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Firm R&D Behavior and Evolving Technology in Established Industries

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Abstract

One of the key mechanisms of firms' strategic renewal is R&D, and a key driver of the intensity of R&D is industry context. A number of theories develop propositions linking industry factors to firm R&D behavior, but these theories lack consensus. To date empirical tests have been unable to resolve the competing predictions due to lack of time-varying measures of technology. We create new measures for technology then conduct a test of the competing theories. Our results indicate that the data best match a model of innovative behavior in which firms invest in R&D principally to regain eroded advantage rather than to pursue the new frontier.

1. INTRODUCTION

One of the key mechanisms of firms' strategic renewal is research and development (R&D), and a key driver of the intensity of R&D is industry context. A number of theories develop propositions linking industry factors to firm R&D behavior. While these theories agree on the factors affecting R&D, they lack consensus on whether the factors increase or decrease R&D. It is difficult to assess prescriptions for strategic renewal through R&D without a solid understanding of industry context and its impact on firm behaviors and outcomes.

Our goal in this paper is to better understand the role of R&D and innovation as a mechanism for strategic renewal in established industries. We take an empirical approach that tests which theory best matches fact in these industries. We begin by synthesizing a diverse body of theory and empiricism addressing firm behavior in innovative markets. While the theories reach conflicting conclusions, they agree on three exogenous[1] factors driving innovation: demand, technological opportunity and appropriability. To date empirics have been unable to resolve the theoretical conflicts because there are no time-varying measures for two of these factors (technological opportunity and appropriability). Without time-varying measures it is not possible to tease apart their effects from other factors that may derive from them.

Accordingly to make headway we first construct time-varying measures of technological opportunity and appropriability. We then combine these measures with measures for other industry factors to conduct an empirical test of firms' innovative behavior in twenty-five industries over twenty years.

Our results indicate that the data best match a model of innovative behavior in which firms invest in R&D principally to regain eroded advantage rather than to pursue the new frontier. This is consistent with the "escape competition" behavior in endogenous growth models (Mookherjee and Ray 1991, Peretto 1999, Aghion, Harris, Howitt and Vickers 2001, Mukoyama 2003). Firms who are imitated face greater incentives to innovate because they are in neck and neck competition and will remain so until they innovate again. Our results indicate that the intensity of this "erosion-innovation cycle" is accelerated by market size, market growth, the number of rivals and the ease of expropriating spillovers. It is actually decreasing in the level of technological opportunity. Thus firm innovative behavior appears to be driven by strategic renewal in the face of competition rather than purposeful pursuit of the technology frontier.

In addition to our main results regarding firm innovative behavior, our new measures allow us to say something about industry evolution. Contrary to studies that treat technological

[1] Note that all factors are endogenous to some degree, but these three factors are assumed to move more slowly than other factors such as industry concentration.

opportunity and expropriability as time invariant, our results suggest first that they vary substantially over time. Indeed, the impact of these factors on firm behavior is greater within industry over time, than it is across industries. Second, and also contrary to conventional wisdom, technological opportunity is increasing over time, while expropriability (effectiveness using rival spillovers) is decreasing over time.

While we need a new model to offer firms prescriptions with any confidence, there are two immediate implications from the results. First, firms are able to strategically renew themselves. They do so not only through improved offerings (the immediate goal of R&D), but through enhanced R&D capability (the frontier moves). The second implication is that as the frontier moves, it becomes more difficult to keep pace through free-riding (spillovers) on the R&D of rivals. Thus as industries mature it becomes increasingly likely that firms are innovating under their own power.

2. MODELS OF INNOVATIVE MARKETS

Three streams of economics literature model the innovative behavior of firms: Industrial Organization (IO), evolutionary economics and endogenous growth.[2] All three streams are rooted in the Solow (1957) observation that the dominant explanation for per capita growth in the United States for first half of the 20th century is technological progress. Thus their goal is informing technology policy. These literatures are also important to strategy however because they model firm behavior and outcomes as a function of economic conditions. Thus they inform the conditions under which firms are both likely and able to strategically renew themselves.

Each theoretical approach relies on distinct assumptions, and thus they tend to draw different conclusions regarding the impact of industry conditions on innovation. They do however agree on the set of exogenous factors affecting innovation: demand, technological opportunity and appropriability. Furthermore they agree on the impact of demand on innovation. Innovation is increasing in both the level of demand and the degree of buyer heterogeneity. Where they disagree is on the impact of the technological factors: technological opportunity and appropriability. Our study focuses on the two technological factors.

[2] Note there are also two models in strategy examining innovation and market conditions: Adner and Levinthal (2001) and Knott (2003). Of these only Knott considers the two technology factors. Knott employs an agent-based model where firms can innovate and imitate each period. Innovation occurs only when firms lose share, and imitation is of a random rival only if the rival has superior knowledge. Innovation is increasing in expropriability, but decreasing in technological opportunity.

2.1 Technological opportunity

Technological opportunity is the notion that there is exogenous variation in the cost and difficulty of innovating across technical areas (Jaffe 1986), that industries have different production possibilities for translating research resources into new techniques of production (Cohen and Levin 1989) and that industries differ in the productivity of their R&D (Klevorick, et al 1995). The best means to characterize technological opportunity however is to examine how it has been modeled, because the operational definitions will affect the conclusions.

2.1.1 Operational definitions of technological opportunity

Industrial Organization. Spence (1984) models technological opportunity as a function which transforms knowledge into firm costs. Dasgupta and Stiglitz (1980) and Levin and Reiss (1984, 1988) model technological opportunity as the elasticity of unit cost with respect to own R&D (cost decreasing R&D). Levin and Reiss (1988) also model technological opportunity as the elasticity of price with respect to own R&D (demand increasing R&D). Thus in general the IO models capture technological opportunity as the elasticity of R&D/knowledge on output, where output is broadly defined to include intermediate "goods" (cost, knowledge stock, patents).

Evolutionary Economics. Nelson and Winter (1982) model technological opportunity as the rate of exogenous change in the cost frontier. Klepper (1996) models technological opportunity as a diminishing returns function which transforms process R&D into marginal cost reductions.

Endogenous Growth. Romer (1990) models technological opportunity as the productivity of researchers' human capital in generating new knowledge from the stock of existing knowledge. This is the same definition as Grossman and Helpman (1992). Jovanovic and Rob (1989) model technological opportunity as the degree to which the distribution of ideas improves per period. Aghion, Harris, Howitt and Vickers (2001) model technological opportunity as the incremental decrease in cost associated with a unit advance in technology (where the probability of a unit advance is a function of R&D expenditures). Thus in general, the endogenous growth models also capture technological opportunity as productivity of R&D investment.

2.1.2 Propositions regarding the impact of technological opportunity

While the operational definition of technological opportunity is fairly consistent across models, the propositions about its impact on R&D behavior vary.

Industrial Organization. The IO models tend to examine R&D spending by profit maximizing firms amongst a set of homogeneous rivals. Dasgupta and Stiglitz (1980) build a model of R&D investment in the absence of spillovers. Research intensity is increasing in technological opportunity. Spence (1984) considers dynamic cost competition among a set of homogeneous rivals in the presence of spillovers. Firms maximize profits by choice of R&D taking rival behavior as given. He concludes that research intensity is increasing then decreasing with the level of technological opportunity. The intuition behind the result is that if technological opportunity is low, then R&D has little effect on costs, and so there is little incentive to do it. At the other extreme, if technological opportunity is high, then very small amounts of R&D will reduce costs. Accordingly it is at intermediate levels of technological opportunity where innovation is highest. Levin and Reiss (1984, 1988) construct a model of a profit maximizing firm choosing levels of R&D, taking into account the elasticity of the firm's own investment (technological opportunity) as well as that from spillovers of rival R&D (expropriability). As with Spence, firms are identical and the spillover pool is defined as the sum of all rival R&D adjusted for leakage. What differs from Spence is that own R&D and rival R&D are imperfect substitutes, each with their own elasticity. Since technological opportunity is the elasticity only with respect to own R&D, innovation increases with technological opportunity (as in Dasgupta and Stiglitz 1980).

Evolutionary economics. Evolutionary economics examines how firm behavior, market structure and outcomes are jointly determined in models of innovative and imitative activity by profit-maximizing firms competing along a downward-sloping demand curve. A major distinction from IO models is that firms differ in their levels of knowledge, and accordingly their cost functions and profits. Nelson and Winter (1982) use computational methods to evaluate their model. When industries are concentrated (four firms), technological opportunity has no apparent impact on the level of R&D investment. When the industry is more competitive however (sixteen firms), R&D investment is substantially higher for all technological regimes. However the impact of technological opportunity depends on the level of appropriability. When technological progress is slow, then R&D investment is higher for easy imitation; when technological progress is fast, R&D investment is higher for hard imitation. Klepper (1996) derives comparative dynamics indicating that R&D investment decreases over time. This follows logically from the assumption of diminishing returns to R&D and implies that R&D is increasing in technological opportunity.

Endogenous growth. Endogenous growth theory consists principally of stochastic models that cast innovation by profit seeking firms as engines of growth. These models share many features of evolutionary economics: 1) characterization of knowledge as an intermediate good produced by profit maximizing firms through imitation and invention, 2) heterogeneity in the distribution of knowledge, and 3) imitation that depends on the level of heterogeneity. Romer (1990) builds a three sector model where the research sector has two outputs: designs (which are excludable) and the set of knowledge on which those designs rest (which is non-excludable). Increases in the productivity of the researchers (technological opportunity) unambiguously increases innovation and growth. Aghion, Harris, Howitt and Vickers (2001) build a model where firms maximize the net present value of profits taking into account profit from any current knowledge gap, profit from moving ahead, cost of own R&D and losses associated with followers catching up. Like Nelson and Winter (1982) the complexity of their model drives them toward numerical evaluation. Their results indicate that R&D is increasing in technological opportunity. In contrast, and Grossman and Helpman (1992) and Jovanovic and Rob (1989) conclude that R&D and growth decrease with technological opportunity.

2.2 Appropriability

Appropriability pertains to firms' ability to capture the returns to their R&D (Cohen and Levin 1989). There are two principal means by which firms do this. The first is through formal legal mechanisms such as intellectual property rights. The second is through mechanisms to prevent rivals from expropriating their knowledge through spillovers. These mechanisms include complementary assets, efforts to locate away from rivals, and secrecy. There are few settings where patents or other legal mechanisms play a substantial role in appropriating returns (Levin et al 1987, Cohen et al 2000). Thus the primary factor driving appropriability is spillovers. Indeed most theoretical models capture appropriability through spillovers.

Spillovers in these models actually have three dimensions: a structural dimension: the amount of rival knowledge (the spillover pool), a behavioral dimension: the rate at which knowledge leaks between firms, and a technical dimension: the ability of rivals to make use of that knowledge. We focus on this technical dimension and label it *expropriability*, to distinguish it not only from the other forms of appropriability, but from other dimensions of spillovers.

2.2.1 Operational definitions of expropriability

Industrial Organization. Spence (1984) modeled the behavioral dimension of spillovers through a term representing the percentage of industry R&D that leaks to rivals. This captures the intensity of both innovators' efforts to protect knowledge and imitators' efforts to extract knowledge. Spence applied this to his structural dimension (the sum of rival R&D). He did not have a technological component. Levin and Reiss (1984, 1988) modeled expropriability as the elasticity of unit cost with respect to the "appropriable pool" of rival R&D. This they defined as the technological dimension of appropriability. The appropriable pool included the structural dimension (the sum of rival R&D) as well as a behavioral dimension--the percentage of that pool that leaks to rivals.

Evolutionary Economics. Expropriability is modeled as the ease of imitation—the probability that a firm will be able to imitate best practice (lowest cost) for a given level of R&D. Nelson and Winter (1982) treat this parametrically. Klepper (1996) assumes the leader's technology is perfectly imitable after a one year lag.

Endogenous Growth. Romer (1990) captures spillovers as the pool of knowledge underlying the ideas that have been produced. This pool is freely available as a non-rival input in the creation of new ideas. Grossman and Helpman (1992) capture expropriability through the imitation rate--the proportion of innovator products that are copied by imitators per unit of time. Expropriability in Jovanovic and Rob (1994) is an ease of imitation parameter similar to Spence, but with two important distinctions. First, in Spence, the parameter is applied to the pool of all rival knowledge, while in Jovanovic and Rob the parameter is applied to the share of knowledge obtained from a random rival. Second, spillovers in the endogenous growth models are asymmetric—firms can't learn from rivals with less knowledge. Aghion, Harris, Howitt and Vickers (1992) model expropriability as the ease of imitating the leader's technology. Eeckhout and Jovanovic (2002) examine investment choice by firms who maximize the present value of profits in a model where firms imitate superior cost functions. Like Levin and Reiss, they distinguish between the behavioral dimension of spillovers (the amount of rival knowledge available to the firm) and the technological dimension, the productivity of rival knowledge. (Ease of imitation combines both the ability to obtain the knowledge and productivity of the knowledge once obtained).

2.2.2 Propositions regarding the impact of expropriability

While there is greater variation in the operational definitions of expropriability, there is consensus around a definition of the ability of firms to make use of rival knowledge. This general definition generates differing propositions about the impact of expropriability on firm R&D behavior.

Industrial Organization. Spence (1984) only considers the behavioral dimension of spillovers--the share of knowledge that leaks between firms. Because rival R&D substitutes for own R&D, investment decreases in with the leakage rate. For Levin and Reiss (1984, 1988) own knowledge and rival knowledge are imperfect substitutes. They reach the same conclusion as Spence with regard to the leakage rate (increases in the leakage rate decrease R&D intensity), With regard to the technological component of spillovers, they find that increased productivity of rival knowledge increases R&D intensity.

Evolutionary economics. Of the evolutionary economics models, only Nelson and Winter (1982) treat expropriability parametrically.[3] When industries are concentrated (four firms), expropriability has no apparent impact on the level of innovative R&D. When the industry is more competitive (sixteen firms), R&D investment is significantly higher for both expropriability regimes. However the impact of expropriability depends on the level of technological opportunity. When technological progress is slow, then R&D investment is higher for easy imitation; when technological opportunity is fast, R&D investment is higher for hard imitation.

Endogenous growth[4]. Imitation and innovation are modeled identically to one another in Grossman and Helpman (1982), thus their model concludes that innovation and growth are increasing in imitation. This is a similar conclusion to that reached in Jovanovic and Rob (1989). In numerical analysis of their model, Aghion, Harris, Howitt and Vickers (2001) conclude that growth is increasing then decreasing in imitation (regardless of whether technological opportunity is high or low). Eeckhout and Jovanovic (2002) who distinguish between the behavioral and technological dimensions of spillovers reach conclusions similar to Levin and Reiss (1984, 1988): investment decreases with the leakage rate but increases with the elasticity of spillovers.

3. THE EMPIRICAL RECORD ON INNOVATIVE MARKETS

As summarized previously, there is no theoretical consensus on the impact of either technological opportunity or expropriability on firms' innovative behavior. Predictions for technological opportunity are that it increases (Dasgupta and Stiglitz 1980, Levin and Reiss 1988, Aghion and Howitt 1992, Nelson and Winter 1982, Klepper 1996), decreases (Jovanovic and Rob 1989, Grossman and Helpman 1992, Knott 2003) and increases then decreases (Spence 1984) innovation. Similarly for expropriability the predictions are that it increases (Levin and Reiss 1988, Jovanovic and Rob 1989, Grossman and Helpman 1992, Eeckhout and Jovanovic 2002, Knott 2003), decreases (Spence 1984) and increases and decreases (Nelson and Winter 1982, Aghion et al 2001) innovation. Accordingly resolution requires empiricism.

[3] Klepper (1996) does not parameterize expropriability (leader technology is freely imitated following a one year lag), thus offers no propositions about its impact

[4] Romer (1990) does not parameterize expropriability (freely available as non-rival input), thus offers no propositions about its impact

A number of empirical tests of market structure and innovation have been conducted over the past forty years. Cohen and Levin (1989) provide nice summaries of several of these studies. None of these has resolved the theoretical controversy. In part this stems from the lack of time-varying measures for the two constructs we consider here: technological opportunity and expropriability. Without time varying measures for technology it isn't possible to tease apart its effects from the factors derived from it, such as market structure. We now review what measures have been used and with what results.

3.1 Technological opportunity.

Technological opportunity receives less attention in empirical tests than does expropriability. Presumably this occurs because the level of technological opportunity is assumed immutable, whereas the level of appropriability is affected by property rights policies. Technological opportunity has been captured empirically two ways. The first classifies firms into technology clusters, where clusters are taken to represent different technological opportunity sets. These studies find that clusters explain significant variance in patenting (Jaffe 1986) and R&D intensity (Scott 1984, Levin and Reiss 1988), but the studies don't characterize how the high patent clusters differ from low patent clusters. An alternative measure of technological opportunity is a set of survey measures of R&D managers' assessments of industry conditions. These assessments include the relevance of science to industrial technology and the importance of university research to the level of industrial innovation. The survey studies find that R&D intensity increases with the importance of university research and with the relevance of three of five scientific fields (Klevorick, Levin, Nelson and Winter 1995, Cohen and Walsh 2000). However Levin and Reiss (1988) find that cross-industry variations in contributions of science to industrial technology do not account for variation in cost elasticities.

3.2 Expropriability

The empirical record regarding expropriability and innovation is similarly equivocal. Studies break down into two classes: Those examining the impact of spillover pools on R&D, and those examining survey based measures of appropriability and imitation. The studies of spillovers consistently indicate that R&D intensity and outcomes increase with the size of the spillover pool (Jaffe 1986, 1988). However the spillover pool as constructed in these studies (sum of R&D spending by firms in the industry) is highly correlated with market size, and thus the spillover variable may be capturing market size effects (Schmookler 1966). Moreover the constructs in the models pertain to the behavioral (percentage of pool that leaks) or technological (elasticity of the pool on focal firm output) dimensions of spillovers whereas the empirical tests consider the structural dimension (size of the pool).

The survey-based studies come closer to the theoretical constructs through questions regarding learning mechanisms and imitation lags. The learning measures are self reports by R&D managers of the mechanisms that are most effective for learning about technology; the imitation lag measure is a self-report of the time it takes to imitate a major patented new product invention. Levin, Cohen and Mowery (1985) find that the imitation lag measure has no significant effect on R&D intensity. Levin (1988) looking at the learning mechanisms finds none of them to be significant in explaining R&D intensity. Cohen and Walsh (2000) using new survey data find that R&D intensity increases with the importance of ideas from rivals, but decreases with the importance of information from suppliers and market mediated information from rivals. Finally, Levin and Reiss (1988) identified three survey measures potentially related to the productivity of spillovers (the importance of rivals to technological progress, the importance of government research to technological progress, and technological maturity). None of these explained variation in the productivity of the spillover pool.

Thus results with survey data are equivocal. One reason for this may be that the measures are taken at single points in time. As a result, tests are necessarily cross-sectional. Accordingly the measures may have no explanatory power after including other factors that are jointly determined by technology. An alternative explanation is that these are proxy measures—none of which captures leakage of rival knowledge or returns to rival knowledge directly.

4. EMPIRICAL APPROACH

Our empirical approach to assessing the relationship between firm R&D behavior and industry technological characteristics follows a two stage approach. In the first stage we form time-varying estimates of the technological characteristics of industry – *technological opportunity* and *expropriability*. The stage is important because existing theory has generally assumed that technological characteristics are exogenous and fixed over reasonably long periods of time. Empirical tests have been unable to challenge these assumptions because the technology measures used to date have been gathered from cross-sectional surveys (Klevorick, Levin, Nelson and Winter 1995, Cohen, Nelson, and Walsh 2000). We develop accounting based measures of technological opportunity and expropriability, which, in addition to the advantages of time variation, are based on publicly available data and thus will facilitate future analyses in industries not covered by surveys. In the second stage, we use the technology estimates together with other industry characteristics to model firm behavior in response to changes in technological opportunity and expropriability. We discuss each stage of the estimation procedure and itts associated results in turn.

Stage One: Characterizing Technology

In the first stage we develop time-varying measures of technological opportunity and expropriability that closely match the modeling constructs. In particular the measures capture the productivity of own firm R&D (technological opportunity) and of rival R&D (expropriability). To construct both measures, we follow empirical models of R&D productivity (Griliches and Mairesse 1984) and spillover effects (Jaffe 1986). We employ a standard production function methodology modeling output as a function of capital, labor, R&D inputs, and rival spillovers, without a constant returns to scale constraint.

$$Y_{it} = K_{it}^{\beta} L_{it}^{\gamma} R_{it}^{\alpha} S_{it}^{\theta} \,. \tag{1}$$

Logging both sides of the model,

$$y_{it} = \beta k_{it} + \gamma l_{it} + \alpha r_{it} + \theta s_{it} + c + \varepsilon_{it} \,, \tag{2}$$

where:

Y_{it}	is sales for firm i in year t , where $y_{it} = \ln(Y_{it})$
K_{it}	is capital (property, plant and equipment), where $k_{it} = \ln(K_{it})$
L_{it}	is labor as full time equivolent employees, where $l_{it} = \ln(L_{it})$
R_{it}	is R&D spending by firm i, where $r_{it} = \ln(R_{it})$
S_{it}	is R&D spending by rival firms (spillover pool), where $s_{it} = \ln(S_{it})$
C	is the intercept term.

We interpret the coefficients on own R&D and rival R&D (spillover pool) as meaningful industry characteristics. Technological opportunity, α , is taken to be the output elasticity of firm R&D spending, R_{it}. While expropriability, θ , is taken to be the output elasticity of the spillover pool of rival R&D, $S_{it.}$.

In order to estimate industry specific measures of technological opportunity and expropriability, we split our sample in 25 industry groups based on the industry classifications employed in the Cohen, Nelson, and Walsh (2000) industry survey. In order to generate year specific metrics, we model each industry *j* separately using a random coefficients specification (Swamy and Tavlas 1995). 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. Random coefficient models are those in which each coefficient has two components: 1) the direct effect of the explanatory variable and 2) the random component that proxies for the effects of omitted variables. Our use of a random coefficients specification follows from the need to capture time-varying estimates for expropriability and technological opportunity.[5] The model we implement employs year specific random coefficients which transforms equation 2 as follows:

$$y_{it} = \left(\beta_j + \varepsilon_{jt}^{\beta}\right)k_{it} + \left(\gamma_j + \varepsilon_{jt}^{\gamma}\right)l_{it} + \left(\alpha_j + \varepsilon_{jt}^{\alpha}\right)r_{it} + \left(\theta_j + \varepsilon_{jt}^{\theta}\right)s_{it} + (c_j + \varepsilon_{jt}^{c}) + \varepsilon_{it}. \qquad (3)$$

Thus, rather than assume that technological opportunity and expropriability are constant over time (within industries) as has been prior practice, we are able to statistically test the hypothesis that $\varepsilon_{jt}^{\alpha} = \varepsilon_{jt}^{\theta} = 0$. Assuming that this hypothesis is rejected, we then extract from the random coefficients on r_{it} and s_{it} estimates of industry-year specific technological opportunity and expropriability as the Bayesian best linear predictors of $\alpha_{jt} = E\left(\alpha_j + \varepsilon_{jt}^{\alpha}\right)$ and $\theta_{jt} = E\left(\theta_j + \varepsilon_{jt}^{\theta}\right)$. These time varying estimates of technological opportunity and expropriability then become the basis for our analysis of firm behavior in the subsequent stage.

Stage Two: Test of Firm Behavior

Our main empirical test examines the impact of industry characteristics on firms' innovative behavior. The main distinctions between this test and the technology characterization in the last section are 1) that here we examine firm behavior (R&D investment level) rather than output, and 2) we pool data across industries rather than examining industries separately. Following convention, we model R&D intensity of firm *i* in industry *j* as a function of a set of firm variables and industry structure (Shrieves 1978, Bound et al 1984, Jaffe 1988). In addition, we include our measures of technological opportunity and expropriability. The model specification is:

$$r_{i,t+1} = \gamma_0 + \gamma_1 y_{it} + \gamma_2 k_{it} + \gamma_3 m_{jt} + \gamma_4 \Delta m_{jt} + \gamma_5 n_{jt} + \gamma_6 \alpha_{jt} + \gamma_7 \theta_{jt} + \delta_i + \upsilon_t + \varepsilon_{it} \qquad (4)$$

where the variables (with firm index, *i*, industry index, *j*, and time index, *t*) are defined as follows:[6]

[5] An alternative to the random coefficients specification would be that of estimating the model separately for each industry and each year. Doing so would generate industry-year specific coefficients under the assumption that the error term is independent across models. Since we believe error terms are correlated across industries, a random coefficients approach is more appropriate.

[6] Note this model ignores two market structure variables that appear in some theories of innovation: firm heterogeneity and buyer heterogeneity. While we include firm heterogeneity in a robustness check, we do not have a direct measure for buyer heterogeneity. Market growth is a partial proxy in that markets grow only through lower cost (requires heterogeneity in willingness to pay), greater differentiation (requires heterogeneity in buyer tastes), or more buyers. The lack of a more direct measure should be considered a

r_{it} is log firm R&D expenditures

y_{it} is log firm sales

k_{it} is log firm net property, plant and equipment

m_{jt} is log market size as total industry sales: $m_{jt} = \sum y_{ijt}$

Δm_{it} is market growth: $\Delta m_{it} = m_{it} - m_{i,t-1}$

n_{jt} is log number of firms in industry j in year t

α_{jt} is Technological Opportunity in industry j (from Stage 1)

θ_{jt} is Expropriability of industry j (from Stage 1).

Specification Challenges

The estimation process is significantly complicated by two related technical issues. First, our interpretation of the coefficients on R&D and spillovers as technological opportunity and expropriability is potentially confounded by the fact that these are generated variables – that is, they are the result of an estimation procedure. As such, they are subject to potential estimation error that arises because of omitted variables in the first stage model. This may in turn bias the standard error estimates in the second stage model. Second, the first and second stage models form a system of equations such that, for example, the sales variable in equation 4 is endogenous to the outcome of the R&D model in equation 2.

The ideal solution to both the generated regressor and simultaneity issues is to estimate the two equations jointly. However, at this time, a full simultaneous estimation methodology is not possible for two reasons. First, the first stage model is a random coefficient specification for which no implementable simultaneous equation estimator exists. Second, the generated regressors are the predicted coefficients from the first stage random coefficient model rather than the predicted outcome of that model. However, while we cannot implement the first best empirical solution, we can implement a number of alternative solutions that each address different parts of the empirical issues. As such, our analysis will proceed in a linear fashion. In the first set of analyses, we model the two stages sequentially, ignoring the issue of generated regressors and simultaneity. We then implement a number of potential remedies to the estimation issues. While none of the methodologies that we employ is in itself perfect, taken together they provide significant confidence in the estimation results.

Data and Variables

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limitation of the empirics, albeit one that is shared by all tests of innovation and market structure in Cohen and Levin (1989)

Data for the empirical analysis 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, we collected Compustat data for all active and inactive firms over the period 1981 through 2000 that conducted R&D. 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. The variables for R&D, sales, capital (net property, plant and equipment) and labor are taken directly from Compustat. Market size is calculated as the total sales of all firms in a given industry-year. Market growth is the year over year change in the log of market size. Finally, the number of firms is simply the count of firms in a given industry-year. 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 25 industries, 2785 firms, and 23543 firm-year observations for which complete data on the above variables is available. In the final estimation panel, this sample is reduced to 20417 observations because we employ lagged variables which eliminate the first year of observation from the panel.

In general we adopt the Jaffe (1986, 1988) conventions for empirical estimation of R&D production functions. However we make two departures, one for methodological convenience, the other for theoretical consonance. We discuss each of these in turn.

There are two empirical issues with respect to measuring R&D investment: whether to use stocks or flows, and with what lag. We use flows with no lag. This approach relies on Knott, Bryce and Posen (2003) which characterized the knowledge accumulation function in the pharmaceutical industry and found that R&D stocks reached steady state within three years. Thereafter, spending was largely that required to compensate for obsolescence and to grow at the industry rate. This finding of steady-state explains two empirical regularities: econometric equivalence between stock and flow models and econometric equivalence of models with different lags (Griliches and Mairesse 1984, Adams and Jaffe 1996). We extended the Knott et al (2003) results to seventeen of the Carnegie Mellon Survey (CMS) industries to gain confidence in the steady-state finding. All the industries reached steady-state within three years.[7] Given our

[7] Results available from the authors.

setting of mature industries and given the fact that estimating the accumulation function consumes three years of observations, we use current R&D investment (flows with no lag).

There are two issues with respect to the spillover variable. First is the issue of functional form, and second is the issue of lag. We use a leader-distance form for spillovers with no lag.[8] The leader-distance form is an effort to capture the imitating best practice construct in evolutionary economics (Nelson and Winter 1982). It is a firm-specific measure of the knowledge that a firm could potentially expropriate from rivals. Under the leader-distance form, the spillovers available to each firm are computed as the difference between the knowledge of the industry leader minus that of the focal firm. This leader-distance measure differs from the empirical IO convention of using pooled spillovers, but matches the structural dimension of spillovers in evolutionary economics. Its use is motivated by prior work demonstrating that pooled spillovers present problems of estimation bias, and that leader-distance offers the best econometric fit to the data (Knott, Posen and Wu 2007). We construct the leader-distance measure using R&D flows without lags. We do so because the spillover stock is essentially aggregate R&D stocks and thus we adopt rules identical to those used for R&D stocks.

5. RESULTS

In this section, we present the estimation results for the models specified above. Our discussion proceeds in two stages, the first focusing on the results for the estimation of the R&D and spillover elasticities that we interpret as technological opportunity and expropriability, and the second focusing on the effect of intertemporal variation in technological opportunity and expropriability on firms' R&D behavior.

First Stage – Estimating Technological Opportunity and Expropriability

Table 1 presents descriptive statistics for the data used in the analysis. Table 2 presents the results of the industry specific models of the firm production function in equation 3 following a random coefficient methodology. The coefficient estimates in the table represent the mean values of the parameters. The model results are consistent with prior estimates of the R&D production function (Jaffe 1986) in that most industries exhibit slightly increasing returns to scale (sum of coefficients is greater than one), and that the returns to factors are highest for labor, followed by capital, R&D and finally spillovers.

Insert Tables 1 and 2 about here

[8] Results are robust to alternative functional forms of the spillover pool.

Our principal concern in this stage however is the temporal components of technological opportunity, $\alpha_j + \varepsilon_{jt}^{\alpha}$, and expropriability, $\theta, + \ \varepsilon_{jt}^{\theta}$. Note that even in cases where the mean value is non-significant, there may be, and in most cases is, variation within industry over time that is statistically significant. We present the time varying estimates of technological opportunity and expropriability for each of the twenty-five industries in Figure 1. Three elements of the results are worth noting.

Insert Figure 1 about here

First the measures are time varying. For each industry, we tested the null hypothesis that the random components of all coefficients are zero, $\varepsilon_{jt}^{\beta} = \varepsilon_{jt}^{\gamma} = \varepsilon_{jt}^{\alpha} = \varepsilon_{jt}^{\theta} = \varepsilon_{jt}^{c} 0$. This null was rejected at the p>0.0001 level in each industry (with the exception of ISIC 2413 - plastic resins). This resulting conclusion, that technology is not time invariant, is consistent with, for example, empirical work that relates the changing knowledge environment to entry and exit patterns (Agarwal & Gort 2001; Sarkar et al 2006), as well as evidence for the impact of changes in patent law on firms' use of patenting as an appropriation mechanism (Hall & Ziedonis 2001). Moreover, this result suggests the need for caution in interpreting panel study results that assume technology is fixed over the window of study.

Second, technological opportunity and expropriability appear to be negatively correlated (Figure 2a) . Finally, there appear to be trends. In general technological opportunity appears to be increasing over time, while expropriability appears to be decreasing over time. Though this is evident in the industry histories, it becomes more evident if we compare across industries (Figure 2b). These trends are counter-intuitive. The conventional view is that technological opportunity is high early in an industry's history, and becomes exhausted over time. Similarly, expropriability is assumed to be low early-on because the requisite knowledge has not been adequately codified and institutionalized (Zucker, Darby and Brewer 1989). Our results suggest instead that information flows are highest before buyer-supplier configurations become established and thus are consistent with the product diffusion patterns observed by Gort and Klepper (1982). Gort and Klepper explain their patterns through a shift in the source of industry knowledge over time from easily expropriable external knowledge to highly appropriable industry-specific knowledge.

Insert Figure 2 about here

Since the new measures potentially replace the survey measures from the Yale (Levin et al 1987; Klevorick et al 1995) and Carnegie Mellon (Cohen et al 2000) studies, we compare them to the survey measures in Figure 3. The figures indicate there is no significant correlation between the new measures and the survey measures. While this is disappointing, it matches the experience of Levin and Reiss (1988). They tested three survey variables as potential measures of expropriability and found none were significant in explaining the productivity of spillovers. Similarly they tested "contribution of science to industries' technological progress" and found it did not account for variation in cost elasticities. Accordingly while the survey measures do seem to capture interesting phenomena, they do not adequately capture the technological opportunity and expropriability constructs in the models discussed previously. Our finding that expropriability is increasing overtime does however quantify the impact of the increased secrecy reported between the Yale survey and the Carnegie Mellon survey (Cohen et al 2000).

Insert Figure 3 about here

Second Stage – Estimating Firm R&D Behavior

Our central interest is in characterizing firm R&D behavior – exploring how firms' R&D choices respond to changes in technological opportunity and expropriability. We begin by presenting the simplest specification which ignores the issues of generated regressors and simultaneity. We then proceed to deal with these complications in turn.

Table 3 presents results for OLS (models 1-4) and fixed effects (models 5-8) specifications of equation 4. All models are estimated using the Huber-White robust variance estimation that provides consistent estimates in the presence of heteroskedasticity and autocorrelation.

Insert Table 3 about here

We examine the coefficient estimates in model 10. Before we get to the results on technological opportunity and expropriability, it is worthwhile to briefly comment on the other results from the model. Results for the firm controls indicate that R&D intensity increases with the level of sales and capital. These results match expectations, as well as results from prior empirical studies (Shrieves 1978, Bound et al 1984 and Jaffe 1988).

With regard to the industry controls, results are as follows. R&D intensity increases with the number of *firms*. The coefficient on the number of firms is 0.234, and has the greatest significance level across the industry variables. This result matches those from Geroski and Pomroy (1990), Blundell, Griffith and VanReenan (1995) and Nickel (1996). While the result conflicts with early IO models, it is anticipated by Grossman and Helpman (1992), Aghion, Harris, Howitt and Vickers (2001) and Knott (2003). The role that the number of firms plays in these models is in establishing the probability that at least one firm will imitate. Since a single imitation is sufficient to erode shares, having a greater number of firms increases each firm's need to innovate to restore lost shares.[9] In addition, results indicate that R&D intensity increases in *market size* and *market growth*. The coefficient estimate for market size is 0.101 and significant at the 0.001 level. The coefficient estimate for demand growth is 0.175, and is also significant at the 0.001 level. These results for demand are consistent with all models and prior empirics. In sum, the consistency of these results with the prior literature provides the first layer of comfort in our estimated coefficients on the variables of interest.

As for our main variables of interest, coefficient estimates indicate that R&D intensity increases with the level of *expropriability* (returns to rival R&D), θ, but decreases with the level of *technological opportunity* (returns to own R&D), α. The coefficient on technological opportunity is -0.124 and is significant at the 0.05 level. The technological opportunity result will surprise some readers since investment in a factor typically increases with its returns. However this result is also anticipated by Levin and Reiss (1988), Jovanovic and Rob (1989), Grossman and Helpman (1982) and Knott (2003). The logic underlying the result is that if sales are driven by marginal advantage over rivals, then higher technological opportunity implies a lower investment necessary to achieve that marginal advantage. The coefficient on expropriability is 0.410, and is significant at the 0.01 level. The expropriability result will also surprise readers who feel that appropriability is the primary impetus for innovation. However, the result is

[9] One market structure variable that appears implicitly in evolutionary economics and explicitly in endogenous growth models is firm heterogeneity. In those models R&D tends to increase with heterogeneity. This occurs because heterogeneity increases the potential for imitation by laggards which is a stimulus to innovation by leaders. We tested models using dispersion in firm R&D as our measure of firm heterogeneity but found 1) that heterogeneity was highly correlated with the number of firms, 2) it was positive and significant alone, but 3) changed sign when entered with the number of firms. These preliminary results are consistent with the endogenous growth models, but more careful attention must be paid to market structure endogeneity before drawing any real inferences.

anticipated by Levin and Reiss (1988), Jovanovic and Rob (1989), and Knott (2003). The result suggests that an important impetus for continuous innovation is imitation by rivals.[10]

Finally, comparing the FE to the OLS models provides a sense of the within industry (across time) versus across industry effects of technological opportunity and expropriability. Comparing model 4 to model 8, we see that the coefficient on technological opportunity drops in magnitude by 55 percent, from -0.277 to -0.124, while the coefficient on expropriability drops by 28 percent from 0.570 to 0.410. This provides some insight into our earlier discussion about the use of non-time varying measures. Our results suggest that for technological opportunity, while there is significant action across industries, an equal amount of action occurs within industries over time. Indeed, for expropriability, a majority of the action is within industry over time, rather than across industries.

Second Stage Robustness Models

We noted two empirical issues that complicate the estimation procedure – generated regressors and simultaneity. In this section, we proceed with model specifications to treat each issue independently, and then we present specifications that treat these issues jointly.

As noted above, the first issue is that we use these generated variables (expropriability and technological opportunity) in our second stage model. We implement two separate modifications of the second stage specification to account for the use of generated regressors. The starting point for both methodologies, following Gawande (1997) and Gawande & Bandyopadhyay (2000), is the assumption that the generated regressors reflect a poorly measured estimate of the true variable. The basic modeling assumption is that:

$$\alpha_j = \hat{\alpha}_j + \upsilon_j \tag{5}$$

$$\theta_j = \hat{\theta}_j + \omega_j \tag{6}$$

where: (1) $\hat{\alpha}$ and $\hat{\theta}$ represent, respectively, the true values of technological opportunity and expropriability, (2) α and θ represent the generated regressors, and (3) υ and ω represent the normally distributed error component (with means of zero and variances of $\sigma^2_{\upsilon,j}$ and $\sigma^2_{\omega,j}$) arising from the first stage Cobb Douglas random coefficient estimation.

[10] Some models discussed in Section 2 proposed non-monotonic relationships between the technology variables and firm behavior. Accordingly we ran a robustness check that added squared terms for both expropriability and technological opportunity. These terms were insignificant in a fully specified model (2SLS-FE-Fuller transformation).

The first methodology for overcoming measurement error, suggested by Kmenta (1997) and implemented in Stata as eivreg, adjusts the variance of the generated regressor variables by an estimate of precision of the generated regressor. The difficult part of this procedure is in coming up with an appropriate measure of precision in the range [0,1]. In our context, this problem is made easier by the fact that the first stage random coefficient model that we use to generate Bayesian predictions of the industry-year technological opportunity and expropriability (α and ϕ) also generates Bayesian predictions of the standard deviation of those estimates. In the case of estimates of technological opportunity, the mean z-score is 2.44, while for expropriability it is 1.82, suggesting that α and θ are measured with rather high precision with a probability of error of less than 1 and 5 percent respectively. Thus, we estimate the Kmenta model using precision estimates of 0.99 and 0.95 respectively. Our results, which are robust to this alternative specification, are presented in Table 4. Model 1 recounts the original, fully specified fixed effects results from Table 3. Models 2 through 4 present the robustness to the Kmenta specification as per above. The coefficient estimates and their standard errors are nearly unchanged by this alternative specification. In the interest of robustness, we decreased the estimated precision three-fold to 0.97 and 0.85. The results do not change.

Insert Table 4 about here

The second methodology follows Fuller's (1987) text on measurement error as implemented for generated regressors by Gawande & Bandyopadhyay (2000). As opposed to Kmenta's method, which adjusts the variance in the estimation of the second stage model, this method adjusts the actual coefficient used in the estimate. The constructed predictors, $\tilde{\alpha}$ and $\tilde{\theta}$, are generated as:

$$\tilde{\alpha} = \bar{\alpha} + \left(\frac{\bar{\sigma}_{\alpha}^2 - \bar{\sigma}_{\upsilon}^2}{\sigma_{\upsilon,j}^2} \right) \left(\alpha_j - \bar{\alpha} \right) \tag{7}$$

$$\tilde{\theta} = \bar{\theta} + \left(\frac{\bar{\sigma}_{\theta}^2 - \bar{\sigma}_{\omega}^2}{\sigma_{\omega,j}^2} \right) \left(\theta_j - \bar{\theta} \right) \tag{8}$$

where, in addition to the variables discussed above: (1) $\bar{\alpha}$ and $\bar{\theta}$ are the means of α and θ, (2) $\bar{\sigma}_{\upsilon}^2$ and $\bar{\sigma}_{\omega}^2$ are the means of $\sigma_{\upsilon,j}^2$ and $\sigma_{\omega,j}^2$, and (3) $\bar{\sigma}_{\alpha}^2$ and $\bar{\sigma}_{\theta}^2$ are the sample variances of α and θ. All averaging is done within industry across time. When there are very large estimated standard errors on α and θ, i.e., when precision is very low, this may lead to negative values in the numerator of the bracketed component. Thus, following Gawande (1997) and Gawande & Bandyopadhyay (2000), we eliminate observations of α and θ that fall in the lowest precision range (approximately the bottom 15 percent). We then replace α and θ in the estimation with $\tilde{\alpha}$ and $\tilde{\theta}$. The results are presented in Table 5. Model 1 recounts the main FE specification from Table 1. Models 2 through 4 add in the adjusted measures of technological opportunity and expropriability sequentially. The specification leads to a reduction in the estimated magnitude of the coefficients on α and θ, although there is also a reduction the standard error. As such, both variables remain highly significant. In sum, the coefficient estimates on technological opportunity and expropriability appear to be estimated with sufficient precision in the stage 1 model (equation 2) to mitigate specification issues relating to generated regressors in the stage 2 model (equation 4).

Insert Table 5 about here

The second estimation issue discussed earlier was that of simultaneity. To account for simultaneity which may lead to biased coefficient estimates and misleading standard errors, we employ a two stage least squares specification. In particular, in our current estimation of equation 4, sales is treated as if it were exogenous, even though it is itself a function of the prior variables in equation 2. The two stage least squares methodology involves the joint estimation of equations 2 and 4 such that, in the equation 4 results (the R&D model), the sales variable is taken as the outcome of equation 2 (the sales model). As we noted earlier, it is not, at this time, technically feasible to implement a simultaneous estimator employing a random coefficient specification. As such, we treat equation 2 as a fixed effects specification with year indicators in our estimation. We employ a generalized method of moments estimator which is robust to specification issues related to heteroskedasticity.

The results are presented in Table 6. Model 1 recounts the main FE estimation, while models 2 through 4 add in the 2SLS estimates of technological opportunity and expropriability sequentially. This endogenous treatment of sales significantly increases the estimated coefficient on sales. Implicitly, the coefficient on sales reflects the rate at which R&D Intensity (R&D / sales) declines with increasing sales.[11] Increasing the coefficient on sales implies that R&D

[11] One can subtract ln(sales) from both sides of equation 4. This transforms the left hand side into ln(R&D/sales) and the right hind side is $(\gamma_1 - 1)$ Sales. Thus, if the coefficient on sales in the untransformed model is 1, then R&D intensity is independent of sales. When the untransformed coefficient is less than 1, R&D intensity is declining in increasing sales.

intensity declines less slowly with increasing sales. With regard to the main variables of interest, the results are robust to this alternative specification. In fact, the endogenous treatment of sales indicates that our main models may be underestimating the role of technological opportunity and expropriability. The coefficient estimate on technological opportunity increases nearly three-fold, while the estimate on expropriability increases more than two-fold. At the same time, the estimated standard errors change very little.

Insert Table 6 about here

In the final set of models, we treat both of the specification issues – generated regressors and simultaneity – jointly. In particular, we estimate a two stage GMM model with technological opportunity and expropriability transformed by the Fuller method. The results are presented in Table 7. Once again, model 1 recounts the main FE estimation, while models 2 through 4 present the two-stage Fuller transformed models with technological opportunity and expropriability added sequentially. This joint robustness model leads to a reduction in the magnitude of the coefficient estimates on technological opportunity and expropriability. However, the magnitude of the standard errors are also reduced. Indeed, the level of significance of our estimated coefficients increased with the implementation of this specification - the results are robust.

Insert Table 7 about here

In sum, we have implemented a number of techniques to control for empirical specification issues related to the use of generated regressors and simultaneity between our two models. In each of the robustness specifications, our main results are conserved: technological opportunity exhibits a negative coefficient, while expropriability exhibits a positive coefficient.

6. SUMMARY

One of the key mechanisms for strategic renewal of firms is research and development (R&D), and a key driver of R&D investment is industry context. A number of theories develop propositions linking industry factors to firm R&D behavior. While these theories agree on the factors affecting R&D, they lack consensus on whether the factors increase or decrease R&D. Without a cohesive theory linking industry factors to innovative behaviors and outcomes it is difficult to offer firms prescriptions for strategic renewal.

Our goal in this paper was to better understand the role of R&D as a mechanism for strategic renewal in established industries. We took an empirical approach testing which theory best matched fact in these industries. To do so we first developed new time-varying measures for technological opportunity and appropriability. These measures not only offered better matches to the mathematical constructs in the theoretical models, but they also allowed us to tease apart the effects of technology from other factors (such as industry structure) that are presumed to be derived from technology. In so doing the new measures and new tests not only shed light on the role of technology, they also improved estimates for the other factors.

Our results indicate that the data best match a model of innovative behavior in which firms invest in R&D principally to regain eroded advantage rather than to pursue the new frontier (Knott 2003). This is consistent with the "escape competition" behavior in endogenous growth models (Aghion, Harris, Howitt and Vickers 2001). Firms who are imitated face greater incentives to innovate because they are in neck and neck competition with a technologically equal rival and will remain so until they innovate again. Our results indicate that the intensity of this "erosion-innovation cycle" is accelerated by market size, market growth, the number of rivals and the ease of expropriating spillovers. It is actually decreasing in the level of technological opportunity. Thus firm innovative behavior appears to be driven by strategic renewal in the face of competition rather than purposeful pursuit of the technology frontier.

While the impact of industry factors on behavior is the main contribution of our study, two other important contributions of our study are the measures of technological opportunity and expropriability and the attendant insights regarding the evolution of industries.

With respect to the measures, we now have time-varying, accounting-based measures for constructs which previously relied on cross-sectional survey based measures. These new measures will allow researches to study R&D behavior in a broader set of industries and will also allow researchers to study the longitudinal components of that behavior.

With respect to the evolution of industries, conventional wisdom suggested first that technology varied substantially across industry, but was slow moving within industry. Our results suggest instead that there is greater variance within industry over time than there is across industry.

Second, conventional wisdom also suggested a general trend wherein technological opportunity decreases over time (as firms approach the technological frontier), while expropriability increases over time (as knowledge became codified and diffused across employees, suppliers and buyers (Zucker, Darby and Brewer 1989)). Our results suggest the opposite. Technological opportunity increases over time, while expropriability decreases over time.

One final implication of our results is that expropriability and technological opportunity, while treated as exogenous in most models and all empirics, may in fact be endogenously determined by firm behavior. Since our goal was to be faithful to existing models as we tested them, we too treated technological opportunity and expropriability as exogenous. The slow moving nature of both variables suggests however that they may in fact be endogenous. Such endogenous technological opportunity is a central feature of Romer (1990). The knowledge stock combines with researcher labor in each period to generate new "designs" and as a byproduct enhance the knowledge stock. Similarly Levin and Reiss (1988) anticipate that appropriability may be endogenously determined by firm behavior and technological opportunity. Indeed as was shown in Figure 2, appropriability and technological opportunity are negatively correlated.

While we need a new model to offer firms prescriptions with any confidence, the immediate implications of this study are first that firms are able to strategically renew themselves. They do so not only through improved offerings (the immediate goal of R&D), but through enhanced R&D capability (the frontier moves). The second implication is that as the frontier moves, it becomes more difficult to keep pace through free-riding (spillovers) on the R&D of rivals. Thus as industries mature it becomes increasingly likely that firms are innovating under their own power.

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Table 1 Data summary

20417 firm-year observations

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Sales (ln)	3.97	2.46	-6.21	12.09	1.00						
(2) Capital (ln)	2.38	2.57	-6.91	11.26	0.91	1.00					
(3) Market Size (ln)	10.35	1.10	6.81	12.90	0.07	0.12	1.00				
(4) Market Growth (ln)	0.08	0.13	-1.51	1.27	-0.03	-0.05	0.12	1.00			
(5) Firms (ln)	4.32	0.91	1.79	5.71	-0.35	-0.31	0.46	0.17	1.00		
(6) R&D (ln)	1.32	2.14	-6.91	9.09	0.72	0.78	0.25	0.03	0.01	1.00	
(7) Spillover (ln)	6.07	1.49	0.00	9.09	-0.24	-0.22	0.66	0.19	0.49	-0.08	1.00

Table 2. First Stage Random Coefficient Estimates

Dependent Variable: ln(sales)

ISIC	1500	2100	2320	2400	2413
	Food	**Paper**	**Petroleum**	**Chemicals**	**Plastic Rsn.**
Capital (ln)	0.019	0.385***	0.259	0.187*	0.780***
	(0.153)	(0.067)	(0.177)	(0.075)	(0.091)
Labor (ln)	0.804***	0.665***	0.579+	0.948***	0.282*
	(0.164)	(0.106)	(0.298)	(0.094)	(0.128)
R&D (ln)	0.218*	-0.074	0.136	-0.078	-0.089
	(0.088)	(0.070)	(0.092)	(0.059)	(0.072)
Spillover (ln)	0.021	-0.028	-0.040	0.069*	-0.031
	(0.105)	(0.018)	(0.047)	(0.031)	(0.031)
Constant	4.905***	3.534***	5.189***	4.133***	2.306***
	(0.700)	(0.271)	(1.223)	(0.336)	(0.566)
N	178	219	200	706	149
Wald chi2	968.92***	7320.95***	597.18***	3373.39***	2267.89***

ISIC	2423	2429	2500	2700	2800
	Drugs	**Misc Chem**	**Plastic**	**Metal**	**Metal Prods.**
Capital (ln)	0.129***	0.119	0.236**	0.133	0.118**
	(0.037)	(0.091)	(0.080)	(0.106)	(0.038)
Labor (ln)	1.271***	0.686***	0.791***	0.966***	0.829***
	(0.054)	(0.137)	(0.081)	(0.174)	(0.057)
R&D (ln)	-0.213***	0.187**	0.058+	0.019	0.113***
	(0.027)	(0.062)	(0.035)	(0.060)	(0.024)
Spillover (ln)	0.097**	0.017	0.120***	0.117***	0.006
	(0.037)	(0.029)	(0.025)	(0.025)	(0.017)
Constant	4.058***	3.935***	3.357***	3.718***	4.280***
	(0.309)	(0.394)	(0.276)	(0.419)	(0.198)
N	3574	291	229	191	798
Wald chi2	11030.64***	3888.01***	3853.69***	4544.11***	11166.72***

ISIC	2910	2920	3010	3100	3110
	Gen. Mach.	**Spc. Mach.**	**Computer**	**Elect. Eq.**	**Motor/Gen.**
Capital (ln)	0.059+	0.053	0.125***	0.167**	0.112**
	(0.032)	(0.046)	(0.035)	(0.052)	(0.039)
Labor (ln)	0.952***	0.862***	0.944***	0.801***	0.802***
	(0.065)	(0.058)	(0.047)	(0.076)	(0.041)
R&D (ln)	0.028	0.124***	0.027	0.058	0.121***
	(0.028)	(0.027)	(0.027)	(0.051)	(0.020)
Spillover (ln)	0.032*	0.005	0.054+	-0.023	0.022
	(0.014)	(0.025)	(0.028)	(0.056)	(0.022)
Constant	4.244***	4.378***	4.087***	4.086***	3.966***
	(0.142)	(0.192)	(0.232)	(0.268)	(0.209)
N	1005	776	2234	522	972
Wald chi2	24561.82***	4276.63***	7267.71***	2472.96***	8813.43***

ISIC	3210	3211	3220	3230	3311
	Elect. Comp.	**Semicond.**	**Comm.**	**TV/Radop**	**Med. Eq.**
Capital (ln)	0.294***	0.110**	0.119***	0.225+	0.120***
	(0.033)	(0.039)	(0.035)	(0.135)	(0.030)
Labor (ln)	0.710***	0.676***	0.820***	0.843***	1.073***
	(0.041)	(0.057)	(0.049)	(0.171)	(0.035)
R&D (ln)	-0.006	0.212***	0.107***	0.019	-0.092***
	(0.027)	(0.035)	(0.015)	(0.137)	(0.022)
Spillover (ln)	-0.019	0.004	0.076***	0.206*	0.104**
	(0.023)	(0.023)	(0.019)	(0.088)	(0.037)
Constant	3.567***	3.714***	3.614***	3.428***	3.851***
	(0.141)	(0.149)	(0.133)	(0.504)	(0.251)
N	926	1321	2590	221	3166
Wald chi2	8701.54***	2838.98***	7797.96***	573.47***	10006.51***

ISIC	3312	3314	3410	3430	3600
	Prec. Instr.	**Nav. Eq.**	**Car/Truck**	**Auto parts**	**Oth. Manu.**
Capital (ln)	0.015	0.087+	0.296***	0.287***	0.272***
	(0.032)	(0.049)	(0.078)	(0.042)	(0.058)
Labor (ln)	1.018***	0.853***	0.657***	0.738***	0.443***
	(0.053)	(0.043)	(0.092)	(0.052)	(0.065)
R&D (ln)	0.022	0.089*	0.070	0.028	0.235***
	(0.020)	(0.038)	(0.055)	(0.022)	(0.033)
Spillover (ln)	0.037+	-0.024	0.068***	0.044**	0.018
	(0.019)	(0.018)	(0.013)	(0.014)	(0.025)
Constant	4.353***	4.302***	3.568***	3.373***	3.813***
	(0.175)	(0.187)	(0.227)	(0.161)	(0.191)
N	1544	413	297	519	482
Wald chi2	7594.78***	8986.83***	11588.22***	9171.75***	3874.34***

Table 3. Second Stage Firm R&D Behavior Model

Dep. Var: R&D (ln) (t+1)	Ordinary Least Squares (OLS)			
	1	2	3	4
Sales (ln)	0.118***	0.129***	0.121***	0.129***
	(0.010)	(0.010)	(0.010)	(0.010)
Capital (ln)	0.605***	0.596***	0.603***	0.596***
	(0.009)	(0.009)	(0.009)	(0.009)
Market size (ln)	-0.028**	-0.038***	-0.038***	-0.043***
	(0.010)	(0.010)	(0.010)	(0.010)
Market growth (ln)	0.582***	0.652***	0.601***	0.658***
	(0.074)	(0.076)	(0.074)	(0.076)
Firms (ln)	0.641***	0.625***	0.633***	0.618***
	(0.013)	(0.013)	(0.013)	(0.014)
Tech. Opportunity		-0.322***		-0.277***
		(0.066)		(0.067)
Expropriability			0.713***	0.570**
			(0.177)	(0.181)
Constant	-3.199***	-3.084***	-3.157***	-3.053***
	(0.099)	(0.102)	(0.102)	(0.103)
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20437	20417	20417	20417
R-sq	0.675	0.675	0.675	0.676

Dep. Var: R&D (ln) (t+1)	Fixed Effect (FE)			
	5	6	7	8
Sales (ln)	0.139***	0.140***	0.140***	0.141***
	(0.013)	(0.013)	(0.013)	(0.013)
Capital (ln)	0.385***	0.384***	0.384***	0.383***
	(0.010)	(0.010)	(0.010)	(0.010)
Market size (ln)	0.104***	0.113***	0.092***	0.101***
	(0.023)	(0.023)	(0.023)	(0.024)
Market growth (ln)	0.163***	0.170***	0.169***	0.175***
	(0.036)	(0.036)	(0.036)	(0.036)
Firms (ln)	0.226***	0.213***	0.247***	0.234***
	(0.034)	(0.034)	(0.034)	(0.034)
Tech. Opportunity		-0.135*		-0.124*
		(0.056)		(0.056)
Expropriability			0.427**	0.410**
			(0.136)	(0.136)
Constant	-2.326***	-2.368***	-2.331***	-2.369***
	(0.203)	(0.204)	(0.203)	(0.204)
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20437	20417	20417	20417
R-sq	0.467	0.467	0.467	0.467

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: R-sq for FE models reports within r-sq. The total R-sq for the FE models is in the 0.94 range.

Table 4. Robustness to Generated Regressors (Kmenta Errors-in-Variable Method)

Dep. Var: R&D (ln) (t+1)	FE	FE (Kmenta)		
	1	2	3	4
Sales (ln)	0.141***	0.140***	0.140***	0.141***
	(0.013)	(0.007)	(0.007)	(0.007)
Capital (ln)	0.383***	0.384***	0.384***	0.383***
	(0.010)	(0.007)	(0.007)	(0.007)
Market size (ln)	0.101***	0.113***	0.091***	0.100***
	(0.024)	(0.020)	(0.020)	(0.021)
Market growth (ln)	0.175***	0.170***	0.169***	0.175***
	(0.036)	(0.034)	(0.034)	(0.034)
Firms (ln)	0.234***	0.213***	0.249***	0.235***
	(0.034)	(0.027)	(0.028)	(0.028)
Tech. Opportunity	-0.124*	-0.136**		-0.125*
	(0.056)	(0.052)		(0.052)
Expropriability	0.410**		0.457***	0.439***
	(0.136)		(0.127)	(0.127)
Constant	-2.369***	-1.946***	-1.881***	-1.919***
	(0.204)	(0.200)	(0.200)	(0.200)
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20417	20417	20417	20417
R-sq	0.467	0.467	0.467	0.467

+ p<0.10,* p<0.05, ** p<0.01, *** p<0.001

Note: R-sq for FE models reports within r-sq.

Table 5. Robustness to Generated Regressors (Fuller Transformed Errors-in-Variable Method)

Dep. Var: R&D (ln) (t+1)	FE	FE (Fuller)		
	1	2	3	4
Sales (ln)	0.141***	0.120***	0.120***	0.120***
	(0.013)	(0.014)	(0.014)	(0.014)
Capital (ln)	0.383***	0.392***	0.392***	0.391***
	(0.010)	(0.011)	(0.011)	(0.011)
Market size (ln)	0.101***	0.154***	0.134***	0.145***
	(0.024)	(0.027)	(0.027)	(0.027)
Market growth (ln)	0.175***	0.178***	0.186***	0.187***
	(0.036)	(0.046)	(0.046)	(0.046)
Firms (ln)	0.234***	0.217***	0.230***	0.221***
	(0.034)	(0.037)	(0.037)	(0.037)
Tech. Opportunity	-0.124*	-0.055**		-0.056**
	(0.056)	(0.020)		(0.020)
Expropriability	0.410**		0.265**	0.270**
	(0.136)		(0.090)	(0.090)
Constant	-2.369***	-2.735***	-2.614***	-2.686***
	(0.204)	(0.242)	(0.239)	(0.241)
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20417	20417	20417	20417
R-sq	0.467	0.466	0.466	0.466

+ p<0.10,* p<0.05, ** p<0.01, *** p<0.001

Note: R-sq for FE models reports within r-sq.

Table 6. Robustness to Two Stage Least Squares Estimation (2SLS)

Dep. Var: R&D (ln) (t+1)	FE	2SLS - FE		
	1	2	3	4
Sales (ln)	0.141***	0.652***	0.656***	0.656***
	(0.013)	(0.025)	(0.025)	(0.025)
Capital (ln)	0.383***	0.100***	0.098***	0.097***
	(0.010)	(0.017)	(0.017)	(0.017)
Market size (ln)	0.101***	0.115***	0.061*	0.087***
	(0.024)	(0.025)	(0.024)	(0.025)
Market growth (ln)	0.175***	0.158***	0.151***	0.169***
	(0.036)	(0.040)	(0.040)	(0.040)
Firms (ln)	0.234***	0.013	0.096*	0.059
	(0.034)	(0.041)	(0.041)	(0.041)
Tech. Opportunity	-0.124*	-0.378***		-0.355***
	(0.056)	(0.063)		(0.064)
Expropriability	0.410**		0.968***	0.916***
	(0.136)		(0.156)	(0.156)
Constant	-2.369***	---	---	---
	(0.204)	---	---	---
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20417	20173	20173	20173
R-sq	0.467	0.321	0.319	0.320

+ p<0.10,* p<0.05, ** p<0.01, *** p<0.001

Note: R-sq for FE models reports within r-sq.

Table 7. Robustness to Two Stage Least Squares Estimation (2SLS) with Fuller Transformation

Dep. Var: R&D (ln) (t+1)	FE	2SLS - FE - Fuller Transformation		
	1	2	3	4
Sales (ln)	0.141***	0.632***	0.634***	0.633***
	(0.013)	(0.027)	(0.027)	(0.027)
Capital (ln)	0.383***	0.112***	0.110***	0.110***
	(0.010)	(0.019)	(0.019)	(0.019)
Market size (ln)	0.101***	0.141***	0.118***	0.131***
	(0.024)	(0.028)	(0.028)	(0.028)
Market growth (ln)	0.175***	0.163***	0.170***	0.173***
	(0.036)	(0.049)	(0.050)	(0.050)
Firms (ln)	0.234***	0.023	0.038	0.026
	(0.034)	(0.044)	(0.044)	(0.044)
Tech. Opportunity	-0.124*	-0.069***		-0.070***
	(0.056)	(0.021)		(0.021)
Expropriability	0.410**		0.291**	0.297**
	(0.136)		(0.093)	(0.093)
Constant	-2.369***	---	---	---
	(0.204)	---	---	---
Year indicators	Sig.	Sig.	Sig.	Sig.
N	20417	16833	16833	16833
R-sq	0.467	0.314	0.312	0.313

+ p<0.10,* p<0.05, ** p<0.01, *** p<0.001

Note: R-sq for FE models reports within r-sq.

Figure 1. Technological Opportunity and Expropriability – Bayesian Time Varying Estimates

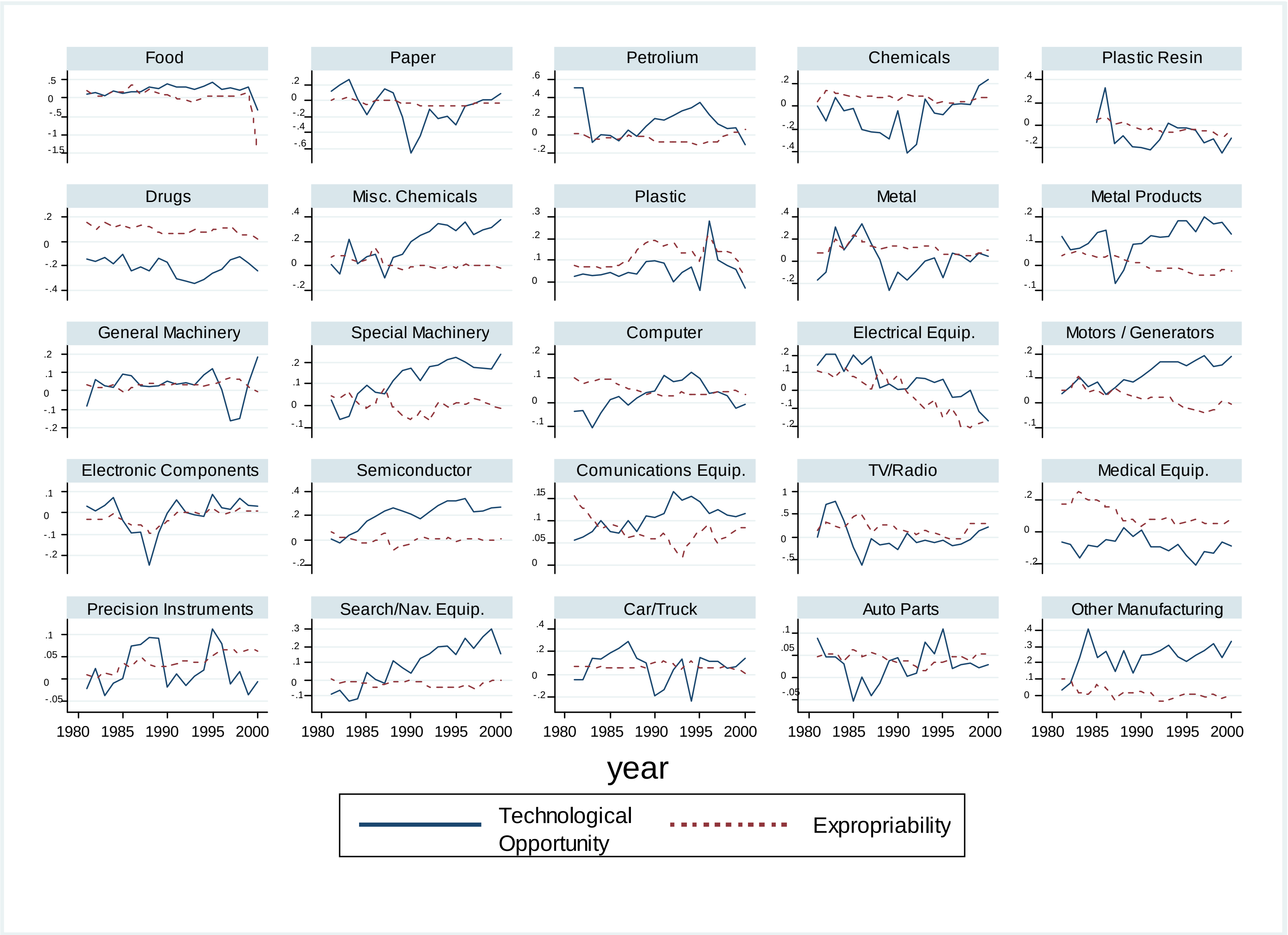

Figure 2. Comparing technological characteristics across industry

Figure 2a. Comparing mean values of technological opportunity and expropriability by industry

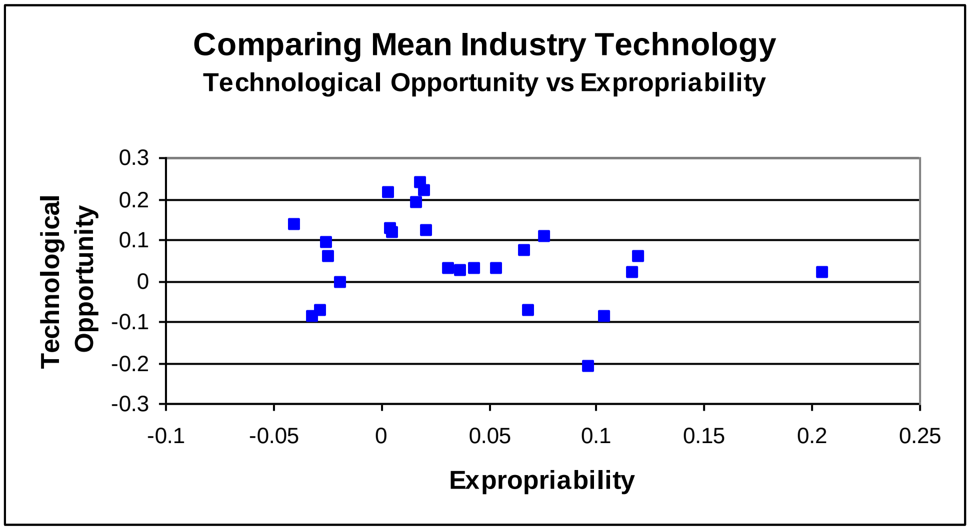

Figure 2b. Comparing mean annual change in technological opportunity and expropriability by industry

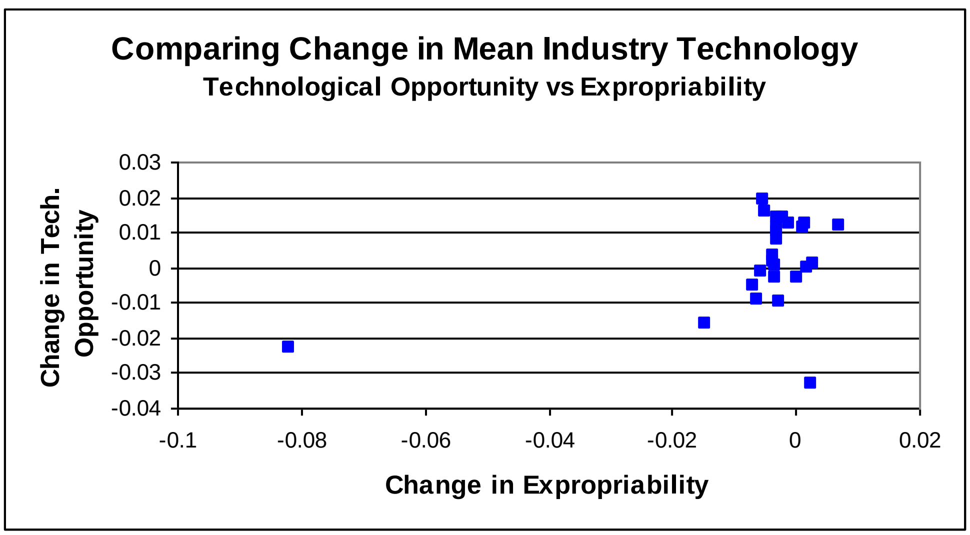

Figure 3a. Comparing expropriability measures to CMU survey measures of appropriability

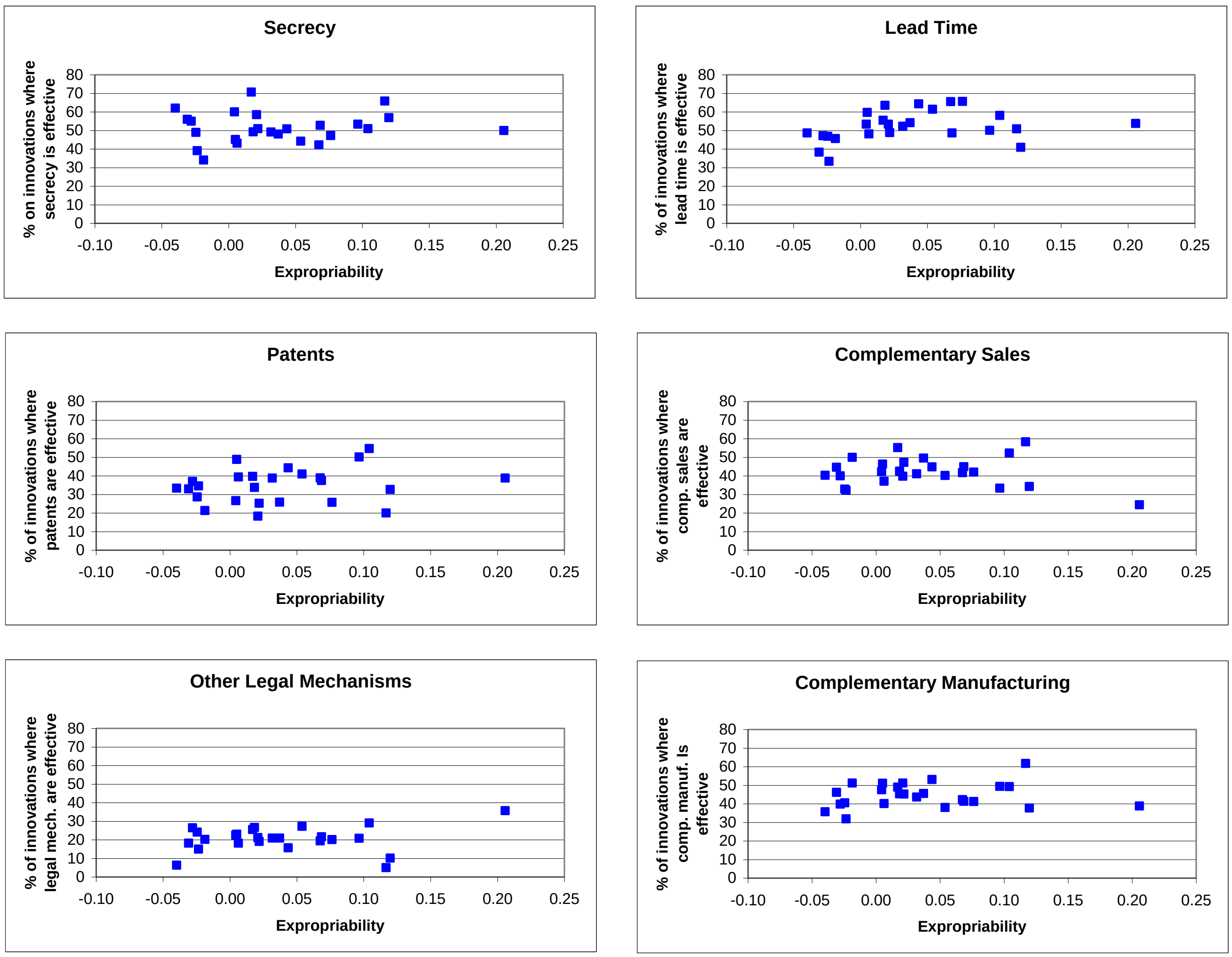

Figure 3b. Comparing technological opportunity to Yale survey measures of closeness to science