canadian electrical products and chemicals industries. Bernstein and Nadiri (1989), however, found no such positive effect in their study of spillovers in American manufacturing.

sufficiently strong in some cases to more than offset the negative appropriability incentive.

IV. CONCLUSION

We have argued that firms invest in R&D not only to pursue directly new process and product innovation, but also to develop and maintain their broader capabilities to assimilate and exploit externally available information. Recognition of the dual role of R&D suggests that factors that affect the character and ease of learning will affect firms' incentives to conduct R&D. We hypothesised that such factors include the degree to which knowledge is targeted to a firm's needs, and, more generally, the character of knowledge within each of the scientific and technological fields upon which innovation depends. Our analytic model suggests these factors should both exercise a direct effect on inventive activity, and condition the influence of more conventionally considered determinants.

Aside from market demand, applied economists have identified technological opportunity and appropriability as the principal industry-level determinants of the firm's inventive activity (Cohen and Levin, 1989). We suggest, however, that since the effect of both of these classes of variables depend importantly upon the assimilation of external knowledge, their influence is mediated by the firm's capacity to recognise, assimilate, and exploit information. Therefore, those variables that affect the ease and character of learning should, in turn, influence how technological opportunity and appropriability conditions influence R&D spending. The empirical results generally confirm that the influence of both appropriability and technological opportunity conditions is affected by determinants of the ease of learning, particularly the targeted quality of knowledge inputs. This, in turn, suggests that the characteristics of knowledge that affect the ease of firm learning may represent an important class of determinants of R&D investment.

The observation that R&D creates a capacity to assimilate and exploit new knowledge sheds new light on a range of questions. For example, it provides a ready explanation of why some firms may invest in basic research even when the preponderance of findings spill out into the public domain. Specifically, firms may conduct basic research less for particular results than to be able to identify and exploit potentially useful scientific and technological knowledge generated by universities or government laboratories, and thereby gain a first-mover advantage in exploiting new technologies. Likewise, basic research may permit firms to act as a rapid second mover in the face of spillovers from a competitor's innovation. This perspective implies that variables that influence the firm's incentives to learn should affect the incentives to conduct basic research. For example, as automobile manufacturing depends increasingly on fields that draw heavily on basic science, such as microelectronics and ceramics, we expect that manufacturers will expand their basic research efforts in physics and chemistry to evaluate and exploit new findings in these areas. Similarly, as a firm's technological progress depends upon an increasing number of fields of

basic science, a firm will increase its basic research as it mounts efforts in each field. Thus, even if a firm is not widely diversified, but the knowledge inputs relevant to technical advance become more varied, we may expect an increase in basic research. In contrast, Nelson (1959) hypothesises that firms which are more diversified in terms of product markets will invest more heavily in basic research because, assuming imperfect markets for information, they will be better able to exploit the potentially wide-ranging findings.

Recognition of the dual role of R&D also offers important implications for the analysis of the adoption and diffusion of innovations. Although the importance of various forms of learning have been highlighted in the diffusion literature, it has not been widely appreciated in this context that a firm's R&D contributes to its ability to learn.⁴⁸ Our perspective implies that the ease of learning, and, thus, technology adoption, is affected by the character of the knowledge inputs in question. For example, we would suggest that an innovation which is purely capital embodied is less costly to adopt than more disembodied innovations that require more complementary internal effort, and more pre-existing expertise in an area. We also conjecture that a product innovation developed on the basis of a well established underlying knowledge base will diffuse more rapidly among users than one grounded in a more recently developed body of scientific or technological knowledge. Finally, R&D's contribution to absorptive capacity also implies that, particularly for new intermediate goods that require substantial complementary R&D effort on the part of adopters, the R&D expenditures of the innovating industry and those of the adopting industry are jointly determined in the long run.

In addition to offering theoretical and empirical implications, our analysis suggests a lesson for technology policy. Economists have long cautioned policymakers about the welfare costs of policies, such as patents, that curtail the negative incentive effects of intra-industry spillovers by conferring monopoly power. Recently, Spence (1984) has highlighted a cost of a different sort. By increasing the appropriability of the rents due to new knowledge, society foregoes the socially beneficial efficiency effects of spillovers associated with the diminution of redundant R&D effort. Our analysis of the role that R&D plays in firm learning adds another dimension to the evaluation of the welfare effects of patents and similar policies. In particular, it implies that the negative incentive effects of spillovers and, thus, the benefits of policies designed to mitigate these effects, may not be as great as supposed.

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⁴⁸ An important exception is Mansfield *et al.* (1977) whose finding that diffusion occurs more rapidly in more R&D intensive industries supports our general argument. See Thirle and Ruttan (1987) and Stoneman (1987) for recent reviews of the literature on adoption and diffusion. Both of these works briefly describe the way in which the notion of learning has been treated in this literature.

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