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

Anne Marie Knott

John M. Olin School of Business
Washington University
One Brookings Drive
Campus Box 1133
St. Louis, MO 63130-4899
314.935.4679
knott@wustl.edu

May 2008

PRELIMINARY DRAFT:
PLEASE DO NOT COPY OR CITE WITHOUT PERMISSION

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

Abstract

*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*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 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 firms ability to benefit from spillovers.*

"I wouldn't worry about it. People who aren't smart
don't become smart by listening to people who are"

Customer's response to concern that joint design reviews
would reveal our technology to the competitor.

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 characterize the functional form of absorptive capacity as an interaction between the firm's own R&D and spillovers. [1] This interaction term has been found to be significant in OLS and 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 which 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. While organizational IQ, like individual IQ, is highly complex, 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 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

[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: 141) Absorptive capacity is operationalized in Cohen and Levinthal 1989:572 as a variable γ which is increasing in the firm's own R&D at a rate defined by β (where β is a function of industry appropriability and technological opportunity).

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 on 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 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 couldn't 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.

Absorptive Capacity: Theory and empiricism

Cohen and Levinthal (1989:128) 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 FTC line of business data on R&D investments. What they show is that high levels appropriability (interpreted as low spillovers) increase R&D intensity.

While 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 intra-industry 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 varying conclusions about the impact of absorptive capacity on firm incentives for R&D. Campisi, Mancuso and Nastasi (2001), Martin (2002), Grunfeld (2003) each develop models where spillovers are endogenously determined by the potential for absorptive capacity. Campisi et al, and Martin conclude that R&D investment is unaffected by absorptive capacity. Grunfeld 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 firms'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 results indicate that this interaction term is positive and significant in OLS and instrumental variable (IV) models of R&D productivity.[2] 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?

Is knowledge redundant?

One means to resolve the puzzle is to suggest that lower spending by rivals doesn't 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 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:

$$ln(Y)_{it} = \beta_{0t}+\beta_1*ln(own\ R\&D)_{it} +\beta_2*ln(spillovers)_{it} +\beta_3*ln(own\ R\&D)_{it} *ln(spillovers)_{it} \quad (1)$$

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. 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, 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 through 7 are the contributions (in ln form) from each input to a firm's output. These values are

[2] Results are not significant in first-difference (FD) specifications.

obtained by applying representative coefficients to the input values from columns 2 through 4. Column 8 is each firm's R&D output (obtained by summing the values across columns 5 through 7, and then converting out of ln form). Column 9 is the aggregate R&D output for all the firms given awards (obtained by multiplying firm output (column 8) by the number of firms (column 1). Columns 10 and 11 is the share of output gain attributed to spillovers alone.

Insert Table 1 about here

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). While spillovers alone account for a 20 to 40 factor increase in output, absorptive capacity increases that by an additional factor of 15 to 19. We could argue that the coefficients aren't quite right, but small changes in the coefficient values won't change the basic result. This two-firm result stands in sharp contrast to the intuition that in the absence of incentive problems, all 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, 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. While 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.

Insert Figure 1 about here

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.

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 can't 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:

$$Y = K^{\alpha}L^{\beta}R^{\gamma}S^{\delta} \tag{2}$$

Where:

Y	is output (sales)
K	is capital
L	is labor
R	is R&D
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:

$$\Pi = K^{\alpha}L^{\beta}R^{\gamma}S^{\delta} - K - L - R \tag{3}$$

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

$$R = (1/\gamma K^{\alpha}L^{\beta}S^{\delta})^{(1/(\gamma-1))} \tag{4}$$

Figure 2 presents the relationship between R&D output elasticity, γ, 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 γ over the normal range of values (0,1).

Insert Figure 2 about here

If firms differ in their R&D elasticity, γ, and if firm R&D investments correspond optimally to the differences in γ, then we should observe two things. First, we should observe the positive correlation between investments and returns in Figure 2. Second, econometric models which don't 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 obverse is true—having higher returns yields higher investment. I derive the mathematical equivalence between heterogeneity in R&D elasticity and absorptive capacity in Appendix A. Since 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 (γ) of 0.125. The second plot is output under an assumption of heterogeneous firms. Here each R&D investment level corresponds to an R&D elasticity for which that investment level is optimal (as in Figure 2). Finally, the third plot is a combination of homogeneous R&D ($\gamma = 0.125$) with an absorptive capacity elasticity of 0.25. The figure indicates that the slopes for heterogeneity and absorptive capacity are similar for most of the range of the data (R&D greater than $25 million), whereas homogeneous R&D elasticities yield output that is essentially constant over the same range.

Insert Figure 3 about here

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 which mimics past GLS regressions. I then employ a random coefficients model which 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 don't 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.

<u>A note on random coefficient models.</u> 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 which treats coefficients as being non-fixed (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 which restricts all members of a cross-section to share the same coefficient (Ameniya 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 1994. 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:

$$ln(sales)_{it} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i})*ln(capital)_{it} + (\beta_2 + \beta_{2i})*ln(labor)_{it} + (\beta_3 + \beta_{3i})*ln(R\&D)_{it-1} + (\beta_4 + \beta_{4i})*ln(spillovers)_{it-1} + (\beta_5 + \beta_{5i})*(ln(own\ R\&D)*ln(spillovers))_{it-1} + \mu_i + \varepsilon_{it} \quad (5)$$

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, β_{3i}, differ significantly from the mean, β_3. This would indicate heterogeneity in firms’ R&D elasticities. I also expect to find that the coefficient β_5, the direct effect of absorptive capacity, is insignificant when allowing heterogeneity in β_3.

Note it is possible that absorptive capacity has a different functional form than 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, β_{4i}, and R&D spending. If there is a threshold effect I should see a discontinuity.

Data

I conduct the test using a twenty-year panel of industries from the Carnegie Mellon Survey (CMS) of R&D labs (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 US. Data for the study comes 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 thirty-four CMS industries, I collected Compustat data for all active and inactive firms over the period 1981 through 2000. Excluded from this data set were firms that are publicly traded subsidiaries of other publicly traded firms (since their results would have already been reported within their parent firm's results) as well as firms trading on non-major stock exchanges (since the data are often pro forma rather than realized) and firms with headquarters located outside of the US.

Firm level data items include (in $MM unless otherwise stated): sales (Y_{it}), capital as net property, plant and equipment (K_{it}), labor (L_{it}), and R&D (R_{it})[3]. While 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 it is the period over which stocks reach steady state in most industries (Knott, Bryce and Posen 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 as well as 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*: $S_{fjt} = \Sigma R_{ijt} \ \forall \ i \neq f$.[4] This *pooled* form is faithful to early IO models of the impact of spillovers on incentives for R&D (Spence 1984, Levin & Reiss 1984). Because these models assume homogeneous firms, functional form is innocuous because all firms have

[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 also adjusts the pool for technical and geographic proximity.

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: $S_{fjt} = max(R_{ijt}) - R_{fjt}$. In principle, this is the amount of knowledge a firm gains through imitating best practice. An alternative form implicit in the endogenous growth models (Jovanovic and Rob 1989, Jovanovic and MacDonald 1994, Eeckhout 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 $S_{fjt} = \Sigma R_{ijt} \; \forall R_{ijt} > R_{fjt}$. 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 surfeit.

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 thirty-four industries included in the CMS study, nine were dropped due to insufficient data. Industries were deemed to have insufficient data if they contributed less 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 2811 firms and 23543 firm-year observations for which complete data on the above variables is available. Summary statistics for these data are presented in Table 2.

Insert Table 2 about here

Results

Results for the formal test of the IQ versus absorptive capacity are presented in Tables 3 and 4. Table 3 compares estimates of Equation 1 (GLS regression which can't 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.

Insert Tables 3 and 4 about here

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 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 R&D. Second, the sum of the elasticities for inputs which 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.

Absorptive Capacity. The first notable result regarding our main hypotheses is that absorptive capacity, β_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 don't 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). β_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) holds for R&D flows (Table 3) as well as 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]

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 β_3, presented in Tables 3 and 4 reveal

---

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

[6] Note, 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 since 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.

little about firm heterogeneity. While a Chi squared test of parameter constancy (test of the hypothesis that the R&D coefficients are identical across firms, $e^{\beta0}{}_i = e^{\beta1}{}_i = e^{\beta2}{}_i = e^{\beta3}{}_i = e^{\beta4}{}_i = 0$), is rejected at the 0.0001 level, that too offers little information about the degree of heterogeneity. Fortunately xtrc collects statistics (coefficient estimates as well as standard errors) for the firm specific components, β_{0i} to β_{4i}.

Figure 4 presents a histogram of the β_{3i} values for all 1404 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: $(\beta_3 - \beta_{3i})/\mathrm{se}(\beta_{3i})$ indicates that twenty-five percent of the firms (345 of 1404) have elasticities that differ significantly from β_3.[8] Thus there is substantial heterogeneity in firm R&D elasticity, lending support to the IQ view.

Insert Figure 4 about here

Properties of R&D and spillover elasticities.

Since 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.

<u>Spillover elasticity</u>. 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), β_4, is 0.27. However, twenty-nine percent of the firms have elasticities that differ significantly from the value for β_4. Thus there is considerable heterogeneity in spillover elasticity just as there is in R&D elasticity. This is interesting and suggests that firms

[8] Note that in random coefficients estimation each explanatory variable is modeled as having a direct effect, and a set of proxy effects of omitted variables through which the explanatory variable affects the dependent variable. The standard error for the coefficient estimate, β_x, is for the direct effect only. Accordingly there is no constraint that the proxy effects captured through β_{xi}, fall within $\pm$ two std errors of the direct effect.

differ in their ability to assimilate knowledge from rivals. Thus there *are* differences in "absorptive capacity," but they appear to be innate rather that behavioral. We examine this proposition in greater detail in a later section.

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 β_{3i} and β_{4i} to be positively correlated. An alternative view is that firms specialize—they are either *producers* or *consumers* of knowledge—those who aren't proficient *producers* focus their efforts *consuming* the knowledge of those who are. If this is the case we expect β_{3i} and β_{4i} to be negatively correlated. Figure 5 crossplots firm values for β_{3i} and β_{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].

Insert Figure 5 about here

Since I derive the elasticity estimates using the *leader-distance* form for spillovers, the strong negative correlation between R&D and spillover elaticities 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 high IQ firms derive almost no benefit from spillovers.

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 can't be done econometrically

[9] The ability to make effective use of rival knowledge is also a skill, thus we can't 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.

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 twenty 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, while 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 protecting their R&D from leakage. [10]

Insert Figure 6 about 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 (panel a) and spillovers (panel b). Each panel includes a diagonal reflecting constant elasticity. Observations to the upper left reflect improving elasticities, while 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 either through deliberate efforts (presumably the upper left observations) or drift (the lower right) in R&D routines, with a slight bias toward the upper left.

Insert Figure 7 about here

Inter-industry versus intra-industry 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[11]. To increase confidence that results are unbiased, I ran separate models for each industry to gather industry mean elasticities. I summarize these results in Figures 8a and 8b which plot R&D and spillover elasticity, respectively, versus industry concentration (number of firms). The figures indicate that

[10] Knott and Posen (2008) provides a more detailed examination of trends in industries' elasticities over time, links elasticities to survey measures of appropriability and technological opportunity, and tests the impact of industry elasticities on firm behavior. Results in that paper are consistent with results here.
[11] Such as the non-linear effect of market size proposed by Grunfeld (2003).

R&D elasticity decreases with the number of firms while spillover elasticity increases with the number of firms. Thus firms in concentrated industries don't 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.

Insert Figure 8 about here

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)? While there are no duopoly industries at the four digit SIC level, there are industries with two dominant firms and a set of fringe firms. One obvious example is microprocessors (a subset of semi-conductors 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 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[12]. 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 intra-industry variance in elasticity against mean elasticity for each industry in the sample. For both R&D and spillovers the intra-industry variance in elasticity is about 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.

Insert Figure 9 about here

[12] Coefficient estimates for each industry are available from the author.

Behavioral test of nature versus nurture.

While 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 (since spillovers are a public good). Under the absorptive capacity view, I expect spillover elasticity to increase with R&D investment, and expect R&D elasticity to be insensitive to R&D investment (since R&D elasticity is assumed to be constant across firms).

Figure 10 crossplots R&D investment with each set of elasticities. Figure 10a 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). This relationship is consistent with the IQ view and inconsistent with the absorptive capacity view. Figure 10b shows the relationship between spillover elasticity and R&D investment. That figure indicates 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.

Insert Figure 10 about here

<u>Absorptive capacity as a threshold effect</u>. 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, since it captures firms' ability to make use of rival knowledge. Given that, if absorptive capacity is subject to a threshold effect (or any other non-linearity), I should detect the non-linearity in the relationship between R&D spending and spillover elasticity. Figure 10b does not exhibit any obvious non-linearity. Accordingly the inability to find a significant effect for the interaction does not appear to be a problem of functional form.

Discussion and implications

The conventional view of absorptive capacity suggests 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 which accounts for this heterogeneity exhibits absorptive capacity (β_5 is never positive nor 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 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)[13]. The only way for firms to increase returns to their own R&D productivity is to raise IQ. Since elasticities vary over time, this appears to be possible.

How firms go about raising IQ is a ripe question for future research, as is the more fundamental question of what determines organizational IQ. While 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.

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

[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 who have developed capability to exploit rival R&D.

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, since 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. Since 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, while 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.

While the main contribution of this paper is advancing and testing a competing explanation for the correlation between R&D and returns, 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.

Appendix A. Mathematical Equivalence Between

Heterogeneity in R&D Elasticity and Absorptive Capacity

Homogeneous R&D elasticity	**Heterogeneous R&D elasticity**	**Homogeneous R&D + interaction**
$Y = K^{\alpha}L^{\beta}R^{\gamma}S^{\delta}$ *where γ is fixed*	$Y = K^{\alpha}L^{\beta}R^{\gamma}S^{\delta}$ *where γ is increasing in R:* $R = (1/\gamma K^{\alpha}L^{\beta}S^{\delta}()^{(1/(\gamma-1))}$	$lnY = \alpha lnK + \beta lnL + \gamma lnR + \delta lnS + \phi(lnR^{*} lnS)$ *where γ is fixed*
$dY/dR= K^{\alpha}L^{\beta}S^{\delta}\gamma R^{\gamma-1}$	$dY/dR= K^{\alpha}L^{\beta}S^{\delta}\gamma R^{\gamma-1}\, d\gamma/dR$ *since γ is increasing in R, greater slope than homogeneous case*	$dY/dR= R^{[\phi lnS+\ \gamma-1]}\, K^{\alpha}L^{\beta}\phi lnS+ K^{\alpha}L^{\beta}\gamma$ *greater slope than homogeneous case by ϕlnS*

References

Adams, J. D., And A. B. Jaffe. 1996. "Bounding the Effects Of R&D: An Investigation Using Matched Establishment-Firm Data." RAND Journal of Economics, 27: 700–721.

Arrow, K. 1962. "Economic Welfare and the Allocation of Resources for Invention", in The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton University Press.

Campisi, D., P. Mancuso and A. Nastasi 2001. R&D Competition, Absorptive Capacity, and Market Shares. Journal of Economics, 73 (1) 57-80.

Cohen, W. and D. Levinthal. 1989. Innovation and Learning: The Two Faces of R&D, Economic Journal, 99: 569-96

Cohen , W. and D. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. Admistrative Science Quarterly, 35: 128-152.

Cohen, W.M., R.R. Nelson And J.P. Walsh. 2000. "Protecting Their Intellectual Assets: Appropriability Conditions And Why U.S. Manufacturing Firms Patent (Or Not), NBER Working Paper 7552.

Eeckhout, J. and B. Jovanovic. 2002. Knowledge Spillovers and Inequality. American Economic Review, 92:1290-1307.

Grunfeld, L.A. 2003. Meet me halfway but don't rush: absorptive capacity and strategic R&D investment revisited, International Journal of Industrial Organization 21: 1091-1109.

Jaffe, A. 1986. "Technological Opportunity and Spillovers of R&D", American Economic Review, 76: 984-1001.

Jovanovic, B and G. MacDonald. 1994. Competitive Diffusion, Journal of Political Economy 102:24-52.

Jovanovic, B and R. Rob. 1989. "The Growth and Diffusion of Knowledge." Review of Economic Studies, 56: 569-582.

Klepper, S. 1996. Exit, Entry, Growth and Innovation Over the Product Life Cycle. American Economic Review. 86 562-583.

Knott, A., D. Bryce and H. Posen. 2003. "On Strategic Accumulation of Intangible Assets", Organization Science, 14 (2) 192-207.

Knott, A and H. Posen. 2008. Firm R&D behavior and evolving technology in established industries, Organization Science, forthcoming

Levin, R. and P. Reiss. 1984. Test of A Schumpeterian Model of R&D And Market Structure" In Z. Griliches, Ed., R&D, Patents And Productivity. Chicago: University Of Chicago Press.

Martin, S. 2002. Spillovers, Appropriability and R&D. Journal ofEconomics 75 (1) 1-32.

McGahan, A. and M. Porter 1997. How Much Does Industry Matter? Really, Strategic Management Journal 18 (S1) 15 - 30

Nelson, R and S. Winter 1982. An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Rumelt, R. 1991 How Much Does Industry Matter? Strategic Management Journal,12, 167-185

Spence, A.M. 1984. "Cost Reduction, Competition And Industrial Performance", Econometrica, 52: 101-121.

Swamy P. and G. Tavlas. 1995. Random Coefficient Models: Theory and applications. Journal of Economic Surveys 9(2): 165-196

Table 1. Implications from stylized facts for subdividing R&D award

	Inputs ($million)			ln(contributions to output)			Output ($million)	
Firms	Own R&D	Spillovers	Interaction	Own R&D	Spillovers	Interaction	Firm	Industry
1	200	0	0	4.67	0.00	0.00	106	106
2	100	100	10000	4.06	4.07	2.96	65163	130326
3	67	133	8911	3.70	4.02	2.92	41934	125802

Table 2. Data Summary 23543 observations (1981-2000)

Variable	Mean	Std. Dev	Min	Max
ln(sales)	3.782	2.538	-6.908	12.094
ln(capital)	2.215	2.587	-6.908	11.262
ln(labor)	-0.839	2.121	-6.908	6.776
ln(R&D)	1.202	2.147	-6.908	9.094
ln(pool)	7.464	1.414	1.397	10.216
ln(ldr dist)	6.050	1.479	0.000	9.094
ln(sum above)	7.249	1.762	0.000	10.216
AbsCap(pool)	9.584	16.667	-56.726	84.296
AbsCap(ldr dist)	7.105	12.997	-47.779	67.445
AbsCap(sum above)	8.503	15.594	-56.726	80.279

All values are measured in $MM before logs

Table 3. Comparing GLS and random coefficients estimates of R&D production function (R&D flows)

Dependent variable = ln(sales)

	GLS regression						Random coefficients regression					
Model	1	2	3	4	5	6	7	8	9	10	11	12
ln(capital)	**0.193**	**0.191**	**0.205**	**0.205**	**0.210**	**0.209**	**0.159**	**0.145**	**0.167**	**0.162**	**0.171**	**0.155**
	(.008)	**(.007)**	**(.007)**	**(.008)**	**(.008)**	**(.008)**	**(.041)**	**(.032)**	**(.034)**	**(.034)**	**(.039)**	**(.032)**
ln(labor)	**0.899**	**0.901**	**0.870**	**0.869**	**0.872**	**0.872**	**0.626**	**0.606**	**0.649**	**0.586**	**0.614**	*0.597
	(.01)	**(.01)**	**(.01)**	**(.01)**	**(.01)**	**(.01)**	**(.054)**	**(.044)**	**(.044)**	**(.047)**	**(.049)**	(.043)
$\ln(R\&D)_{t-1}$	-0.003	-0.005	**0.042**	**0.041**	**0.041**	**0.040**	**0.121**	**0.180**	**0.140**	**0.221**	**0.138**	**0.197**
	(.006)	(.006)	**(.006)**	**(.006)**	**(.006)**	**(.006)**	**(.032)**	**(.107)**	**(.039)**	**(.092)**	**(.032)**	**(.096)**
$\ln(\text{rival pool})_{t-1}$	**0.266**	**0.262**					**0.392**	**0.443**				
	(.007)	**0.007**					**(.083)**	**(.109)**				
$\text{AC (rival pool)}_{t-1}$		**1.1E+08**						-1.7E+05				
		(2.0E+09)						(2.8E+04)				
$\ln(\text{leader distance})_{t-1}$			**0.190**	**0.188**					**0.274**	**0.366**		
			(.006)	**(.006)**					**(.065)**	**(.094)**		
$\text{AC (leader distance)}_{t-1}$				^3.14E+08						-2.2E+04		
				(1.9E+08)						(1.3E+03)		
$\ln(\text{sum above})_{t-1}$					**0.160**	**0.157**					**0.378**	**0.417**
					(.006)	**(.006)**					**(.071)**	**(.099)**
$\text{AC (sum above)}_{t-1}$						**1.0E+08**						1.2E+05
						(4.0E+09)						(3.1E+04)
Constant	**2.047**	**2.079**	**2.783**	**2.795**	**2.767**	**2.789**	0.722	0.104	**2.056**	*1.407	0.723	0.636
	(.054)	**(.545)**	**(.042)**	**(.043)**	**(.045)**	**(.046)**	(.834)	(1.109)	**(.431)**	(.638)	(.728)	(.782)
Wald chi-squared	48290.0	48379.0	47930.0	47933.0	47309.7	47336.9	629.2	315.5	803.7	352.8	699.3	348.7
R-square within	0.599	0.599	0.584	0.584	0.583	0.583						
R-square between	0.845	0.846	0.862	0.862	0.858	0.858						
observations	23543	23543	23543	23543	23543	23543	20098	18862	20098	18862	20098	18862

standard errors in parentheses below coefficients

coefficients in bold significant at 1% level

^significant at 10% level

*significant at 5% level

Table 4. Comparing GLS and random coefficients estimates of R&D production function (R&D stocks)

Dependent variable = ln(sales)

	GLS regression						Random coefficients regression					
Model	1	2	3	4	5	6	7	8	9	10	11	12
ln(capital)	**0.142**	**0.140**	**0.135**	**0.134**	**0.136**	**0.135**	**0.193**	**0.185**	**0.235**	**0.199**	**0.193**	**0.192**
	(.008)	**(.008)**	**(.008)**	**(.008)**	**(.008)**	**(.008)**	**(.043)**	**(.06)**	**(.048)**	**(.05)**	**(.044)**	**(.059)**
ln(labor)	**0.831**	**0.833**	**0.837**	**0.838**	**0.841**	**0.842**	**0.547**	**0.611**	**0.534**	**0.617**	**0.580**	**0.604**
	(.011)	**(.011)**	**(.011)**	**(.011)**	**(.011)**	**(.011)**	**(.062)**	**(.067)**	**(.084)**	**(.07)**	**(.06)**	**(.067)**
ln(R&D stock)$_{t-1}$	**0.100**	**0.097**	**0.111**	**0.110**	**0.109**	**0.107**	**0.107**	**0.069**	**0.146**	0.088	0.113	0.074
	(.007)	**(.007)**	**(.006)**	**(.007)**	**(.007)**	**(.007)**	**(.085)**	**(.074)**	**(.058)**	(.058)	(.078)	(.07)
ln(rival pool stock)	**0.170**	**0.166**					**0.394**	**0.394**				
	(.008)	**(.007)**					**(.142)**	**(.134)**				
AC (rival pool stock)		**1.4E+08**						1.4E+05				
		(2.6E+09)						(8.3E+05)				
ln(leader distance stock)			**0.179**	**0.178**					**0.315**	*0.322		
			(.008)	**(.008)**					**(.122)**	(.157)		
AC (leader distance stock)				**8.8E+08**						1.4E+04		
				(2.3E+08)						(3.1E+04)		
ln(sum above stock)					**0.154**	**0.152**					**0.400**	**0.436**
					(.007)	**(.007)**					**(.141)**	**(.14)**
AC (sum above stock)						**2.3E+08**						1.4E+05
						(5.1E+09)						(8.8E+05)
Constant	**2.594**	**2.630**	**2.744**	**2.760**	**2.743**	**2.766**	0.044	0.371	0.843	1.222	-0.006	-0.084
	(.062)	**(.063)**	**(.057)**	**(.057)**	**(.062)**	**(.062)**	(1.293)	(1.303)	(1.088)	(1.208)	(1.325)	(1.385)
Wald chi-squared	37043.0	37122.0	35966.7	36000.0	35424.0	35470.9	259.6	141.3	184.1	172.0	271.8	140.2
R-square within	0.581	0.582	0.577	0.577	0.577	0.578						
R-square between	0.879	0.880	0.883	0.883	0.877	0.877						
observations	15898	15898	15532	15532	15532	15532	13200	12420	12819	12039	12819	12039

standard errors in parentheses below coefficients
all coefficients in bold significant at 1% level or better
^significant at 10% level
*significant at 5% level

Figure 1. Visual test of knowledge redundancy for chemicals (ISIC=2400)

patents granted 1995 to 1999 (by class) ISIC 2400 chemicals

95 R&D	2	8	15	23	29	40	43	44	52	53	55	62	65	68	72	73	106	118	126	128	132	134	137	141	148
0.0																									
0.2																									
0.2																									
0.2																									
0.3																									
0.4																									
0.4																									
0.5																									
0.5																									
0.6																									
0.6																									
0.7																									
0.8																									
0.8																									
0.8																									
1.4																									
3.2																									
4.6																					1				
8.4																									
13.2																									
13.7																									
15.5																									
22.3																									
22.3																									
23.2																									
24.0																								3	
26.5																2				1					
26.5																									
27.7																									
27.8																									
28.0							2							2		1	2					16	4	6	
29.9																	1	1							
30.9																									
44.8																									
156.7		6	10			1		1		1							1		1		2	3		3	
236.4	1	3	1	1	3				7		1	1	18		1		13	2				1		1	3

95 R&D	156	162	181	204	205	206	210	211	215	219	220	222	224	239	241	242	249	250	251	252	264	300	313	324	340
0.0																									
0.2																									
0.2																									
0.2																									
0.3																									
0.4																									
0.4																									
0.5																									
0.5																									
0.6																									
0.6																									
0.7																									
0.8																									
0.8																									
0.8																									
1.4																									
3.2																									
4.6																									
8.4																									
13.2																									
13.7																									
15.5																									
22.3																									
22.3																									
23.2																									
24.0						1																			
26.5						1											1								
26.5																									
27.7				1																					
27.8					1																				
28.0					1		1					7		1						2	1				1
29.9	5						1					4		1				1	1	1					
30.9																									
44.8																									
156.7	1					1		2	5		1	14								6	1	1		1	
236.4	3	4	1	11	7	1	1	3		7			1	2	1	6				13			2		

95 R&D	343	359	383	385	401	403	422	423	424	425	426	427	428	429	430	433	435	435	436	442	451	473	501	502	508
0.0																									
0.2																									
0.2																1									
0.2																									
0.3																									
0.4																									
0.4																									
0.5																									
0.5																									
0.6																									
0.6																									
0.7																									
0.8																									
0.8																									
0.8																									
1.4																									
3.2																									
4.6																									
8.4																									
13.2												1													
13.7																									
15.5																									
22.3																									
22.3																									
23.2																									
24.0									10							1									
26.5					1				1								1		4						
26.5																									
27.7												1	1												
27.8					1				16				1												
28.0							6		15		1	1									1				6
29.9						1						1	1												1
30.9																									
44.8																									
156.7			1		3				103	1	4	2	2			1	1							1	
236.4	3	3		1			2	3	1		1	21	52	1	3					4		1	5		

95 R&D	510	512	514	516	521	522	523	524	525	526	528	544	548	549	554	556	558	560	562	568	570	604	606	total
0.0																								0
0.2																								0
0.2																								1
0.2																								0
0.3																								0
0.4																								0
0.4																								0
0.5																								0
0.5																								0
0.6																								0
0.6																								0
0.7																								0
0.8																								0
0.8																								0
0.8																								0
1.4																								0
3.2																								0
4.6																								1
8.4																								0
13.2						2																		3
13.7																								0
15.5																								0
22.3																								0
22.3																								0
23.2																								0
24.0	4						2	3																24
26.5			2																			1		15
26.5																								0
27.7							2	1	1															7
27.8	6		12																					37
28.0	22																							99
29.9						13	3	4	1		3					1	2							47
30.9																								0
44.8																								0
156.7	241	1	17	1				2	2										3			1	1	450
236.4	3				4	2	7	39	14	4	9	3	2	1	1		1	1		3	3			318

Figure 2. Optimal investment versus R&D productivity (IQ)
(Assumes joint contribution from all other inputs=100)

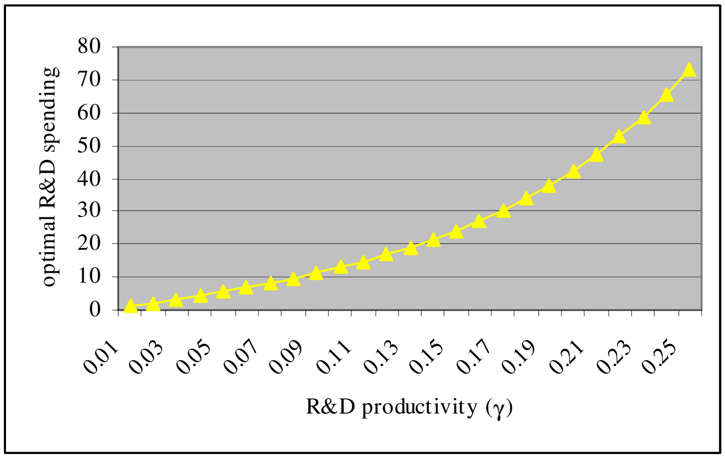


Figure 3. Absorptive capacity mimics heterogeneity

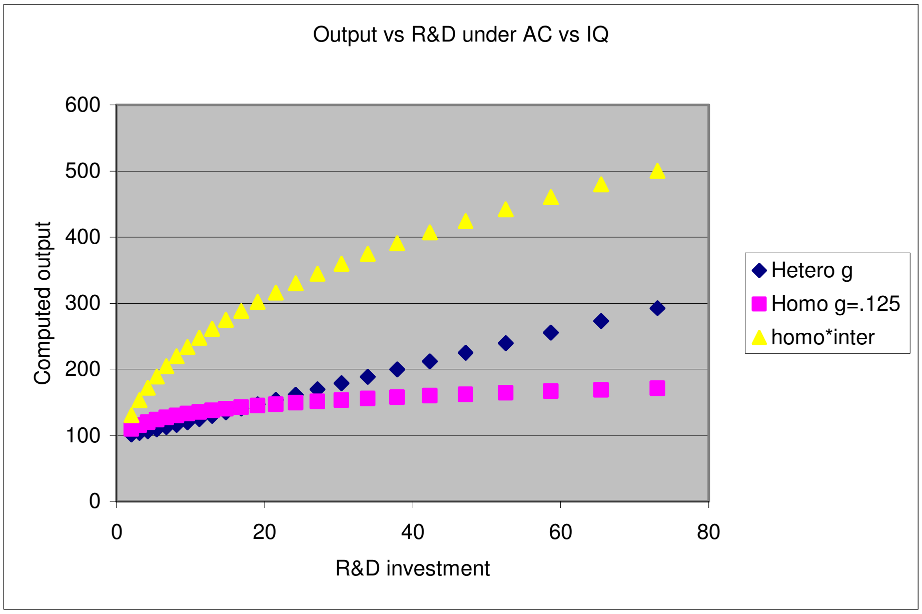
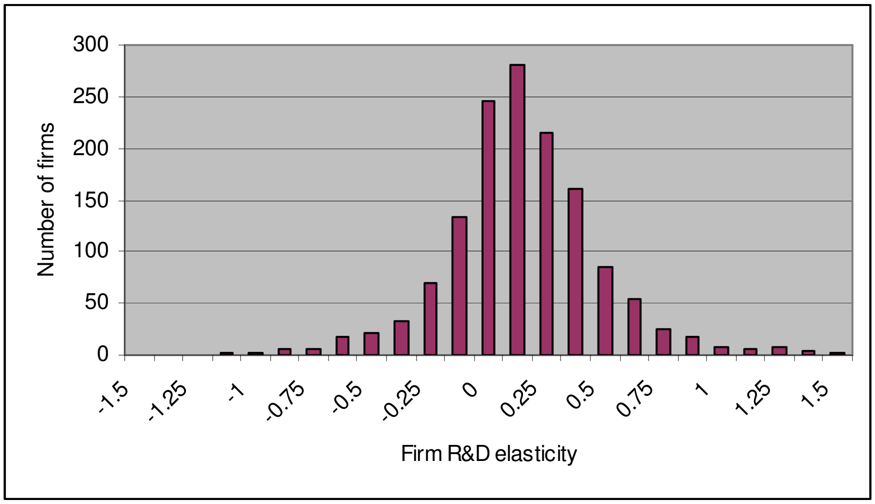
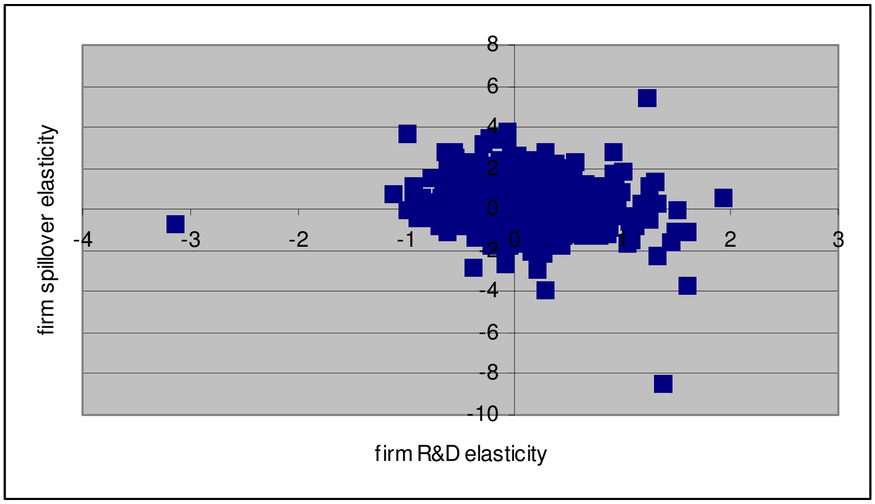


Figure 4. Histogram of firm specific components of R&D elasticity



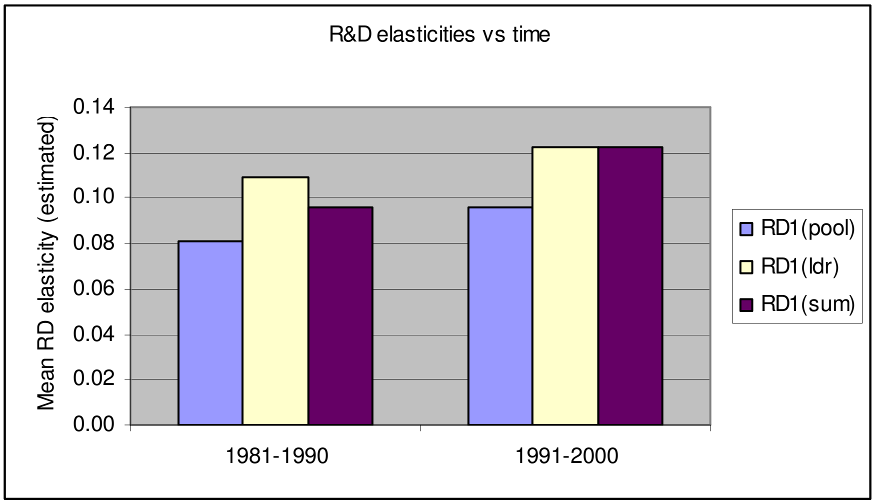
mean =0.094

Figure 5. Comparing elasticities for own R&D versus spillovers



*Slope = - .442****

Figure 6. Time variance of elasticities for balanced panel of firms (20 observations each)



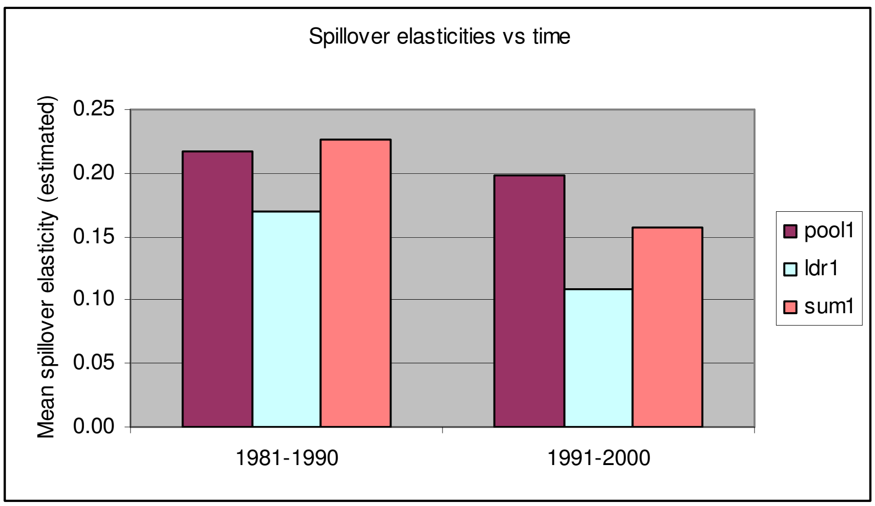
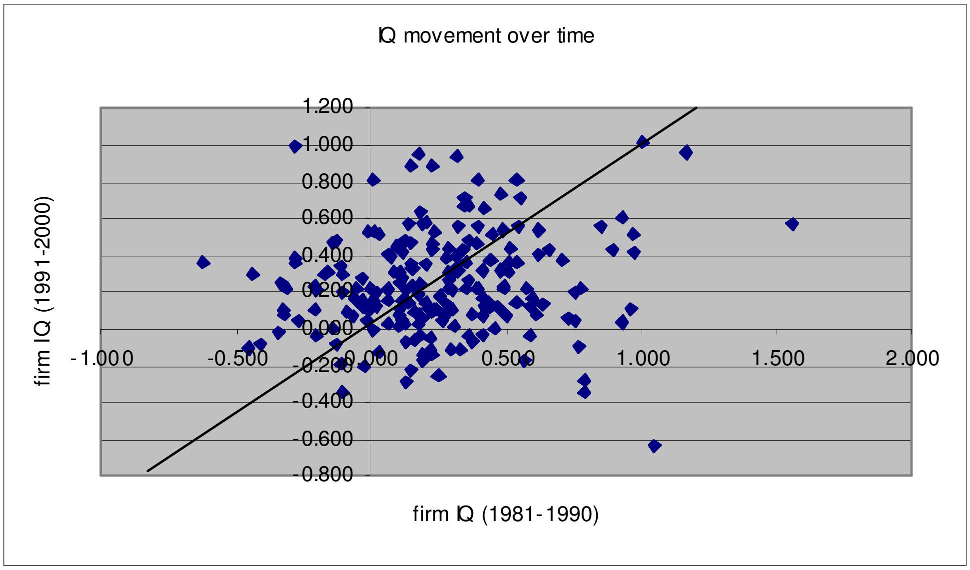


Figure 7. Individual firm movement in elasticities



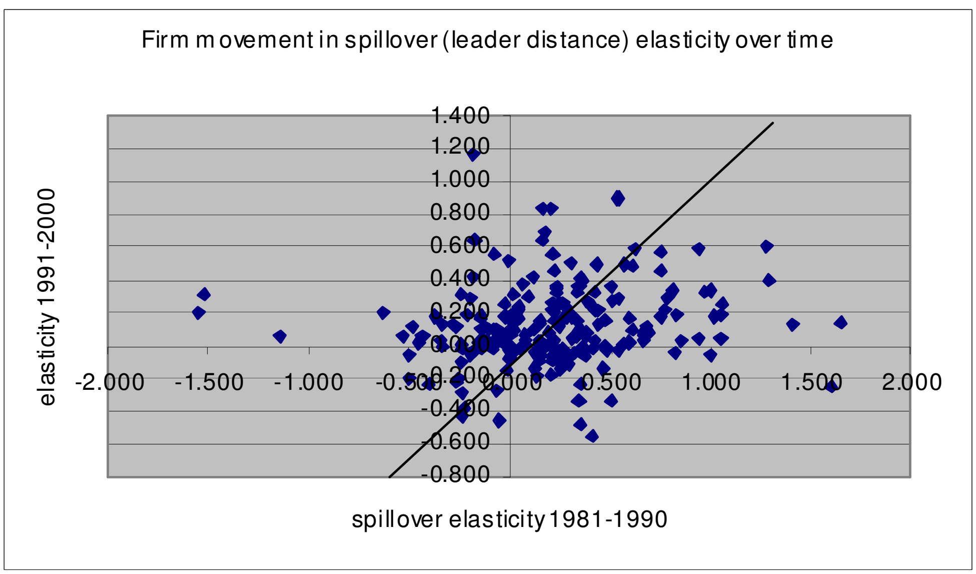
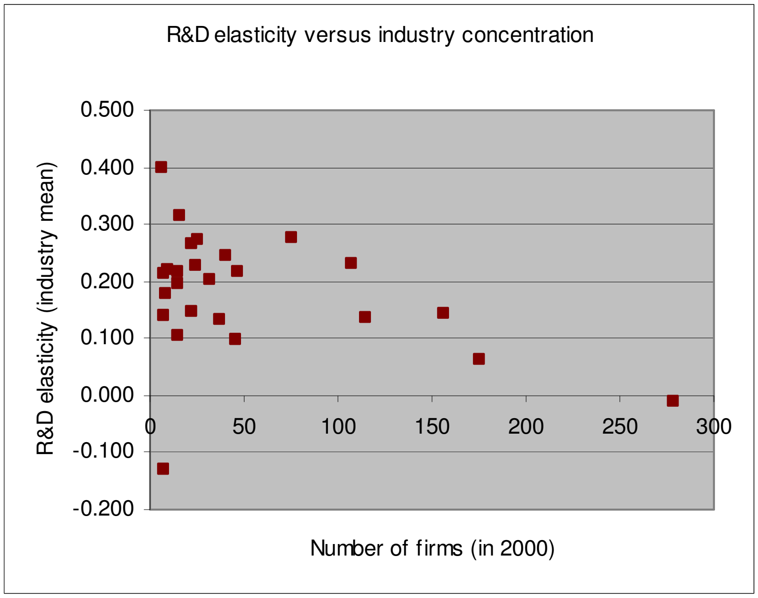


Figure 8. Relationship between elasticities and market structure (number of firms)



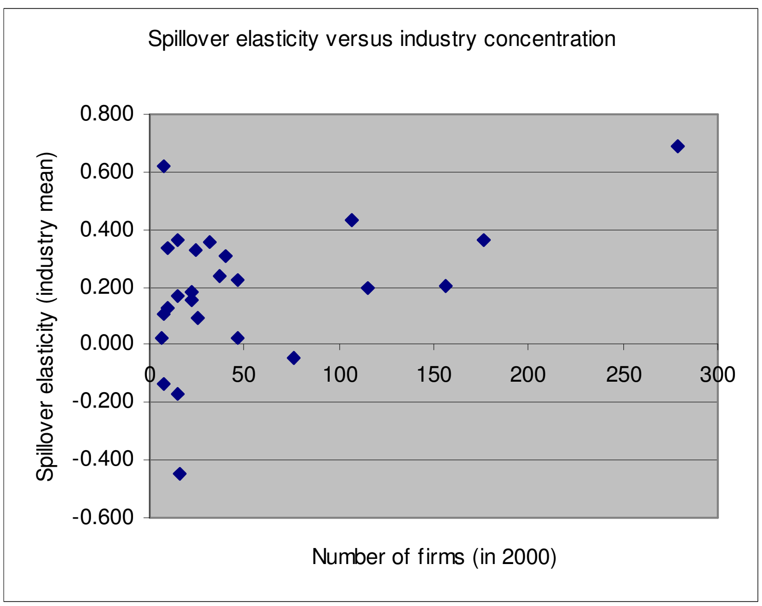
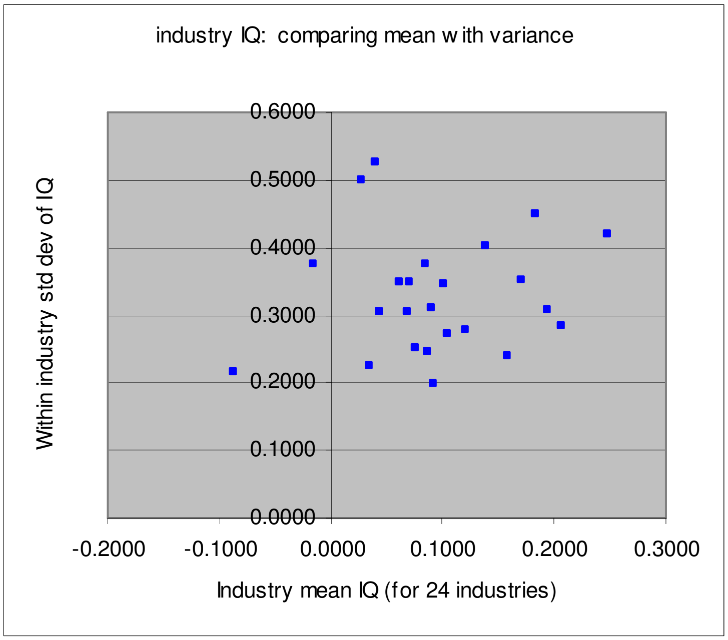
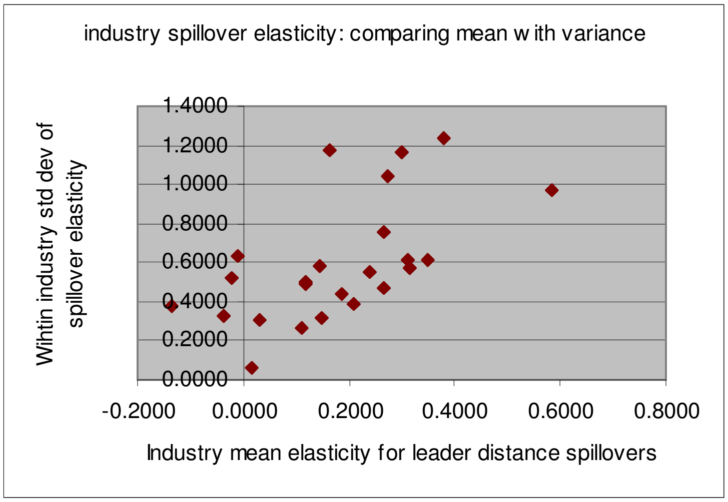


Figure 9. Intra-industry variance in IQ and spillover elasticity

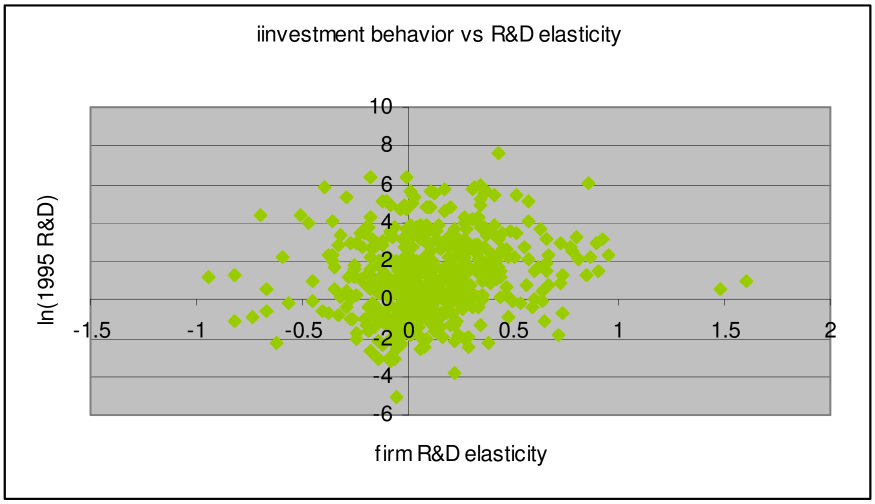




Comparison of variances

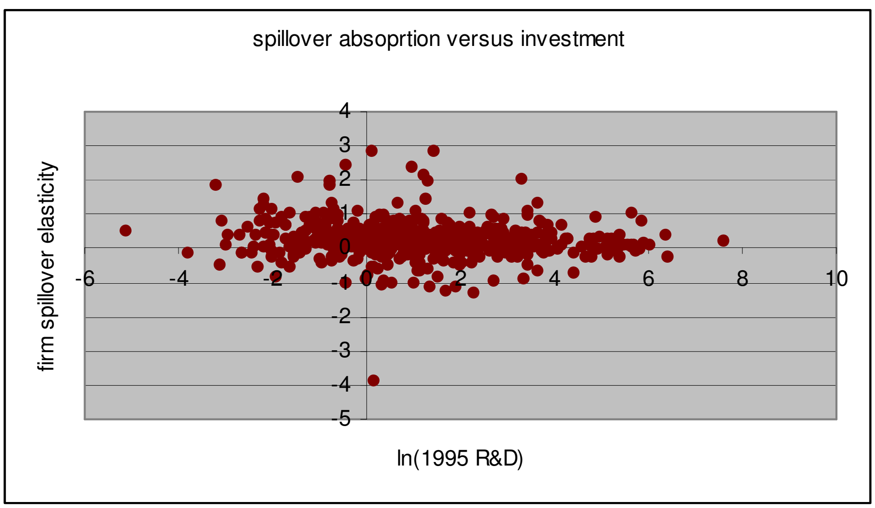
	IQ	spillover elasticity
across industry	0.075	0.161
within industry	0.328	0.599

Figure 10. Behavioral test: Higher R&D elasticity leads to higher investment…



*Slope = 1.06****

…or higher investment leads to higher spillover elasticity



*Slope = -.029***