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Industry innovation: where and why*

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Abstract

Productivity growth and R&D intensity differ substantially across U.S. manufacturing industries. Possible causes include industry differences in technological opportunity, market size, and appropriability of innovations. I embed these hypotheses in an endogenous growth model à la Romer (1990). Under each hypothesis I find that R&D-intensive industries do not deserve a higher R&D tax credit. I also find that the hypotheses have different predictions for the cross-industry correlation between research intensity and research productivity. A large market and a high degree of appropriability raise the private value of an innovation; in equilibrium firms spend more on R&D per innovation. In contrast, technological opportunities are exploited to the point that R&D spent on the marginal innovation is equal across industries. Using data on R&D, productivity growth, and new products I find that R&D-intensive industries have fewer new products per dollar of R&D and average TFP growth relative to research *intensity*. The market size and technological opportunity hypotheses together can explain these facts.

1 Introduction

Productivity growth rates differ substantially across U.S. industries. In a sample of 450 U.S. manufacturing industries, average annual productivity growth over 1959 to 1989 ranges from -3.6% (!) in electron tubes to 10.7% in electronic computing equipment.[1] The standard deviation of the industry growth rates is 1.2%. Why do industries differ in their rate of productivity growth? I focus on explanations involving R&D and innovation. The

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[1]SICs 3671 and 3573, respectively. Source: NBER Productivity Database.

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industrial organization literature stresses three hypotheses for differences in industry research intensity (R&D/Sales): technological opportunity, market size, and appropriability.[2]

The technological opportunity hypothesis, associated with Scherer (1965) and Rosenberg (1974), holds that industries differ in the fertility of research. For example, designing faster computer chips has recently seemed easier than designing lighter steel. Adams (1993) and Evenson (1993) argue that basic research conducted in government labs and in universities "recharges" commercial research. Depending on these basic research results, commercial opportunities can be plentiful or scarce. For example, breakthroughs in solid-state physics have created commercial opportunities in semiconductors in the last thirty years.

The market-size hypothesis, espoused by Griliches and Schmookler (1963) ad Schmookler (1966), holds that innovations entail upfront R&D costs that depend little on the number of times the innovation is eventually used. A larger market makes the R&D easier to privately recoup, so larger industries should attract more R&D. Some versions of this hypothesis, owing to Schumpeter (1950), hold that the proper measure of scale is firm rather than industry size.

The appropriability hypothesis holds that industries differ in the extent to which innovators can capture the social returns to their innovations. Levin et al. (1987) conduct surveys of R&D managers to gauge appropriability and its sources. Industries such as pharmaceuticals report high appropriability; industries such as food processing bemoan a lack of appropriability. Levin et al. also find that appropriability derives less from legal protection (patents, copyrights, and trademarks) than from secrecy combined with learning by doing in production.

To develop implications of these hypotheses, I embed them in an endogenous growth model *à la* Romer (1990). Comparing the decentralized equilibrium to the social optimum, I find that industry differences in technological opportunity and market size do not widen the gap between the social and private returns to R&D, and industries with poor appropriability are more likely to undertake too little R&D. Thus, contrary to the presumption in policy circles, none of the hypotheses imply that R&D-intensive industries deserve a higher R&D tax credit. Indeed, the appropriability hypothesis implies that less R&D-intensive industries (e.g., potato chips) deserve a larger credit than do more R&D-intensive industries (e.g., computer chips).[3]

I further find that the hypotheses have divergent predictions for research

[2]See the survey by Cohen and Levin (1989).

[3]In his comments on this paper, Craig Burnside points out that industries with little appropriability may be R&D intensive if they also have extremely good technological opportunities.

productivity across industries, where research productivity refers to innovative output per dollar of R&D. The technological opportunity hypothesis implies no systematic variation in research productivity across industries, whereas the other two hypotheses predict that research-intensive industries will have low research productivity. The intuition is that a large market and a high degree of appropriability raise the private value of an industry's innovations. In equilibrium firms are willing to spend more on R&D per innovation. In contrast, plentiful technological opportunities attract R&D to the point where the marginal innovation is no easier to generate than in industries with less plentiful opportunities.[4] I compare these competing predictions to U.S. industry data on R&D, productivity, and new products. In the model *marginal* research productivity is conveniently proportional to *average* research productivity, which is observable.

A number of previous studies have estimated the impact of technological opportunity, market size, and appropriability on industry research intensity, including Scherer (1982), Pakes and Schankerman (1984), Levin et al. (1985), and Jaffe (1986, 1988). Most of these studies feature regressions of industry research intensity on (say) measures of industry technological opportunity. As surveyed by Cohen and Levin (1989), the canonical finding is that one-half of industry differences in research intensity can be attributed to available measures. The present paper complements these studies by testing the implications of the hypotheses for the correlation between industry research intensity and research productivity. No direct measures of technological opportunity, market size, or appropriability are used.[5]

The rest of the paper proceeds as follows. Section 2 extends Romer's endogenous growth model to multiple industries, highlighting the role of technological opportunity, market size, and appropriability parameters in determining industry research intensity, research productivity, and productivity growth. Section 3 contrasts the socially optimal allocation to the equilibrium allocation derived in Section 2. Section 4 provides evidence on the hypotheses. The evidence points to the market-size hypothesis.

2 A multi-industry endogenous growth model

The three explanations for differing industry productivity growth and research intensity – technological opportunity, market size, and appropriability – are embedded here in an extension of Romer's (1990) model. Two

[4]This is analogous to capital being allocated to equate marginal products across countries with (exogenously) different total factor productivity (TFP). Just like countries with higher TFP are more capital intensive, industries with better research opportunities are more research intensive.

[5]I describe in detail below why I do not use industry size as a measure of market size.

industries are compared without loss of generality. Time subscripts are often suppressed to avoid clutter.

Households maximize the present discounted value of momentary utility

$$\int_0^\infty e^{-\rho t} \frac{C(t)^{1-\sigma} - 1}{1-\sigma} dt$$

subject to the budget constraint

$$C + \dot{K} \leq Y = wH + fK$$

where C is consumption, K is the infinitely-durable capital stock (the dot denoting rate of change), Y is final output, w is the real wage, H is human capital, r is the real interest rate, ρ is the discount rate, and σ is the inverse of the intertemporal elasticity of substitution. Households supply their fixed human capital inelastically. The labor market is competitive and pays the same wage to workers in all industries. The Euler equation for each household is

$$\frac{\dot{C}(t)}{C(t)} = \frac{r-\rho}{\sigma}, \tag{2.1}$$

Firms produce the final good by combining intermediate goods Y_1 and Y_2:

$$Y = Y_1^\theta Y_2^{1-\theta} \tag{2.2}$$

with $\theta \in (0,1)$. The parameter θ governs nominal output shares for the respective intermediate goods and therefore serves as the <u>market-size</u> parameter. These final good producers maximize instantaneous profits given by

$$\Pi_Y = Y_1^\theta Y_2^{1-\theta} - pY_1 - qY_2,$$

where p and q are the prices of Y_1 and Y_2 in terms of the final good Y, whose price at each instant is normalized to 1. All firms take p and q as given. Combining the first-order conditions for final good firms' optimal choices of Y_1 and Y_2 yields

$$Y_2 = \frac{(1-\theta)p}{\theta_q} Y_1. \tag{2.3}$$

The intermediate goods (Y_1 and Y_2) are produced using human capital and physical capital. Conditional on available capital-good varieties, production of intermediate goods exhibits constant returns:

$$Y_1 = H_{Y_1}^\alpha [\int_0^{A_1} x_1(i)^{1-1/\epsilon} di]^{\frac{1-\alpha}{1-1/\epsilon}} \tag{2.4}$$

$$Y_2 = H_{Y_2}^{\alpha}[\int_0^{A_2} x_2(j)^{1-1/\epsilon}dj]^{\frac{1-\alpha}{1-1/\epsilon}}$$

where A's denote measures of capital-good varieties available to each industry and x's denote quantities of capital goods rented. Labor's share is $\alpha \in (0,1)$. Capital-good types are imperfectly substitutable ($1 < \epsilon < \infty$). Note that capital-good varieties are specialized to each industry. Though this is extreme, it is realistic in that empirical capital and materials flow matrices are quite spares: most industries buy most of their materials and capital from a few industries. Renting human capital from households and capital-good varieties from capital-good monopolists, intermediate-goods producers maximize instantaneous profits given by

$$\Pi_{Y_1} = pH_{Y_1}^{\alpha}[\int_0^{A_1} x_1(i)^{1-1/\epsilon}di]^{\frac{1-\alpha}{1-1/\epsilon}} - \int_0^{A_1} p_1(i)x_1(i)di - wH_{Y_1}$$

$$\Pi_{Y_2} = qH_{Y_2}^{\alpha}[\int_0^{A_2} x_2(j)^{1-1/\epsilon}di]^{\frac{1-\alpha}{1-1/\epsilon}} - \int_0^{A_2} p_2(j)x_2(j)dj - wH_{Y_2}$$

where the $p_l(\cdot)$'s are rental rates on capital-good varieties. Each of the intermediate-goods markets is competitive, so buyers and sellers take p, q, w, and the rental rates as given at each instant. The first-order conditions for these intermediate-good firms' choices of human and physical capital inputs are

$$\begin{aligned} w &= p\alpha H_{Y_1}^{\alpha-1}[\int_0^{A_1} x_1(i)^{1-1/\epsilon}di]^{\frac{1-\alpha}{1-1/\epsilon}} \\ w &= q\alpha H_{Y_2}^{\alpha-1}[\int_0^{A_2} x_2(j)^{1-1/\epsilon}dj]^{\frac{1-\alpha}{1-1/\epsilon}} \end{aligned} \tag{2.5}$$

$$\begin{aligned} p_1(i) &= p(1-\alpha)H_{Y_1}^{\alpha}[\int_0^{A_1} x_1(i)^{1-1/\epsilon}di]^{\frac{1-\alpha}{1-1/\epsilon}-1}x_1(i)^{-1/\epsilon} \\ p_2(i) &= q(1-\alpha)H_{Y_2}^{\alpha}[\int_0^{A_2} x_2(j)^{1-1/\epsilon}dj]^{\frac{1-\alpha}{1-1/\epsilon}-1}x_2(j)^{-1/\epsilon} \end{aligned} \tag{2.6}$$

Each capital-good variety is produced by a monopolistic competitor. Varieties are designed by research firms that receive infinitely-lived patents on each design. For each design the research firm sells an exclusive production license for the price P_{A_1} or P_{A_2}, depending on the industry to which the design is specialized. Capital-good firms are legally barred from holding more than one license. To keep things simple and tractable this model neglects many well-documented features of innovation, such as imitation and obsolescence (see Pakes, 1986, and Caballero and Jaffe, 1993, for models and estimates).

Producing a unit of each capital good requires 1 unit of the final good Y. Since capital goods are infinitely durable, the monopolist incurs the production cost once and then rents out its capital good forever after.[6] The stock of capital is therefore

$$K = \int_0^{A_1} x_1(i)di + \int_0^{A_2} x_2(j)dj. \tag{2.7}$$

Ignoring the sunk license fee, capital-good monopolists maximize

$$\begin{aligned} \Pi_{x_1(i)} &= p_1(i)x_1(i) - rx_1(i) \\ \Pi_{x_2(j)} &= p_2(j)x_2(j) - rx_2(j). \end{aligned} \tag{2.8}$$

The capital-goods market is monopolistically competitive because of the Dixit-Stiglitz technology (2.4) downstream. Since capital-good varieties are symmetric in (2.4), all capital-good firms face the same price elasticity of demand (ϵ) and charge the same markup. Since marginal cost (r) is also the same for each capital good, the rental rate on each variety is the same and is denoted $\bar{p}$. Inserting (2.6) into (2.8), the first-order condition (marginal revenue = marginal cost) for each capital good firm is

$$(1 - 1/\epsilon)\bar{p} = r. \tag{2.9}$$

By symmetry, equilibrium production and profits are the same for each variety of x_1 and the same for each variety of x_2. Using (2.9) for r in (2.8), equilibrium profits (ignoring the patent license fee) for each capital-good monopolist are

$$\begin{aligned} \Pi_{x_1} &= \frac{1}{\epsilon}\bar{p}x_1 \\ \Pi_{x_2} &= \frac{1}{\epsilon}\bar{p}x_2 \end{aligned} \tag{2.10}$$

As shown, capital-good monopolists earn profits (excluding the one-time license fee) equal to $\frac{1}{\epsilon}\%$ of their revenues. Note that in equilibrium the x's can change over time.

In Romer (1990) the license market is competitive and licenses are perfectly enforced so research firms extract the present discounted value of (2.10). I assume instead that they can extract only the fraction $\phi < 1$ (the appropriability parameter) of the *initial* profits earned by licensees. Thus license fees for new varieties are simply

$$P_{A_1} = \phi_1 \Pi_{x_1}$$

[6]Since the x's can be converted back into output, the equilibrium can entail falling x's.

$$P_{A_2} = \phi_2 \Pi_{x_2}. \tag{2.11}$$

I leave open why research firms cannot fully appropriate downstream profits. Taken literally, capital-good firms earn pure profits equal to the fraction $(1-\phi)$ of their initial profits plus their subsequent profits. (Adding these lump-sum profits to the household budget constraint would not affect the equilibrium.) One explanation would be that some of the profits in (2.10) are dissipated by the legal costs of preventing patent and license infringement and that such costs vary by industry.

A more realistic specification altogether would be finite patent protection. This would require keeping tract of the varieties for which patents had expired and the (higher) quantities at which they are produced because of marginal cost pricing. The length of "effective" patent protection would then play the role of ϕ. Alternatively, one could let each capital-good producer's monopoly power erode exponentially with the rate of decline playing the role of ϕ.

So far I have described consumer-utility maximization, final-goods production, intermediate-goods production, and capital-goods production. What remains to be described is the creation of new varieties of capital goods. There are two research sectors, each specializing in new types of equipment for one of the intermediate-good industries. Innovation production for a research firm j in each sector follows

$$\begin{aligned} \dot{A}_1(j) &= \delta_1 \frac{H_{A_1}(j)}{H_{A_1}^{1-\gamma}} A_1 \\ \dot{A}_2(j) &= \delta_2 \frac{H_{A_2}(j)}{H_{A_2}^{1-\gamma}} A_2 \end{aligned} \tag{2.12$'$}$$

where A's denote stocks of existing varieties, δ's are technological opportunity parameters, $H(j)$'s equal R&D workers hired by firm j, and H's are R&D personnel summed over firms within each research sector. Note the knowledge spillovers in (2.12)': researchers are able to design more new varieties the greater the stock of varieties to learn from.[7] There are no interindustry knowledge spillovers. Aggregating (2.12)' to the research-sector level yields

$$\dot{A}_1 = \delta_1 H_{A_1}^{\gamma} A_1 \tag{2.12}$$

[7]Knowledge spillovers limit appropriability in that they help other firms design varieties. Varieties are imperfect substitutes, however, so patents shield innovations from direct competition.

$$\dot{A}_2 = \delta_2 H_{A_2}^{\gamma} A_2$$

Romer (1990) features $\gamma = 1$. With multiple research sectors and $\gamma = 1$, however, any asymmetry produces a corner solution wherein all research takes place in a single research sector. Research sector-level diminishing returns at each point in time ($\gamma < 1$) produce a more realistic prediction. Such sector-level diminishing returns might stem from duplication of research across firms within a research sector, as in Stokey (1995) and Kortum (1993). Griliches (1990) reports estimates of γ in the patent literature that range from well below one to almost one.[8]

Each research firm is atomistic and takes as given the price at which it can license each variety (2.11) and the level of human capital in its research sector. The latter means that each research firm faces constant returns despite the diminishing returns at the research-sector level. Research firms hire researchers to maximize

$$P_{A_1}\dot{A}_1(j) - wH_{A_1}(j)$$

$$P_{A_2}\dot{A}_2(j) - wH_{A_2}(j)$$

subject to (2.12)'. Since returns are constant at the research firm level, research firms earn zero profits in equilibrium. Their optimal choices of human capital (aggregated across research firms in each sector) satisfy

$$\begin{aligned} w &= P_{A_1}\delta_1 H_{A_1}^{\gamma-1} A_1 \\ w &= P_{A_2}\delta_2 H_{A_2}^{\gamma-1} A_2. \end{aligned} \tag{2.13}$$

Finally, the market for human capital clears:

$$H = H_{Y_1} + H_{Y_2} + H_{A_1} + H_{A_2}. \tag{2.14}$$

The first-order conditions, definitions, and transition equations represented by (2.1) through (2.14) are sufficient to characterize the steady-state growth equilibrium of this model. These equations can be reduced to seven equations in the seven unknowns $r, g_{A_1}, g_{A_2}, H_{Y_1}, H_{Y_2}, H_{A_1}, H_{A_2}$, where g_z denotes the steady-state growth rate of variable $z (g_z = \dot{z}/z)$. The equations are

$$\frac{1-\alpha}{\alpha(\epsilon-1)}[\theta g_{A_1} + (1-\theta)g_{A_2}] = \frac{r-\rho}{\sigma} \tag{2.15}$$

$$H = H_{Y_1} + H_{Y_2} + H_{A_1} + H_{A_2} \tag{2.16}$$

[8]OLS estimates of γ are biased upward if industries and firms with better research opportunities (higher δ's) undertake more R&D.

$$H_{Y_1} = \frac{\epsilon\alpha H_{A_1}^{1-\gamma}}{\delta_1\phi_1(1-\alpha)}$$

$$H_{Y_2} = \frac{\epsilon\alpha H_{A_2}^{1-\gamma}}{\delta_2\phi_2(1-\alpha)} \tag{2.17}$$

$$g_{A_1} = \delta_1 H_{A_1}^{\gamma}$$

$$g_{A_2} = \delta_2 H_{A_2}^{\gamma} \tag{2.18}$$

$$H_{Y_2} = \frac{1-\theta}{\theta} H_{Y_1}. \tag{2.19}$$

2.1 *Industry differences in technological opportunity*

Suppose $\delta_1 > \delta_2$ so that opportunities for innovation are better in research-sector 1 than in research-sector 2. That is, suppose the same amount of research input (researchers and stock of existing varieties) generates more new varieties in the first research sector. Suppose also that $\theta = \frac{1}{2}$ and $\theta_1 = \theta_2$ so that market size and appropriability are the same across the two industries. By (2.19)

$$H_{Y_2} = \frac{1-\theta}{\theta} H_{Y_1} = H_{Y_1}.$$

By (2.17) we then have

$$\frac{\epsilon\alpha H_{A_1}^{1-\gamma}}{\delta_1\phi_1(1-\alpha)} = H_{Y_1} = H_{Y_2} = \frac{\epsilon\alpha H_{A_2}^{1-\gamma}}{\delta_2\phi_2(1-\alpha)}$$

Rearranging we get

$$\frac{H_{A_1}}{H_{A_2}} = [\frac{\delta_1}{\delta_2}]^{\frac{1}{1-\gamma}}.$$

Since $\gamma < 1, \delta_1 > \delta_2$ implies $H_{A_1} > H_{A_2}$. That is, more researchers are hired in the sector with better technological opportunities.[9] Since wages and

[9]This result follows from Cobb-Douglas technology for combining intermediate goods to produce final output. With an elasticity of substitution sufficiently less than one, there may be less R&D done in the research sector with superior opportunities. Faster TFP growth industries have modestly rising nominal shares in the data, however, consistent with elastic demand.

the size of downstream markets are equal, more researchers means higher research *intensity*:

$$\frac{\frac{wH_{A_1}}{\theta Y}}{\frac{wH_{A_2}}{(1-\theta)Y}} = \frac{H_{A_1}}{H_{A_2}} > 1.$$

From the definitions in (2.18) we then have

$$g_{A_1} = \delta_1 H_{A_1}^{\gamma} > \delta_2 H_{A_2}^{\gamma} = g_{A_2}.$$

The allocation of researchers reinforces the better technological opportunities to produce faster growth of varieties in sector 1 than in sector 2.

Now, define research productivity as the ratio of research output g_A to research input wH_A. Research productivities for the two intermediate-good industries are equalized despite differing technological opportunities:

$$\frac{\frac{g_{A_1}}{wH_{A_1}}}{\frac{g_{A_2}}{wH_{A_2}}} = \frac{\delta_1 H_{A_1}^{\gamma-1}}{\delta_2 H_{A_2}^{\gamma-1}} = \frac{\delta_1}{\delta_2}\left[\left[\frac{\delta_1}{\delta_2}\right]^{\frac{1}{1-\gamma}}\right]^{\gamma-1} = 1$$

The intuition for this result is that the sector with better research opportunities conducts more R&D to the point where the marginal productivity of a researcher is the same as in the sector with inferior opportunities. The upshot is that, if industries differ in their research intensity because of differing technological opportunities, there will be no correlation between research intensity and research productivity. Since market size is equal, this holds even if industry research productivity is multiplied by downstream industry sales.

Downstream, one intermediate good industry uses capital goods designed in sector 1 and the other those designed in sector 2. Using symmetry, the standard way of measuring the capital stock (e.g., $K_1 = A_1 x_1$), and output definitions in (2.4), we have

$$Y_1 = A_1^{\frac{1-\alpha}{\epsilon-1}} H_{Y_1}^{\alpha} K_1^{1-\alpha}$$

$$Y_2 = A_2^{\frac{1-\alpha}{\epsilon-1}} H_{Y_2}^{\alpha} K_2^{1-\alpha}$$

TFP growth is therefore proportional to the growth rate of varieties used by each intermediate-good industry. The faster growth of varieties in use translates into faster measured TFP growth in the first industry than in the second industry.

2.2 *Industry differences in market size*

Now suppose $\theta > \frac{1}{2}$ where θ is the Cobb-Douglas share of the first intermediate good in final good production. Suppose also that $\delta_1 = \delta_2$ and $\phi_1 = \phi_2$

so that technological opportunities and appropriability do not differ across the two research sectors. Proceeding as before,

$$H_{Y_2} = \frac{1-\theta}{\theta} H_{Y_1} < H_{Y_1}$$

$$\Longrightarrow \quad \frac{\epsilon\alpha H_{A_1}^{1-\gamma}}{\delta_1\phi_1(1-\alpha)} = H_{Y_1} > H_{Y_2} = \frac{\epsilon\alpha H_{A_2}^{1-\gamma}}{\delta_2\phi_2(1-\alpha)}$$

$$\Longrightarrow \quad H_{A_1}^{1-\gamma} > H_{A_2}^{1-\gamma}.$$

Since $\gamma < 1$, the last inequality implies $H_{A_1} > H_{A_2}$. That is, more researchers work designing capital goods for the bigger intermediate-good market. Research *intensity* is also higher the larger the downstream market. That is, not only does market size encourage research, but research is elastic with respect to market size. Specifically, by rearranging (2.17) and (2.19) one obtains

$$\frac{\frac{wH_{A_1}}{\theta Y}}{\frac{wH_{A_2}}{(1-\theta)Y}} = \frac{\frac{H_{A_1}}{\theta}}{\frac{H_{A_2}}{1-\theta}} = [\frac{\theta}{1-\theta}]^{\frac{\gamma}{1-\gamma}} > 1. \tag{2.20}$$

Using the definition of growth rates in each sector, (2.18),

$$g_{A_1} = \delta_1 H_{A_1}^{\gamma} > \delta_2 H_{A_2}^{\gamma} = g_{A_2}.$$

More researchers serving the bigger market translates into faster innovation and productivity growth in sector 1 than in sector 2.

Defining research productivity as above, we find that research productivity is lower in the larger research sector (sector 1):

$$\frac{\frac{g_{A_1}}{wH_{A_1}} g_{A_2} wH_{A_2}}{=} \frac{\delta_1 H_{A_1}^{\gamma-1}}{\delta_2 H_{A_2}^{\gamma-1}} < 1.$$

The intuition for this result is that the larger downstream market attracts more R&D, which drives down research productivity because of diminishing returns in research. Each innovation has higher value when licensed to capital-good firms supplying a larger market, so despite lower research productivity the value of a marginal research dollar is equalized across research sectors. To recap, if industries differ in their productivity growth because of differing market size, there will be a negative correlation across industries between research intensity and research productivity.

Though differences in market size produce differences in research productivity, they do *not* produce differences in TFP growth relative to research intensity. That is, if we multiply industry research productivity by industry sales we find

$$\frac{\theta Y \frac{g_{A_1}}{wH_{A_1}}}{(1-\theta)Y \frac{g_{A_2}}{wH_{A_2}}} = \frac{\theta}{1-\theta}\left[\frac{H_{A_1}}{H_{A_2}}\right]^{\gamma-1} = 1.$$

The last equality follows from using (2.20). As surveyed by Cohen and Levin (1989), a substantial empirical literature on *firm* size and research intensity has been inconclusive. In the present model the proper measure of scale is industry size. Firm size is indeterminate in research and in intermediate- and final-goods production because of perfect competition and constant returns to scale. The size of capital-good firm *is* pinned down: they are monopolistic competitors with revenues of $\bar{p}x_1$ or $\bar{p}x_2$. But a larger market does not necessarily make for larger capital-good producers, as the following (hopefully) makes clear.

Suppose, in addition to the above assumptions ($\theta > \frac{1}{2}$ and symmetry of other parameters), that at some moment the stocks of capital-good varieties are equal ($A_1 = A_2$). At this moment greater production of the first intermediate good (which follows from $\theta > \frac{1}{2}$) implies $x_1 > x_2$. By (2.10) and their larger size ($x_1 > x_2$), capital-good producers supplying the larger market earn greater *ex post* profits. From (2.11) the upstream research firms selling to the bigger capital-good firms charge higher license fees. Higher license fees stimulate more R&D for the larger market (at this moment $A_1 + A_2$ so that the research sectors have equal stocks from which to learn). This is the intuition behind the market-size hypothesis, and at this moment capital-good firms supplying the larger market are indeed larger. But the greater research done for the larger market generates faster innovation ($g_{A_1} > a_{A_2}$), which in turn shrinks the market for each individual variety sold in the larger market ($g_{x_1} < g_{x_2}$). Eventually the capital-good producers serving the larger market are smaller!

How can the larger downstream market induce greater research intensity if the market for each variety eventually becomes smaller? The answer lies in the endogeneity of the stock of varieties. The faster growth in this stock for the larger market lowers the cost of designing new varieties as shown in (2.12). That is, intertemporal knowledge spillovers facilitate the design of new varieties for the larger market even when the market for each variety is smaller. This highlights a testable implication of the model, namely, that patent value (P_A) declines over successive vintages of patents, and me quickly the more research-intensive the industry.

2.3 *Industry differences in appropriability*

Suppose $\phi_1 > \phi_2$ so that research firms in sector 1 capture a bigger fraction of the downstream profits generated by their innovations than do research firms in sector 2. Suppose also that $\delta_1 = \delta_2$ and $\theta = \frac{1}{2}$ so that technological opportunities and market size are equal. Proceeding as before,

$$H_{Y_2} = \frac{1-\theta}{\theta} H_{Y_1} = H_{Y_1}.$$

$$\rightarrow \frac{\epsilon\alpha H_{A_1}^{1-\gamma}}{\delta_1\phi_1(1-\alpha)} = H_{Y_1} = H_{Y_2} = \frac{\epsilon\alpha H_{A_2}^{1-\gamma}}{\delta_2\phi_2(1-\alpha)}$$

$$\rightarrow \frac{H_{A_1}}{H_{A_2}} = \left[\frac{\phi_1}{\phi_2}\right]^{\frac{1}{1-\gamma}}.$$

Since $\gamma < 1, \phi_1 > \phi_2$ implies $H_{A_1} > H_{A_2}$. That is, more researchers work in the sector where the returns to innovations are more appropriable. Since $\phi = \frac{1}{2}$ the markets are of equal size and greater research means greater research *intensity*. From the definition of growth rates in each sector (2.18),

$$g_{A_1} = \delta_1 H_{A_1}^{\gamma} > \delta_2 H_{A_2}^{\gamma} = g_{A_2}.$$

We have lower research productivity in the sector with greater appropriability:

$$\frac{\frac{g_{A_1}}{wH_{A_1}}}{\frac{g_{A_2}}{wH_{A_2}}} = \frac{\delta_1 H_{A_1}^{\gamma-1}}{\delta_2 H_{A_2}^{\gamma-1}} < 1.$$

As with a larger market, greater appropriability means each innovation has a higher private *value*. The *value of the marginal research product* is equated across research sectors because sectors with a high private value of each innovation have low research productivity. To recap, if industries differ in their research intensity because of differing degrees of appropriability, there will be a negative correlation across industries between research intensity and research productivity. Since market size is equal, this holds even if industry research productivity is multiplied by downstream industry sales.

3 Policy implications

Do R&D-intensive industries deserve a higher R&D tax credit? To answer this question I compare socially optimal R&D to equilibrium R&D. The previous section characterized the decentralized equilibrium so here I describe the socially optimal allocations. The social planner maximizes the Hamiltonian

$$\tilde{H} = \frac{C^{1-\sigma}}{1-\sigma} + \lambda[Y_1^{\theta}Y_2^{1-\theta} - C] + \mu_1\delta_1 H_{A_1}^{\gamma}A_1 + \mu_2\delta_2 H_{A_2}^{\gamma}A_2$$

subject to

$$Y_1 = A_1^{\frac{1-\alpha}{\epsilon-1}} H_{Y_1}^{\alpha} K_1^{1-\alpha}$$

$$Y_2 = A_2^{\frac{1-\alpha}{\epsilon-1}} H_{Y_2}^{\alpha} K_2^{1-\alpha}$$

$$K = K_1 + K_2$$

where λ, μ_1, and μ_2 are shadow values of the stocks of physical capital and varieties. Note that the social planner cannot avoid duplication of research

($\gamma < 1$) but does internalize it. From the first-order conditions for the planner's problem one can show

$$H_{Y_2} = \frac{1-\theta}{\theta} H_{Y_1}.$$

This is the same as (2.19), meaning the equilibrium ratio of workers in the two intermediate-good industries is optimal. One can also show that the socially optimal allocation of researchers across research sectors is

$$\theta\delta_1 H_{A_1}^{\gamma-1} = (1-\theta)\delta_2 H_{A_2}^{\gamma-1}. \tag{3.1}$$

In contrast, the decentralized equilibrium allocation is, from (2.16) and (2.19),

$$\phi_1\theta\delta_1 H_{A_1}^{\gamma-1} = \phi_2(1-\theta)\delta_2 H_{A_2}^{\gamma-1}. \tag{3.2}$$

In Romer (1990) there is no duplication of research, and innovators capture all of the profits of capital-goods monopolists. But researchers do not internalize the impact of their innovations on future research productivity (intertemporal knowledge spillovers). And capital-good monopolists do not price discriminate, leaving some surplus flowing to consumers. As Romer (1990) shows, these forces unambiguously imply that too little R&D is done in the decentralized equilibrium of his model.

Here innovators capture only the fraction $\phi < 1$ of *initial* profits earned by capital-goods monopolists, so they capture even less of the surplus created by each new variety. Firms, however, do not internalize the negative impact of their efforts on other researchers through duplication ($\gamma < 1$). Whether too little or too much R&D is done on balance hinges on the value of parameters such as γ, ϕ, and ϵ. Stokey (1995) and Jones and Williams (1995) investigate these issues.

Since it is ambiguous whether too little or too much R&D is done, we do not know whether an R&D tax credit or an R&D surtax is warranted. We can infer, though, whether certain industries should be favored. Consider a tax credit τ applies to R&D spending (research firms' wage bill) which is financed by lump-sum taxes on households. Instead of (2.13) the first-order conditions for research firms are

$$w(1-\tau_1) = P_{A_1}\delta_1 H_{A_1}^{\gamma-1} A_1 \tag{3.3}$$

$$w(1-\tau_2) = P_{A_2}\delta_2 H_{A_2}^{\gamma-1} A_2.$$

Using (3.3), the analogue to (3.2) is

$$\frac{\phi_1\theta\delta_1 H_{A_1}^{\gamma-1}}{1-\tau_1} = \frac{\phi_2(1-\theta)\delta_2 H_{A_2}^{\gamma-1}}{1-\tau_2}. \tag{3.4}$$

To reduce (3.4) to (3.1) and thereby induce the optimal relative number of researchers in the two industries, the research tax credits must satisfy

$$\frac{1-\tau_1}{1-\tau_2} = \frac{\phi_1}{\phi_2}. \tag{3.5}$$

Since θ and the δ's do not appear in (3.5), industries that are more R&D-intensive because of a bigger market or better technological opportunities do not deserve a higher R&D tax credit (or a lower surtax). Bigger markets and better technological opportunities raise equilibrium and optimal R&D in the same proportion; research firms find bigger markets and better technological opportunities privately attractive, so they pursue them to the same extent that the social planner would. Condition (3.5) also tells us that industries which are more R&D-intensive because of better appropriability (higher ϕ) should receive a *lower* R&D tax credit. I.e., $\phi_1 > \phi_2$ implies $\tau_1 < \tau_2$ because poor appropriability discourages private R&D relative to the optimum level. In short, none of the hypotheses imply that R&D-intensive industries deserve a more generous R&D tax credit.

4 Evidence on research intensity and research productivity

Industry R&D data are not easy to come by. The NSF-Census Survey carefully assigns R&D to industries but covers only 25 2.5 digit SICs. I thus rely on two more disaggregated sources of R&D data: 3-digit data aggregated from Compustat firms and Scherer's (1984) 3.5 digit data based on the Federal Trade Commission (FTC) survey of 443 firms. Both of these sources skew heavily toward large firms, with Compustat covering only companies listed on U.S. stock exchanges. The allocation of Compustat-firm R&D to industries is also suspect; the FTC data are better in this regard, breaking firm data into 276 3.5 digit industries. In the SEC 10-K filings from which Compustat data derives, firms indicate their primary 4-digit industry. But the primary industry often accounts for only a plurality of firm sales. To attenuate this problem while preserving degrees of freedom, I aggregate the Compustat data to the 3-digit level.[10]

I consider two measures of innovative output – total factor productivity (TFP) growth and new products. The NBER Productivity Database contains TFP data at the 4-digit level based on U.S. Census Bureau surveys of manufacturing establishments. For the data on new products I extend the dataset that I used in Klenow (1994). This dataset consists of counts of new products from company news releases compiled since 1985 by Information Access Company. In my earlier paper I discuss at length the shortcomings of

[10]Scherer (1984) reports that the average manufacturing corporation had 33% of its 1972 employment outside of its primary 3-digit field.

these announcements as a measure of the true flow of new products, as well as problems with using new product counts as a proxy for innovative output.

Tables 1 and 2 provide a sampling of the data, listing the 20 most research-intensive industries at the 2-digit and 3-digit levels, respectively. Motor vehicles, computer hardware, and drugs together carry out 43% of total R&D. The distribution of new products is correlated with that of R&D, but not perfectly so. comparatively little R&D goes into each new software product; the opposite is true for each new car and aircraft model. This could mean that the private value of a new car or aircraft design exceeds that for new software, say because the social returns are more easily appropriated. Alternatively the "step size," or innovative output, represented by each new product might vary across these industries, an issue to which I return below.

Table 1:
Research Intensity
Top 20 2-Digit Industries

SICs		R&D/Sales	% of all R&D	% of all New Products	Δ TFP
38	Instruments and related products	5.6%	7.4%	17.2%	1.0%
35	Industrial machinery and equipment	5.0	18.7	25.8	5.3
36	Electric and electronic equipment	4.9	14.2	22.6	2.0
28	Chemicals and allied products	4.8	15.4	4.7	1.2
37	Transportation equipment	3.3	25.0	0.7	0.9
73	Business services	3.1	1.6	19.4	
39	Misc. manufacturing	1.8	0.2	0.5	0.6
30	Rubber and plastics products	1.6	0.6	2.6	1.2
48	Communications	1.4	5.0	0.3	
87	Engineering and mgmt. services	1.4	0.3	0.0	
26	Paper and allied products	1.1	1.4	0.4	0.6
34	Fabricated metal products	1.0	0.4	2.5	0.7
32	Stone, clay, and glass products	0.9	0.3	0.9	0.5
13	Oil and gas extraction	0.9	0.5	0.0	
29	Petroleum and coal products	0.7	4.6	0.3	1.1
20	Food and kindred products	0.6	2.2	0.4	0.9
33	Primary metal industries	0.6	0.7	0.5	0.2
16	Heavy construction	0.6	0.1	0.0	
25	Furniture and fixtures	0.5	0.1	0.5	0.5
61	Nondepository institutions	0.5	0.7	0.0	
	Sum over the top 20:		99.6	99.3	

Sources: R&D and Sales: All Compustat firms, 1983 to 1992.
# of New Products: Information Access company, 1985 to 1994.
ΔTFP (Total Factor Productivity Growth): NBER Database, 1985 to 1989.

Before proceeding it is important to distinguish industries in the model from those in the Standard Industrial Classification. In the model an "industry" is defined by the boundaries of knowledge spillovers. This corresponds more to the technology classes used by the U.S. Patent Office, which differ notoriously from SICs. For this reason Jaffe (1986, 1988) measures technological distance among a sample of firms using the extent to which they patent in similar classes rather than proximity as defined by SICs. I follow the literature in eschewing SIC sales as a measure of the size of the market for the type of R&D done in each SIC.[11]

[11] In his comments on this paper, Craig Burnside shows that, if market size is observable,

Table 2:
Research Intensity
Top 20 3-Digit Industries

SICs		R&D/Sales	% of all R&D	% of all New Products	Δ TFP
293	Drugs	9.3%	7.4%	1.1%	1.4%
367	Electronic components	8.1	2.3	9.2	3.6
366	Communications equipment	8.0	3.3	8.2	1.3
357	Computer and office equipment	7.2	15.6	13.3	9.9
737	Computer software	7.1	1.4	20.3	
386	Photographic equipment	6.4	3.8	1.0	1.4
382	Measuring and controlling devices	5.5	1.6	11.4	0.2
355	Special industrial machinery	5.3	0.3	2.2	-0.1
384	Medical instruments and supplies	5.1	0.8	2.1	0.9
365	Household audio & video equipment	5.0	1.2	0.8	3.6
138	Oil and gas field services	4.6	0.4	0.0	
381	Search and navigation equipment	4.3	1.2	0.6	0.3
267	Misc. converted paper products	4.3	0.8	0.0	
369	Misc. electrical equipment	4.2	0.3	0.4	0.5
376	Guided missiles and space vehicles	3.7	1.1	0.0	0.2
372	Aircraft and parts	3.5	3.6	0.1	0.5
282	Plastics materials and synthetics	3.4	1.9	1.0	2.3
371	Motor vehicles and equipment	3.3	20.0	0.5	1.1
285	Paints and allied products	2.8	0.3	0.2	0.8
	Sum over the top 20:	67.3	72.4		

Sources: R&D and Sales: All Compustat firms, 1983 to 1992.
# of New Products: Information Access Company, 1985 to 1994.
ΔTFP (Total Factor Productivity Growth): NBER Database, 1985 to 1989.

I now test the indirect implications of the three hypotheses for the correlation between research intensity and research productivity. Since none of the datasets are perfect and no two are entirely compatible,[12] I estimate the relationship between research intensity and research productivity in three separate ways, none of which equates SIC size with market size.

Test 1: Compustat R&D and NBER TFP

As discussed by Bound et al. (1984), in 1972 the SEC issued new 10-K reporting requirements for R&D. The Compustat sample consequently starts in 1972. The NBER Productivity Database covers the years 1959 to 1989. The Bureau of Labor Statistics (1989), surveying the literature relating R&D to productivity, reports a lag of one to three years between R&D spending and its *initial* impact on productivity. I therefore match Compustat R&D data

the technological opportunity and appropriability parameters can be identified from the data on R&D intensity and research productivity. With the parameter values in hand, one could decompose the variance of industry R&D intensity due to each hypothesis (ranges since the decomposition is not unique). Burnside provides calculations using SIC sales as a proxy for market size. Using patent data one could implement his strategy using a measure of market size based on Jaffe's methodology.

[12]For example, the R&D data are from firms whereas the productivity data are from establishments; the latter are less diversified and therefore more reliably assigned to industries. The Census classifies R&D labs as auxiliary establishments. Fortuitously for our purposes, this means R&D inputs have not been netted out in the NBER's TFP calculations.

from 1972 to 1987 with NBER TFP data from 1974 to 1989. I aggregate the NBER 4-digit manufacturing industries and the Compustat-firm level data to the 3-digit level.[13]

Since measured TFP growth is driven by new varieties in the model, I use TFP growth to measure innovative output. But since SICs do not correspond to industries in the model sense, using scale-free measure of innovative output such as TFP growth requires scaling R&D by sales in each SIC. The model predicts, for example, that large markets stimulate R&D intensity and TFP growth. Even if an SIC has nothing to do with an industry in the model sense, if its component firms tend to be in large markets then they should be R&D intensive and exhibit low (scaled) research productivity. I therefore calculate

$$corr\left(\frac{R\&D}{Sales}, \frac{\Delta TFP}{\frac{R\&D}{Sales}}\right) \tag{4.1}$$

where research intensity is averaged over 1972 to 1987 and TFP growth is averaged over 1974 to 1989 for each 3-digit industry. I take time averages here and subsequently to help purge series of cyclical components, e.g., cyclical TFP growth induced by unmeasured changes in factor utilization. Note that industries doing no R&D must be excluded since their research productivity is undefined. The sample consists of the 116 R&D-performing 3-digit manufacturing industries over 1972 to 1987. This sample selection on the basis of R&D spending, like classical measurement error in research intensity, negatively biases the estimated correlation.

Table 3 shows the outcome of Test 1. Reassuringly, industry average research intensity and industry average TFP growth are positively correlated across industries (.31 with a standard error of .13).[14] The correlation between industry research intensity and scaled industry research productivity is positive but statistically insignificant (.09, s.e. .06). This finding dovetails most closely with the technological opportunity hypothesis and, because research productivity is scaled by sales, the market-size hypothesis. Recall, too, there are reasons to believe the estimate is biased *negatively.*

Test 2: Scherer's R&D and NBER TFP

Scherer's (1984) R&D data have two principal advantages over the Compustat R&D data. First, the FTC survey from whence it comes has firms break their R&D into line of business, raising our confidence in the industry. Second, Scherer reallocated the R&D from "industry of origin" to "industry of use." He computed "R&D used" as the sum of an industry's own

[13] I weight 4-digit TFP growth by real gross output.

[14] The means and correlation are estimated simultaneously using GMM with a weighting matrix that yields estimates robust to heteroscedasticity. (Industries have varying numbers of Compustat firms, perhaps giving rise to heteroscedasticity.)

Table 3:
Correlations with Industry Research Intensity

	ΔTFP	$\frac{\Delta TFP}{R\&D/Sales}$
Test 1:	.314	.088
Compustat R&D, 1972 to 1987	(.130)	(.059)
NBER TFP, 1974 to 1989		
116 3-digit mfg. industries		
Test 2:	.292	.082
Scherer "Use" R&D, 1974	(.144)	(.100)
NBER TFP, 1975 to 1979		
144 3.5-digit mfg. industries		
	$\frac{\#NewProducts}{Sales}$	$\frac{\#NewProducts}{R\&D}$
Test 3:	.383	-.126
Compustat R&D, 1983 to 1992	(.085)	(.021)
New Products, 1985 to 1994		
187 3-digit industries		
Compustat R&D, 1983 to 1992	.269	-.097
New Products, 1985 to 1994	(.061)	(.030)
342 large companies		

Notes: All entries are correlations with research intensity defined as R&D/Sales. Δ denotes log first differences. TFP = Total Factor Productivity.

process R&D and the product R&D carried out by the industry's suppliers upstream.[15] Gordon (1990) and Griliches (1994) stress that price indices typically overstate industry inflation because they insufficiently incorporate new and improved products. Since price indices serve as output deflators in the NBER Database, industry TFP growth is mismeasured. But new producer goods may contribute to measured productivity downstream. If so then Scherer's R&D by industry of use better aligns innovative input with the TFP measure of innovative output.[16] Scherer's methodology also blends nicely with the model in Section 2 above, wherein upstream research and production of capital goods drive an industry's productivity growth.

The Scherer data, based on the 1974 FTC survey, cover 144 3.5-digit manufacturing industries. To allow for lags in the impact of R&D on TFP growth, I match Scherer's data to industry average TFP growth over 1975 to 1979 from the NBER Database, calculated after aggregating the NBER 4-digit manufacturing industries to Scherer's 3.5-digit industries.

Table 3 shows the outcome of Text 2. Results are reported for R&D by industry of use, the results being much the same with R&D by industry of origin (!). Industry research intensity and industry TFP growth are positively (and marginally significantly) correlated across the 144 industries (.29, s.e. .14). The correlation between industry research intensity and scaled industry research productivity is, as in Test 1, positive but insignificant (.08, s.e. .10). As with Test 1, the results favor the technological opportunity and market-size hypotheses. Also like Text 1, the use of scaled research productivity means SICs need not have anything to do with markets in the model sense.

Test 3: Compustat R&D and new products

Given the multitude of hazards in measuring TFP growth and tracing the impact of upstream R&D on downstream TFP growth, I consider another measure of innovative output that can, with some confidence, be linked to innovative input. This measure is U.S. new product counts over 1985 to 1994, classified by the industry of the company releasing the product. An added attraction of these data is that they encompasses nonmanufacturing industries. The luster is dulled by the fact that not all R&D is devoted to product innovation. I match these new product data to Compustat R&D data over 1983 to 1992.

Although the model in Section 2 calls for the growth rate of product

[15]Scherer used patent information to estimate the share of process vs. product R&D for each industry and also to estimate a technology flow input-output matrix.

[16]TFP data for electronic computing equipment (SIC 3573), however, are based on hedonic price indices that better incorporate quality changes. As a result some computer-product innovation contributes to TFP growth in SIC 3573 rather than in downstream industries. Griliches (1994) expresses concern about applying hedonics to some but not all industries.

variety, I only have data on the *flow* of new products. In the absence of data on the stock of existing products, I use the ratio of new products to R&D as a measure of research productivity, which is strictly valid only if the stock of varieties is the same across industries. The correlation I examine is

$$corr\left(\frac{R\&D}{Sales}, \frac{\#NewProducts}{R\&D}\right). \tag{4.2}$$

Differences in the stock of varieties across industries that are uncorrelated with R&D intensity will bias this correlation toward zero. Note that, unlike TFP growth per dollar of R&D, #New Products per dollar of R&D need not be scaled by sales. This test is valid even when SICs do not correspond to industries in the model sense. For (4.2) research intensity is averaged over 1983 to 1992 and the ratio of new products to R&D is averaged over 1985 to 1994 for each 3-digit industry. Since research productivity is only defined for industries doing some R&D, the sample consists of the 187 3-digit industries (75 outside of manufacturing) doing some R&D over 1983 to 1992.

Table 3 shows the outcome of Test 3. Results are reported for all industries. The results for manufacturing industries alone are qualitatively the same. Industry research intensity and industry "new product intensity" (the ratio of new products to sales) are positively and significantly correlated across the 187 industries (.38, s.e. .09). The correlation between industry research intensity and industry research productivity is significantly negative (-.13, s.e. .02): research-intensive industries introduce fewer new products per dollar of R&D. This result coincides with the market-size and appropriability hypotheses. Firms in research-intensive industries would be willing to spend more R&D per new product if they reap greater rents per new product through a larger market or better appropriability.

Since both the Compustat R&D data and the Information Access new product data are available at the firm level, the correlation between research intensity and research productivity can also be calculated at the firm level. This correlation will shed light on whether *firm* differences in research intensity are me consistent with differing technological opportunity, market size, or appropriability. To keep the task manageable, I considered only the 1000 largest R&D performing Compustat firms measured by 1992 sales. Of these, 342 announced new products that appeared in the new product dataset. The correlation is much the same whether the sample of 1000 or 342 is considered. For the sample of new-product introducers, the correlation between firm R&D intensity and firm new-product intensity is .27 (s.e. .06). The correlation between firm R&D intensity and new products per dollar of R&D is -.10 (.03). Hence the firm-level evidence also points to the market-size and appropriability hypotheses.

An alternative interpretation of this industry and firm evidence is that the "step size" of each new product (variety added or quality improved) is

larger in research-intensive industries. But we have reason to expect the opposite. Suppose industries differ in the fixed costs of introducing inventions. Industries with lower such costs would choose greater research intensity and a smaller step size, biasing the estimated correlation away from its true negative value toward zero.

I hasten to add that these Test 3 results do not comprise evidence against the technological-opportunity hypothesis. The hypotheses are not mutually exclusive, so the negative correlation between research intensity and research productivity suggests only *some* role for market size and/or appropriability. Differing technological opportunity may explain some or even the bulk of the pattern of industry research-intensity. Indeed, the correlations are quite low, suggesting that variations in technological opportunity may be more important than variations in the other parameters. And the results remain subject to the caveat that measurement error in R&D would push the estimated correlation in the direction predicted by the market-size and appropriability hypotheses.

To summarize, Tests 1 and 2 point to industry differences in technological opportunity and market size, and Test 3 suggests differences in market size and appropriability. The market-size and technological-opportunity hypotheses together can explain all of the results.

5 Conclusion

Industry differences in productivity growth and research intensity are substantial. To try to explain them I constructed a multi-industry endogenous growth model with industries differing in technological opportunities, market size, and appropriability. For this model I showed the following: None of the hypotheses imply that R&D-intensive industries deserve a higher R&D tax credit. Industries with better technological opportunities for innovation are more research-intensive but have no higher research productivity. "Larger" industries and industries with better appropriability of returns from innovation are more research-intensive and have lower research productivity.

I then examined U.S. industry data on R&D, productivity growth, and new products to test the competing hypotheses. Using TFP growth, the evidence points to the technological opportunity and market-size hypotheses: there is no systematic correlation across industries between research intensity (R&D divided by sales) and scaled research productivity (research output divided by research intensity). Using new products, the evidence dovetails with the market-size and appropriability hypotheses: research intensity is negatively correlated with new products per dollar of R&D. But this last correlation is low, suggesting a big role for differences in technological opportunity. Since the technological-opportunity and market hypotheses together

can explain all of the findings, these results provide no support for favoring the R&D of one industry over another.

The approach taken here with industries could also be taken with countries. In a cross-section, country research intensity could be related to country research productivity. For a given country, research intensity and research productivity could be compared before and after a trade liberalization as a test of the importance of market size.[17] Or, to test the appropriability hypothesis, research intensity and research productivity could be compared before and after a reform of intellectual property right such as took place in Singapore in 1987.

Solow (1957) attributed his productivity residual to technological change. Evidence in Greenwood et al. (1995) and Klenow (1995) suggest specifically technological change embodied in capital goods. To try to get inside Solow's black box of technological change, this paper has modeled and tested innovation-based explanations for industry Solow residuals. But the hypotheses themselves are black boxes, albeit smaller ones. Technological opportunity for an industry could reflect government-financed industry R&D or spillovers from academic research. Market size for an industry could relate not only to downstream preference and technology parameters but also to trade policies and government purchases. Appropriability for an industry cod encompass tax rates on industry sales and inputs, along with intellectual property protection. In short, much work remains to be done on the sources of industry variation in technological opportunity, market size, and appropriability.

[17]Ades and Glaeser (1994) present evidence that LDC country growth in the 20th century and U.S. state growth in the 19th century are higher the larger the market. Jones (1995) finds that R&D intensity has risen over the postwar period in many rich countries with the scale of the market, but that TFP growth has fallen rather than accelerated. Young (1995) constructs a model which preserves the effect of market size on R&D intensity while eliminating its effect on TFP growth.

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