R&D/Returns Causality: Absorptive Capacity or Organizational IQ

Anne Marie Knott
John M. Olin Business School, Washington University in St. Louis, St. Louis, Missouri 63130, knott@wustl.edu

Absorptive capacity is the principle that assimilating new knowledge requires prior knowledge. The attendant prescription is to invest more in R&D to derive greater benefit from the R&D of others (spillovers). Empirical tests of R&D productivity typically find absorptive capacity (R&D \times rival R&D) to be significant. This result poses a puzzle, however: What can a firm conducting 50% of industry R&D learn from a set of firms each conducting 5%? Aren’t the laggard firms merely playing catch-up? Yet, if this is so, why is the interaction term significant?

One possible resolution to this puzzle is that the correlation between R&D spending and returns is really about innate ability (IQ) rather than investment behavior (absorptive capacity). In this view the causality between capability and behavior is reversed. It is not that firms obtain higher returns by investing more in R&D; it is that some firms have higher returns to R&D, thus they invest more. I conduct an empirical test of the competing views and find that (1) firms differ in the output elasticities of their own R&D (IQ) as well as the elasticities of spillovers from rivals, (2) absorptive capacity becomes insignificant when accounting for that heterogeneity, (3) R&D investment increases with IQ, but (4) R&D investment has no impact on a firm’s ability to benefit from spillovers.

Key words: absorptive capacity; organizational IQ; R&D; spillovers

History: Accepted by Pankaj Ghemawat, business strategy; received January 2, 2006. This paper was with the author 10 months for 3 revisions. Published online in Articles in Advance November 5, 2008.

1. Introduction

The term absorptive capacity captures the notion that in order to assimilate knowledge you first need to have knowledge (Cohen and Levinthal 1989, 1990). The most obvious example of this is that we need to know a language in order to learn almost anything beyond basic human functions. Cohen and Levinthal (1989, 1990) develop a theory of the absorptive capacity of firms. In its most reduced form, the theory holds that a firm’s benefit from external knowledge increases with the level of its own R&D. The prescriptive implication is that firms should invest more in R&D to gain greater benefits from spillovers. Cohen and Levinthal (1989, 1990) characterize the functional form of absorptive capacity as an interaction between the firm’s own R&D and spillovers. This interaction term has been found to be significant in ordinary least squares (OLS) and instrumental variable (IV) models of the firm’s R&D production function (e.g., Jaffe 1986).

This result poses a puzzle, however. In the limit, one wonders if a firm that does 50% of industry R&D has anything to learn from a handful of firms each conducting 5% of industry R&D. Isn’t it likely that all the less R&D-intensive firms are doing is merely imitating what the technological leader already knows? If so, then there should be no gains to spillovers for the technological leader. Yet if there are no gains to spillovers, why is the interaction term significant?

One potential resolution to the puzzle is that R&D investment is endogenously determined by a more fundamental capability, something that we will refer to as organizational IQ. Organizational IQ, like individual IQ, is highly complex, but both terms refer to the capability to make use of new information. In the case of individuals this is measured as the speed and accuracy of solving a set of problems of increasing difficulty. Within any given time constraint an individual

1“A key assumption in the model is that exploitation of competitors’ research findings is realized through the interaction of the firm’s absorptive capacity with competitors’ spillovers” (Cohen and Levinthal 1990, p. 141). Absorptive capacity is operationalized in Cohen and Levinthal (1989, p. 572) as a variable, \( \gamma \), which is increasing in the firm’s own R&D at a rate defined by \( \beta \) (where \( \beta \) is a function of industry appropriability and technological opportunity).
with higher IQ will solve more problems correctly than will someone with lower IQ. In the case of firms, an equivalent construct might be efficiency in solving previously unsolved problems. If so, organizational IQ could be measured as the output elasticity of R&D investments. For any given level of R&D spending, the high-IQ firm will produce more innovations, or, for any given innovation, the high-IQ firm will invest less developing it.

If firms do indeed differ in their R&D elasticity, and if R&D investments, like most other investments, exhibit diminishing returns, then more productive firms will have an incentive to invest more in R&D. Their marginal product of R&D will equal marginal cost at a higher level of investment. This would explain why firms who invest more appear to have higher returns. However, the causality is reversed from the current view. It is not that firms will have higher returns if they invest more in R&D; it is that some firms have higher returns, thus they invest more.

I propose that the phenomenon currently ascribed to absorptive capacity is instead an artifact of prior empirical constraints. In particular, I propose that the complementarity between own R&D and spillovers is significant at least in part because prior empirical models could not accommodate heterogeneity in firm R&D elasticity. This constrained specification leads to the conclusion that firms should invest more in R&D, when in fact that strategy should yield no benefits to low-IQ firms once they reach their optimal level of R&D. With the proper specification, I conclude instead that firms need to be smarter—being smarter (having higher IQ) provides greater returns to own R&D.

This paper proceeds as follows. First I review the theoretical definition and empirical incarnation of absorptive capacity. Next I present an alternative interpretation of the empirical regularity. Finally I conduct an empirical test comparing the two explanations for the correlation between R&D spending and returns.

1.1. Absorptive Capacity: Theory and Empiricism

Cohen and Levinthal (1989, p. 128) define absorptive capacity as “the ability of a firm to recognize the value of new external information, assimilate it and apply it to commercial ends.” The authors test for absorptive capacity by combining survey data on perceived industry appropriability and technological opportunity with Federal Trade Commission line of business data on R&D investments. What they show is that high levels of appropriability (interpreted as low spillovers) increase R&D intensity.

Although Cohen and Levinthal’s empirical work examined the ability of firms to assimilate knowledge from outside industry (in particular from universities), their theoretical contribution was the potential for absorptive capacity to reduce the disincentive effect of intraindustry spillovers on firm R&D investment. Subsequent theoretical and empirical work has examined absorptive capacity both within and across industry; however, I focus attention on behavior within industry. Theoretical work develops various conclusions about the impact of absorptive capacity on firm incentives for R&D. Campisi et al. (2001), Martin (2002), and Grunfeld (2003) develop models where spillovers are endogenously determined by the potential for absorptive capacity. Campisi et al. (2001) and Martin (2002) conclude that R&D investment is unaffected by absorptive capacity. Grunfeld (2003) adds the impact of market size and finds that absorptive capacity causes firms to reduce R&D except with small markets or weak absorptive capacity.

These conclusions have largely gone untested. One exception is Jaffe (1986), who empirically models absorptive capacity as an interaction between the firm’s own R&D and the common pool of industry R&D. This matches the functional form specified by Cohen and Levinthal (1990). Jaffe’s (1986) results indicate that this interaction term is positive and significant in OLS and IV models of R&D productivity. This result implies that the firm deriving the greatest benefit from spillovers is the technological leader. This poses a puzzle: How can the leader derive the greatest benefit from spillovers if rival knowledge is redundant or inferior?

1.2. Is Knowledge Redundant?

One means to resolve the puzzle is to suggest that lower spending by rivals does not necessarily imply redundant knowledge. It is possible that firms within the same industry invest in different types of knowledge and therefore laggards offer potential for spillovers to leaders. I tackle this proposition in two ways.

The first approach demonstrates a distortion that occurs by assuming that rival knowledge is unique. Suppose the government wants to award $200 million for a particular R&D project. The goal is allocating the $200 million such that it derives the greatest innovative output, where innovative output conforms to a standard R&D production function:

\[
\ln(Y)_{it} = \beta_0 + \beta_1 \ln(own \ R&D)_{it} + \beta_2 \ln(spillovers)_{it} + \beta_3 \ln(own \ R&D)_{it} \times \ln(spillovers)_{it}. \tag{1}
\]

The question is whether the government should award all the money to one firm or whether it should divide the award equally among two or three firms.

\[\text{Results are not significant in first-difference (FD) specifications.}\]
Table 1 Implications from Stylized Facts for Subdividing R&D Award

<table>
<thead>
<tr>
<th>Firms</th>
<th>Own R&amp;D</th>
<th>Spillovers</th>
<th>Interaction</th>
<th>Own R&amp;D</th>
<th>Spillovers</th>
<th>Interaction</th>
<th>Output ($ million)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>200</td>
<td>0</td>
<td>0</td>
<td>4.67</td>
<td>0.00</td>
<td>0.00</td>
<td>106</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>100</td>
<td>10,000</td>
<td>4.06</td>
<td>4.07</td>
<td>2.96</td>
<td>130,326</td>
</tr>
<tr>
<td>3</td>
<td>67</td>
<td>133</td>
<td>8,911</td>
<td>3.70</td>
<td>4.02</td>
<td>2.92</td>
<td>125,802</td>
</tr>
</tbody>
</table>

Table 1 works through the analysis using coefficients that fall within the range of empirically observed values. Column 2 represents the size of the award to each firm under three scenarios (one firm, two firms, and three firms). Column 3 computes the spillovers from rivals under each scenario. In the case of one award, for example, there are no rivals and therefore no spillovers. Column 4 is the complementarity (absorptive capacity) obtained by multiplying columns 2 and 3. Columns 5–7 are the contributions (in ln form) from each input to a firm’s output. These values are obtained by applying representative coefficients to the input values from columns 2–4. Column 8 is each firm’s R&D output (obtained by summing the values across columns 5–7 and then converting out of ln form). Column 9 is the aggregate R&D output for all of the firms given awards (obtained by multiplying firm output (column 8) by the number of firms (column 1)). Columns 10 and 11 are the share of output gain attributed to spillovers alone.

What this exercise demonstrates is that an assumption of unique knowledge encourages the government to split the award across two firms. Doing so yields three orders of magnitude higher output than a single award ($130 billion versus $100 million). Spillovers alone account for a 20- to 40-factor increase in output, and absorptive capacity increases that by an additional factor of 15 to 19. We could argue that the coefficients are not quite right, but small changes in the coefficient values will not change the basic result. This two-firm result stands in sharp contrast to the intuition that, in the absence of incentive problems, all of the money should go to a single firm (Arrow 1962).

The second approach to the question of knowledge redundancy considers the empirical record. I examine the relationship between R&D spending and patenting. I limit the analysis to one industry (chemicals) because I need a setting where patenting is a good proxy for knowledge amounts and types. Of the three industries where I expected this to hold (chemicals, medical products, and electronic components), chemicals was the industry where firms were most likely to have at least one patent (35%) and where the number of patents was most closely correlated with R&D ($R^2 = 0.79$). Figure 1 is a matrix comparing patenting activity with R&D expenditures for the chemical firms in the sample. Patent classes are captured by columns, and firms are captured by rows, where firms are listed in ascending order of their 1995 R&D expenditures. Each cell in the matrix is the number of patents granted to a given firm between 1995 and 1999 in a given patent class. Although there are exceptions, the figure tends to suggest that firms doing less R&D are engaged in subsets of the activity of those doing more R&D. This suggests that the assumption of redundancy is plausible. The redundancy assumption is reinforced by the observation that most firms do no patenting. Given the high propensity to patent in this industry, we would expect firms to patent if their knowledge were unique and valuable to rivals.

While the puzzle of greatest benefit of spillovers to technology leaders highlights problems with the absorptive capacity construct, absorptive capacity highlights problems with the conventional view of R&D productivity. In particular the conventional view does not anticipate a correlation between investment and rate of returns. Accordingly, any new formulation of R&D productivity must (1) account for the empirical significance of the interaction term and (2) exhibit correlation between R&D spending and R&D productivity. The IQ view attempts to do this.

2. An Alternative Interpretation of Significant Complementarities: Organizational IQ

One potential explanation for the empirical regularity of significant complementarities between own and rival R&D is that it is an artifact of prior empirical constraints. In particular, the complementarity between own R&D and spillovers mimics the relationship between R&D and returns that should occur if firms differ in the output elasticity of R&D (organizational IQ) and if econometric models cannot capture those differences. With heterogeneity in R&D elasticities, the optimal level of R&D will be larger for high-IQ firms than for firms with lower IQ. This follows from the firm’s final goods production function:

$$Y = K^aL^bR^cS^d,$$  \hspace{1cm} (2)

where $Y$ is output (sales), $K$ is capital, $L$ is labor, $R$ is R&D, and $S$ is spillovers.
Profit is output minus the cost of inputs, where spillovers are assumed to be a public good and therefore obtained at zero cost:

$$\Pi = K^\alpha L^\beta R^\gamma S^\delta - K - L - R.$$  \hfill (3)

The optimal level of R&D (holding $K$, $L$, and $S$ fixed) is therefore

$$R = (1/\gamma) K^\alpha L^\beta S^\delta (1/(\gamma-1)).$$  \hfill (4)

Figure 2 presents the relationship between R&D output elasticity, $\gamma$, implied by Equation (4) where the total contribution from inputs other than R&D equals 100 ($K^\alpha L^\beta S^\delta = 100$). The figure indicates that the optimal level of R&D is increasing in $\gamma$ over the normal range of values $(0, 1)$.

If firms differ in their R&D elasticity, $\gamma$, and if firm R&D investments correspond optimally to the differences in $\gamma$, then we should observe two things. First, we should observe the positive correlation between investments and returns in Figure 2. Second, econometric models that do not accommodate the heterogeneity will allocate the higher returns of a high-IQ firm to a term associated with higher spending—the interaction term. Thus, it will appear that greater investment in R&D yields higher returns when in fact the converse is true—having higher returns yields higher investment. I derive the mathematical equivalence between heterogeneity in R&D elasticity and absorptive capacity in the appendix. Because the equivalence is not obvious, I also capture it graphically in Figure 3. Figure 3 presents three plots of observed output as a function of R&D spending. The first plot is output under an assumption of homogeneous firms with R&D elasticity ($\gamma$) of 0.125. The second plot is output under an assumption of hetero-

---

**Figure 1** Visual Test of Knowledge Redundancy for Chemicals (ISIC = 2,400)

**Figure 2** Optimal Investment vs. R&D Productivity (IQ) (Assumes Joint Contribution from All Other Inputs = 100)

**Figure 3** Absorptive Capacity Mimics Heterogeneity
homogetic R&D elasticities yield output that is of the data (R&D greater than $25 million), whereas homogeneous R&D elasticities yield output that is essentially constant over the same range.

3. Empirical Approach
I test the competing hypotheses for correlated investment and returns by empirically estimating the firm’s final goods production function (Equation (1)). I first test a baseline that mimics past generalized least squares (GLS) regressions. I then employ a random-coefficients model that accommodates heterogeneity in the output elasticity for R&D (as well as all other inputs). I expect to find the following: (1) absorptive capacity (R&D * spillovers) is significant when models do not accommodate firm heterogeneity, (2) there is heterogeneity in firm R&D elasticity (IQ), and (3) absorptive capacity is insignificant in the random-coefficients regression when I account for the heterogeneity.

A Note on Random-Coefficient Models. Random-coefficient models are ones in which each coefficient has two components: (1) the direct effect of an explanatory variable and (2) the proxy effects of omitted variables through which the explanatory variable affects the dependent variable. A random-coefficients model represents a general functional form model that treats coefficients as being nonfixed (across members of a cross section or over time) and potentially correlated with the error term. A conventional OLS model with fixed coefficients is a special case of the general form that restricts all members of a cross section to share the same coefficient (Amemiya 1978, Swamy and Tavlas 1995).

A “fixed-effects” model is actually a partial random-coefficient model in that it relaxes the constraint of fixed coefficients for the intercept but retains fixed coefficients for all other variables. The fixed-effects model transforms a single intercept into a mean value and a set of member deviations from that mean. Typically in strategy the member is a firm, and the firm fixed effects are interpreted as persistent differences in firm capability, e.g., Henderson and Cockburn (1996). The interpretation of firm capability in these models then is a fixed increase in output for any combination of inputs (intercept). I will interpret the random coefficients in a similar manner—persistent differences in firm capability. Here, however, the differences will reflect firms’ ability to convert inputs to outputs (slope).

For the main test I construct a model of Equation (1) for firm $i$ in year $t$ with random coefficients for all inputs as well as the intercept:

$$
\ln(sales)_it = (\beta_0 + \beta_i) + (\beta_1 + \beta_i) \ast \ln(capital)_it
+ (\beta_2 + \beta_i) \ast \ln(labor)_it + (\beta_3 + \beta_i) \ast \ln(R&D)_{it-1}
+ (\beta_4 + \beta_i) \ast \ln(spillovers)_{it-1} + (\beta_5 + \beta_i)
\ast (\ln(ownR&D) \ast \ln(spillovers))_{it-1} + \mu_i + \epsilon_{it}.
$$

I estimate Equation (5) using the Stata program xtrc. xtrc fits the Swamy random-coefficients linear-regression model for panel data (Swamy and Tavlas 1995). I expect to find that some of the random components of R&D elasticity, $\beta_3$, differ significantly from the mean, $\beta_3$. This would indicate heterogeneity in firms’ R&D elasticities. I also expect to find that the coefficient $\beta_4$, the direct effect of absorptive capacity, is insignificant when allowing heterogeneity in $\beta_3$.

Note that it is possible that absorptive capacity has a functional form different from the linear relationship between R&D and benefit from spillovers implicit in Equation (5). In particular there may be a threshold effect, such that R&D below the threshold yields no benefit from spillovers, whereas R&D above the threshold yields either full benefit or the linear relationship. I can test for this after estimation by examining the relationship between spillover elasticity, $\beta_4$, and R&D spending. If there is a threshold effect I should see a discontinuity.

3.1. Data
I conduct the test using a 20-year panel of industries from the Carnegie Mellon Survey (CMS) of R&D laboratories (Cohen et al. 2000). These industries, ranging from auto parts and aerospace to textiles and television, cover the entire array of manufacturing industries conducting R&D in the United States. Data for the study come from the Compustat industrial annual file, which contains annual operating data on companies listed on the New York, American, and NASDAQ stock exchanges along with companies listed on other major and regional exchanges. For each of the 34 CMS industries, I collected Compustat data for all active and inactive firms over the period 1981–2000. Excluded from this data set were firms that are publicly traded subsidiaries of other publicly traded firms (because their results would have already been reported within their parent firms’ results) as well as firms trading on nonmajor stock exchanges (because the data are often pro forma rather than realized) and firms with headquarters located outside of the United States.

Firm-level data items include (in millions of dollars unless otherwise stated): sales ($Y_{it}$), capital as net
property, plant and equipment ($K_d$), labor ($L_d$), and R&D ($R_d$). \(^3\) Whereas Equation (5) tests R&D flows lagged by one year, I also test variations on this functional form. In particular, I test a model using R&D stocks where the stocks are the sum of R&D over the three years preceding the output year ($t - 1$ to $t - 3$). I use three years because work elsewhere indicates that it is the period over which stocks reach steady state in most industries (Knott et al. 2003). If the three-year steady state holds for firms in this sample, then models with stocks and flows should be equivalent. This is true because flows represent the investment required to maintain the stock (compensating for depreciation/obsolescence) plus grow at the industry rate.

From these primary data, I derive three alternative measures for industry spillovers. Having the correct functional form for spillovers is important because it affects both the direct effect of spillovers and its indirect effects through absorptive capacity (which interacts spillovers with own R&D). Empirical tests of R&D productivity typically employ a pooled form of spillovers (Jaffe 1986, Adams and Jaffe 1996), which sums the R&D for all firms in industry $j$ other than focal firm $f$: $S_{ij} = \sum R_{ij} \forall i \neq f$. \(^4\) This pooled form is faithful to early industrial organization models of the impact of spillovers on incentives for R&D (Spence 1984, Levin and Reiss 1984). Because these models assume homogenous firms, functional form is innocuous because all firms have equivalent knowledge. Firm heterogeneity, however, raises the issue of directionality: from whom and to whom does knowledge flow? There are two modeling conventions for directional spillovers, and I construct distinct functional forms to capture each of them. The first form, leader distance, matches “imitating best practice” in evolutionary economics (Nelson and Winter 1982, Klepper 1996). Leader distance is the difference in knowledge between the firm with the greatest knowledge in the industry and that of the focal firm: $S_{ij}^L = \max(R_{ij}) - R_{ij}$.

\(^5\) In principle, this is the amount of knowledge that a firm gains through imitating best practice. An alternative form implicit in the endogenous growth models (Jovanovic and Rob 1989, Jovanovic and MacDonald 1994, Eekhout and Jovanovic 2002), sum above, is the sum of the differences in knowledge between focal firm $i$ and rival firm $j$ for all firms with more knowledge than the focal firm $S_{ij}^L = \sum R_{ij} \forall R_{ij} > R_{ij}$. What this measure represents is the likelihood of finding superior knowledge in a random encounter with a rival firm. It is a density measure that takes into account the number of firms with superior knowledge as well as the amount of each firm’s surplus.

I am agnostic about which functional form spillovers take, so I merely test all three forms as a robustness check of the main model. The spillover variable construction matches that for R&D in all models. I lag spillovers by one period in the main model, and when I use R&D stocks I also use spillover stocks.

Of the 34 industries included in the CMS study, nine were dropped because of insufficient data. Industries were deemed to have insufficient data if they contributed fewer than 100 firm-year observations over the 20-year period or had fewer than three firms in any given year over the 20-year period. The data set that results from this reduction is an unbalanced panel that includes 2,811 firms and 23,543 firm-year observations for which complete data on the above variables are available. Summary statistics for these data are presented in Table 2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(sales)</td>
<td>3.782</td>
<td>2.538</td>
<td>−6.908</td>
<td>12.094</td>
</tr>
<tr>
<td>ln(capital)</td>
<td>2.215</td>
<td>2.587</td>
<td>−6.908</td>
<td>11.262</td>
</tr>
<tr>
<td>ln(labor)</td>
<td>−0.839</td>
<td>2.121</td>
<td>−6.908</td>
<td>6.776</td>
</tr>
<tr>
<td>ln(R&amp;D)</td>
<td>1.202</td>
<td>2.147</td>
<td>−6.908</td>
<td>9.094</td>
</tr>
<tr>
<td>ln(pool)</td>
<td>7.464</td>
<td>1.414</td>
<td>1.397</td>
<td>10.216</td>
</tr>
<tr>
<td>ln(leader distance)</td>
<td>6.050</td>
<td>1.479</td>
<td>0.000</td>
<td>9.094</td>
</tr>
<tr>
<td>ln(sum above)</td>
<td>7.249</td>
<td>1.762</td>
<td>0.000</td>
<td>10.216</td>
</tr>
<tr>
<td>AbsCap(pool)</td>
<td>9.584</td>
<td>16.667</td>
<td>−56.726</td>
<td>84.286</td>
</tr>
<tr>
<td>AbsCap(leader distance)</td>
<td>7.105</td>
<td>12.957</td>
<td>−47.779</td>
<td>67.445</td>
</tr>
<tr>
<td>AbsCap(sum above)</td>
<td>8.503</td>
<td>15.594</td>
<td>−56.726</td>
<td>80.279</td>
</tr>
</tbody>
</table>

Note. All values are measured in millions of dollars before logs.

4. Results

Results for the formal test of IQ versus absorptive capacity are presented in Tables 3 and 4. Table 3 compares estimates of Equation (1) (GLS regression, which cannot accommodate heterogeneity) with Equation (5) (random-coefficients regression, which does accommodate heterogeneity) for all three forms of spillovers with and without absorptive capacity. Table 4 repeats the analysis but replaces R&D flows with R&D stocks.

Before discussing results for the main hypothesis test, it is worth comparing the estimates for the firm production function across the GLS and random-coefficients specifications. Remember that the main difference between the two specifications is that random coefficients accounts for heterogeneity in firm output elasticities. Two things are irregular in the GLS specifications. First, R&D elasticity is negative for the pooled spillover models (1 and 2). If this were true, we would expect no investment in

\(^3\) Zero values have been set to 0.001 before taking logs to avoid the problem that any zero-valued input yields zero output in Equation (1).

\(^4\) Jaffe (1986) also adjusts the pool for technical and geographic proximity.

\(^5\) Whereas Equation (5) tests R&D flows lagged by one year, I also test variations on this functional form.
R&D, Second, the sum of the elasticities for inputs that the firm controls (ignoring spillovers) is greater than one, indicating increasing returns (for example, in model 5: \( \beta_1 + \beta_2 + \beta_3 = 1.123 \)). Generally, we expect constant or decreasing returns to scale in the absence of externalities. In contrast, for the random-coefficients regressions, all elasticities are positive and their sum is slightly less than one (0.91 to 0.96), indicating decreasing returns to scale. Thus, the ability of the random-coefficients specification to accommodate firm heterogeneity seems to yield more realistic estimates of the firm production function.

### 4.1. Absorptive Capacity

The first notable result regarding our main hypotheses is that absorptive capacity, \( \beta_5 \), is significant in all GLS specifications for all three functional forms for spillovers (models 2, 4, and 6 in each table).\(^5\) This mimics past empirics, which find a significant interaction term when models do not accommodate heterogeneity in firm R&D elasticity.

Results change, however, under the random-coefficients specifications, which do accommodate firm heterogeneity (models 8, 10, and 12 in each table). \( \beta_5 \) is no longer significant in any of the random-coefficients models.

Both results (significant absorptive capacity for GLS models and insignificant absorptive capacity in random-coefficients models) hold for R&D flows (Table 3) and R&D stocks (Table 4).\(^6\) These results are consistent with expectations under the IQ view of correlated investment and returns but are inconsistent with the absorptive capacity view.\(^7\)

\(^5\) Note that the flow model with leader-distance spillovers (Table 3, model 4) is significant only at the 10% level, whereas in all other models it is significant at the 1% level.

\(^6\) Note that I also tested a 4-year stock with comparable results and a stock model with distributed lags for R&D, which allowed the contributions of R&D to vary by years of lag. The results regarding absorptive capacity hold, but the elasticities for R&D and spillovers are no longer significant because each additional lag significantly decreases the degrees of freedom because coefficients are firm specific.

\(^7\) Note that the inclusion of the interaction term has a substantial effect on the coefficient for R&D. This reflects the term’s role in capturing the convexity between R&D spending and returns shown in Figure 3.
4.2. Organizational IQ

I turn next to the companion test of the IQ view—that firms differ in their R&D elasticities (IQ). The direct effects of R&D, the $\beta_{3i}$, presented in Tables 3 and 4, reveal little about firm heterogeneity. Although a chi-squared test of parameter constancy (test of the hypothesis that the coefficients are identical across firms, $e_i^0 = e_i^1 = e_i^2 = e_i^3 = e_i^4 = 0$) is rejected at the 0.001 level, that too offers little information about the degree of heterogeneity. Fortunately, xrc collects statistics (coefficient estimates as well as standard errors) for the firm-specific components, $\beta_{0i}$ to $\beta_{4i}$.

Figure 4 presents a histogram of the $\beta_{3i}$ values for all 1,404 firms with sufficient observations to form estimates. I present coefficient estimates for only one model (Table 3, model 9, for leader distance spillovers without absorptive capacity); however, the general results hold for all versions of spillovers and for models with R&D stocks as well as flows. The values range from −3.14 to 1.93 with a mean of 0.09 and a mean standard error of 0.18. A simple t-test (with 15 degrees of freedom) for each firm comparing its estimate to its standard error: $(\beta_{3i} - \beta_{3h})/se(\beta_{3i})$ indicates that 25% of the firms (345 of 1,404) have elasticities that differ significantly from $\beta_{3h}$.

Thus, there is substantial heterogeneity in firm R&D elasticity, lending support to the IQ view.

4.3. Properties of R&D and Spillover Elasticities

Because the use of firm-specific elasticities for R&D and spillovers is new, it is worth examining them in greater detail. I have already discussed R&D elasticities as part of the formal test. I now turn to discussion of spillover elasticities.

4.3.1. Spillover Elasticity

While the main test examines R&D elasticities, the random-coefficients methodology also allows me to examine spillover elasticities—to what extent does an increase in rival R&D increase the output of the focal firm? Spillovers present an opportunity to reinforce the main results regarding IQ versus absorptive capacity, but they are...
also interesting in their own right. Looking first at the coefficients, we see that the direct effect of leader distance spillovers (Table 3, model 9), $\beta_{4i}$, is 0.27. However, 29% of the firms have elasticities that differ significantly from the value for $\beta_{4i}$. Thus, there is considerable heterogeneity in spillover elasticity just as there is in R&D elasticity. This is interesting and suggests that firms differ in their ability to assimilate knowledge from rivals. Thus, there are differences in "absorptive capacity," but they appear to be innate rather than behavioral. We examine this proposition in greater detail in a later section.

4.3.2. Correlation Between R&D and Spillover Elasticities. One interesting question is whether R&D elasticities are correlated with spillover elasticities. There are two possible expectations. The first is that firms are either high IQ or low IQ and that high-IQ firms are able to make good use of knowledge wherever it resides. If this is the case we expect $\beta_{3i}$ and $\beta_{4i}$ to be positively correlated. An alternative view is that firms specialize—they are either producers or consumers of knowledge—those who are not proficient producers focus their efforts on consuming the knowledge of those who are. If this is the case we expect $\beta_{3i}$ and $\beta_{4i}$ to be negatively correlated. Figure 5 crossplots firm values for $\beta_{3i}$ and $\beta_{4i}$. The figure indicates that the elasticities are negatively and significantly correlated with a slope of $-0.442$. This suggests that high-IQ firms focus their efforts on generating their own knowledge and are therefore less adept at expropriating knowledge from rivals. In addition it suggests that low-IQ firms compensate for low ability to generate their own knowledge with enhanced ability to use knowledge developed by others.9

Because I derive the elasticity estimates using the leader-distance form for spillovers, the strong negative correlation between R&D and spillover elasticities is somewhat surprising. High-IQ firms optimally invest more in R&D and are therefore likely to be near the leader. Accordingly, their respective spillover pool (leader R&D – own R&D) is small relative to laggards. That, in addition to having a smaller pool, they also have a lower elasticity on that pool suggests that high-IQ firms derive almost no benefit from spillovers.

4.3.3. Persistence of IQ. Given that elasticities vary across firms it is also worth asking whether they also vary over time. Just as individual IQ varies with age (increasing then decreasing), we might expect that firm IQs vary over time. If so, firms may be able to change (improve) their IQ. Ideally I could form firm-year-specific measures of IQ. This cannot be done econometrically because the number of coefficients to be estimated exceeds the number of observations. As a suggestive analysis, however, I partitioned the sample into two time periods using a balanced panel of firms present for the entire 20 years and estimated Equation (5) for each period. Figure 6 compares the mean elasticities for R&D and spillovers across the two periods. The figure indicates that elasticities do vary over time. In particular for the firms in the sample IQ tends to increase, whereas spillover elasticity tends to decrease. This is true across all three functional forms of spillovers. These results are counterintuitive. The common view is that technological opportunity should decrease over time while the role of spillovers should increase over time. The results here suggest instead that firms become more competent both at R&D and at protecting their R&D from leakage.10

9 The ability to make effective use of rival knowledge is also a skill; thus, we cannot assume that being low IQ “gives” firms high spillover elasticity. Rather, to be in the sample firms must be successful; thus, if they have low IQ they must have developed a compensating capability.

10 Knott and Posen (2008) provide a more detailed examination of trends in industries’ elasticities over time, link elasticities to survey measures of appropriability and technological opportunity, and test the impact of industry elasticities on firm behavior. Results in that paper are consistent with results here.
In addition to mean elasticities in each period, I also examined the elasticities of individual firms. Figure 7 compares firms’ elasticities in the first period to their elasticities in the second period for both R&D (upper panel) and spillovers (lower panel). Each panel includes a diagonal reflecting constant elasticity. Observations to the upper left reflect improving elasticities, and those to the lower right reflect declining elasticities. There appears to be no real gravitational pull associated with the diagonal. Thus, firm elasticity appears to change over time through either deliberate efforts (presumably the upper left observations) or drift (the lower right) in R&D routines, with a slight bias toward the upper left.

4.4. Interindustry vs. Intraindustry Effects
The exclusion of industries with fewer than three firms raises the prospect that I am excluding industries where firms are most likely to exploit absorptive capacity. To increase confidence that results are unbiased, I ran separate models for each industry to gather industry mean elasticities. I summarize these results in Figure 8, which plots R&D (upper panel) and spillover (lower panel) elasticity, respectively, versus industry concentration (number of firms). The figures indicate that R&D elasticity decreases with the number of firms while spillover elasticity increases with the number of firms. Thus, firms in concentrated industries do not appear to derive much benefit from the R&D of rivals. Given that, excluding industries with three firms probably biases us in favor of finding absorptive capacity.

In addition to these general trends for elasticities versus industry size is a question of whether there is anything special about very small industries. For example, are duopoly firms in head-to-head competition more likely to benefit from spillovers (and/or absorptive capacity)? There are no duopoly industries at the four-digit SIC level, but there are industries with two dominant firms and a set of fringe firms. One obvious example is microprocessors (a subset of semiconductors ISIC 3211 with 159 firms) where the two players controlling the PC market are Intel (whose R&D is 32% of industry) and AMD (whose R&D is 5% of industry). The estimated R&D elasticity for Intel is 0.314 (significant at the 5% level); for AMD it is 0.296 (not significant). The corresponding spillover elasticity for both firms is 0.000. These results suggest that at least for this “duopoly” firms are unlikely to benefit from spillovers or absorptive capacity.

A related question is the extent to which heterogeneity is really an industry effect or a firm differences effect. Here the random-coefficients models for each industry indicate two things of note. The main result (insignificant absorptive capacity) is preserved...
in all industries. The second thing of note is that the heterogeneity in firm elasticities is coming principally from within industry rather than across industry. This observation is captured in Figure 9, which plots intraindustry variance in elasticity against mean elasticity for each industry in the sample. For both R&D and spillovers the intraindustry variance in elasticity is approximately four times the cross-industry variance. This result (greater performance variance within than across industry) is consistent with findings from the “how much does industry matter” literature (Rumelt 1991, McGahan and Porter 1997).

Thus, the within- and across-industry analyses tend to reinforce the general results that there is heterogeneity in firm elasticity and that there is no absorptive capacity once we account for that heterogeneity.

4.5. Behavioral Test of Nature vs. Nurture

Whereas Tables 3 and 4 presented results from the formal test of Equation (5), now that we have firm-specific elasticities for R&D and spillovers it is possible to conduct a behavioral test of the two views of absorptive capacity: Do firm R&D investments reflect the underlying mechanics implicit in the IQ view or the absorptive capacity view? Under the IQ view, captured in Figure 2, I expect R&D investment to increase with R&D elasticity and to be insensitive to spillover elasticity (because spillovers are a public good). Under the absorptive capacity view, I expect spillover elasticity to increase with R&D investment and R&D elasticity to be insensitive to R&D investment (because R&D elasticity is assumed to be constant across firms).

Figure 10 crossplots R&D investment with each set of elasticities. Figure 10(a) shows the relationship between R&D investment and R&D elasticity. The figure indicates that R&D investment increases with R&D elasticity (slope is 1.06 and significant).
gests that firms who invest more in R&D derive greater benefits from spillovers. This view has been upheld in empirical tests using an interaction of own R&D and spillovers. I raise the prospect that the empirical regularity may be an artifact of past empirical constraints. I propose instead that firms differ in their R&D elasticities (IQ) and that those with higher IQ invest more in R&D. Thus, it is not that higher investment increases returns (absorptive capacity); it is that having higher returns (IQ) increases investment.

I conduct a formal empirical test of the competing views using a random-coefficients specification for the firm R&D production function, which allows heterogeneity in R&D elasticity. The evidence is consistent with the IQ view and inconsistent with the absorptive capacity view. First, there is substantial heterogeneity in R&D elasticity. Twenty-five percent of firms have R&D elasticities that differ significantly from the population mean. Second, no production function that accounts for this heterogeneity exhibits absorptive capacity ($\beta_5$ is never positive or significant in the random-coefficients specifications). I also conduct an informal behavioral test of the two views. The evidence from the behavioral test is consistent with that from the formal test. In particular, crossplots of elasticities and behavior indicate that R&D investment is positively correlated with R&D elasticity but negatively correlated with spillover elasticity (a more direct measure of absorptive capacity).

The prescriptive implication of these findings is that greater investment in R&D does nothing to increase the returns to R&D. On the contrary, it appears that spending less on R&D “increases” absorptive capacity if we now define absorptive capacity as the effective use of rival knowledge (spillover elasticity). The only way for firms to increase returns to their own R&D productivity is to raise IQ. Because elasticities vary over time, this appears to be possible.

How firms go about raising IQ is a question ripe for future research, as is the more fundamental question of what determines organizational IQ. Although any proposed correlates of IQ are speculative at this point, reasonable candidates are hiring practices (higher proportion and caliber of scientists and engineers), incentive schemes (for patenting/publishing/collaborating), organizational structure (the relationship between R&D and other functions), composition of the R&D portfolio (depth/breadth and temporal balance), mechanisms for learning across projects, and commercialization processes.

13 It is highly unlikely that spending less directly produces any capability. Rather, there is likely a survivor effect. Low-IQ firms who survive are likely those that have developed capability to exploit rival R&D.

**Figure 10** Behavioral Test: (a) Higher R&D Elasticity Leads to Higher Investment or (b) Higher Investment Leads to Higher Spillover Elasticity

This relationship is consistent with the IQ view and inconsistent with the absorptive capacity view. Figure 10(b) shows the relationship between spillover elasticity and R&D investment. That figure indicates that spillover elasticity is insensitive to R&D investment. The slope is actually slightly negative, −0.03, and significant. Thus, greater investment in R&D does not increase firms’ ability to expropriate knowledge from rivals. Again, this relationship is consistent with the IQ view and inconsistent with the absorptive capacity view.

### 4.6. Absorptive Capacity as a Threshold Effect

One final test I can conduct now that I have firm-specific elasticities is a test of alternative functional forms of absorptive capacity. The test exploits spillover elasticity as an alternative measure of absorptive capacity because it captures firms’ ability to make use of rival knowledge. Given that, if absorptive capacity is subject to a threshold effect (or any other nonlinearity), I should detect the non linearity in the relationship between R&D spending and spillover elasticity. Figure 10(b) does not exhibit any obvious nonlinearity. Accordingly, the inability to find a significant effect for the interaction does not appear to be a problem of functional form.

### 5. Discussion and Implications

The conventional view of absorptive capacity suggests that firms who invest more in R&D derive...
Appendix. Mathematical Equivalence Between Heterogeneity in R&D Elasticity and Absorptive Capacity

<table>
<thead>
<tr>
<th>Homogeneous R&amp;D elasticity</th>
<th>Heterogeneous R&amp;D elasticity</th>
<th>Homogeneous R&amp;D + interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Y = K^{\gamma} L^{\delta} R^{\alpha} S^{\beta} ), where ( \gamma ) is fixed</td>
<td>( Y = K^{\gamma} L^{\delta} R^{\alpha} S^{\beta} ), where ( \gamma ) is increasing in ( R ):</td>
<td>( \ln Y = \alpha \ln K + \beta \ln L + \gamma \ln R + \delta \ln S + \phi (\ln R \ast \ln S) ), where ( \gamma ) is fixed</td>
</tr>
</tbody>
</table>
| \( dY / dR = K^{\gamma} L^{\delta} S^{\beta} \gamma R^{-1} \) because \( \gamma \) is increasing in \( R \), greater slope than homogeneous case | \( dY / dR = K^{\gamma} L^{\delta} S^{\beta} \gamma R^{-1} dY / dR \) | \( dY / dR = R^{(\delta - \gamma) / \gamma} K^{\delta / \gamma} \ln S + K^{\delta / \gamma} \gamma \) greater slope than homogeneous case by \( \phi \ln S \)

Perhaps equally interesting is the parallel question regarding antecedents of spillover elasticity. In addition, the fact that the two elasticities are negatively correlated raises a whole host of questions: why are they negatively related; is there a point at which firms decide to innovate versus imitate (and thereafter invest in one capability versus the other); do investments in one inhibit development of the other, e.g., do the innovators’ researchers preclude imitation via “not invented here” syndrome; do firms develop either capability, or is it merely endowed at birth; is the negative correlation merely an artifact of failure by firms with low elasticities for both? There are caveats to these results. First, because I use Compustat data, the measures of rival spillovers exclude private firms. This is of limited concern given the finding that the leader-distance form for spillovers is the most reliable. Because private firms are typically small, they are unlikely to be the R&D leaders in their industry. Accordingly, their R&D investment would be irrelevant to spillover (and by extension absorptive capacity) construction even if data were available.

A more substantial but related concern is that the spillover pools used here are defined by industry. Thus, any potentially relevant knowledge in adjacent industries is ignored. A more nuanced construction of spillover pools would consider technical and geographic proximity, e.g., Jaffe (1986). However, to the extent that relative rankings within technologies are similar to those within industry, it is likely that results with the leader-distance measure would change only by a scale factor. Moreover, although the spillover measures here are coarse with regard to proximity, they are more refined in a potentially more important regard: they exclude rival knowledge that is redundant and/or inferior.

The main contribution of this paper is advancing and testing a competing explanation for the correlation between R&D and returns, but the paper also provides new understanding of R&D capability. First, firms differ in their R&D elasticity. Some firms simply are more productive with their R&D investments than other firms. Second, we now have an alternative measure of “absorptive capacity” that captures firms’ effectiveness in utilizing rival R&D. It is the elasticity of rival spillovers to own output. Like IQ, it varies across firms. However, it appears to be negatively correlated with R&D elasticity. This suggests that firms specialize. Those with high IQ do their own R&D; those with low IQ compensate by developing superior absorptive capacity. These new measures and results provide a technical foundation for the classic dichotomy between innovators and imitators.

Acknowledgments

The author thanks Pankaj Ghemawat, the associate editor, and two anonymous referees for their insights and guidance in developing the paper. In addition, the author thanks seminar participants at the University of Michigan, Universidade Católica Portuguesa, Strategic Management Society, Academy of Management, and Atlanta Competitive Advantage Conference for helpful comments.

References

Henderson, R., I. Cockburn. 1996. Scale, scope, and spillovers: Determinants of research productivity in the pharmaceutical industry. RAND J. Econom. 27(1) 32–59.


