BEGGAR THY NEIGHBOR? THE IN-STATE, OUT-OF-STATE, AND AGGREGATE EFFECTS OF R&D TAX CREDITS

Daniel J. Wilson

Abstract—The proliferation of R&D tax incentives among U.S. states in recent decades raises two questions: (i) Are these tax incentives effective in increasing in-state R&D? (ii) How much of any increase is due to R&D being drawn away from other states? This paper answers (i) “yes” and (ii) “nearly all.” The paper estimates an augmented R&D factor demand model using state panel data from 1981 to 2004. I estimate that the long-run elasticity of in-state R&D with respect to the in-state user cost is about −2.5, while its elasticity with respect to out-of-state user costs is about +2.5, suggesting a zero-sum game among states.

I. Introduction

Over the past two decades, R&D tax credits offered by U.S. states have become widespread and increasingly generous. This phenomenon is illustrated in figure 1, which plots from 1981 to 2006 both the number of states offering R&D tax credits and the average effective credit rate among those states.1 The process began with Minnesota in 1982, one year after the introduction of the U.S. federal R&D tax credit. As of 2006, 32 states provided a tax credit on general, company-funded R&D, and the average effective credit rate has grown approximately fourfold over this period to equal roughly half the value of the federal effective credit rate.2 In fact, a number of states’ R&D credits are considerably more generous than the federal credit.

The proliferation of state R&D credits raises two important questions. First, are these tax incentives effective in achieving their stated objective, to increase private R&D spending within the state? Second, insofar as the incentives do increase R&D within the state, how much of this increase is due to drawing R&D away from other states? This latter question is particularly important given recent U.S. court decisions on the constitutionality of state business credits (discussed further in section V).

There has been surprisingly little empirical research on either of these questions. Most work on R&D tax incentives has investigated the effectiveness of the federal R&D credit. Studies in this area generally follow the approach of estimating the elasticity of R&D with respect to its price (user cost), and exploiting panel data variation across firms, industries, or countries.4 These studies, which generally find a statistically significant R&D cost elasticity at or above unity, are frequently cited in debates over the efficacy of state R&D credits.

It is not at all clear, however, that inferences based on existing firm-, industry-, or country-level data, which report only nationwide R&D expenditures for the unit of observation, can be extended to the state level. R&D may be mobile across states so that the cost of R&D in other states can affect how much R&D is performed in any one state. Thus, the “net” or “aggregate” R&D elasticity with respect to the cost of R&D, for a given state, is actually the difference between (the absolute value of) the elasticity with respect to the cost of performing R&D within the state and the elasticity with respect to the cost of performing R&D outside of the state.

This paper addresses the two questions posed above by estimating an augmented version of the standard R&D factor demand model using a two-way fixed-effects estimator with state panel data from 1981 to 2004. An appealing aspect of using state-level information to identify the elasticities of R&D with respect to in-state and out-of-state costs is that state-level variation in the user cost of R&D is driven entirely by variation in R&D tax credits and corporate income tax rates, both of which are arguably exogenous to firms’ contemporaneous R&D decisions.5

II. Data

State and federal R&D credits offer corporations credits against income tax liability based on the amount of qualified research done by the corporation within the state or country, respectively. U.S. states generally follow the federal Internal Revenue Code (IRC) definition of qualified research: the wages, materials expenses, and rental costs

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2 The effective credit rate corresponds to the \( e \) term defined in section II.

3 The sizable jump in the average credit rate in 1990 was because many states piggybacked on the federal definition of the R&D base amount (explained in section II below), and this was changed in 1990 from a moving-average base to a fixed-period base, which increases the effective credit rate.

4 See, for example, Hall (1993), Swenson (1992), and Berger (1993) for firm-level studies; Baily and Lawrence (1995) and Munnuneas and Nadiri (1996) for industry-level studies; and Bloom, Griffith, and Van Reenen (2002) for a country-level study.

5 This approach of using tax code changes as natural experiments has been employed in the investment literature (see, for example, Cummins, Hassett, & Hubbard, 1994).
of certain property and equipment incurred in performing research “undertaken to discover information” that is “technological in nature” for a new or improved business purpose. State-level data on qualified research from tax returns is unavailable, but state data on industrial (company-performed) R&D expenditures by source of funding (company, federal, and other) from 1981 to 2004 are available from the National Science Foundation (NSF) (Industrial Research and Development, various issues). These data are biannual (odd years) from 1981 to 1996 and annual from 1997 to 2004.6 Note the NSF definition of R&D is somewhat broader than that of the IRC, which excludes late-stage product development.

Like most economic studies concerning R&D, this paper treats R&D as an input into a firm’s production function. The actual input is the services of R&D capital (knowledge) formed by past and present R&D expenditures net of depreciation (obsolescence). The price for this factor is the implicit rental rate, or user cost, after taxes. The neoclassical formula for the user cost of capital, derived in the seminal work of Hall and Jorgenson (1967), can be adapted easily to apply to R&D capital services.

Extending the standard Hall-Jorgenson formula to incorporate both state and federal tax considerations yields the following formula for the user cost of R&D capital (per dollar of investment):

\[
\rho_e = \frac{1 - s (k_e + \bar{k}_e) - \bar{z} (\tau'_e + \bar{\tau}_e)}{1 - (\tau'_e + \bar{\tau}_e)(\tau_e + \delta)}.
\]

where \( t \) indexes time.7 The subscript \( i \) indicates a state-level variable, while the subscript \( f \) is used for federal-level variables. \( \tau_e \) is the real interest rate, and \( \delta \) is the economic depreciation rate of R&D capital. \( \tau'_e \) and \( \bar{\tau}_e \) denote the effective corporate income tax rates, while \( k_e \) and \( \bar{k}_e \) denote the effective R&D tax credit rates. \( s \) is the share of NSF-reported R&D expenditures considered “qualified” R&D in the tax code. According to IRS Statistics on Income data, \( s \) is approximately 0.5. \( z \) denotes the present discounted value (PDV) of tax depreciation allowances. Given that labor and intermediate expenses are immediately deductible as are qualified R&D capital expenses (for all states and the federal government since 1954), \( z = 1 \).

The effective credit rate, \( k_e \) or \( \bar{k}_e \), varies over time and states depending on design, statutory credit rate, and whether the credit is “recaptured” (taxed). There are three basic designs for existing R&D tax credits: (i) nonincremental, where all qualified R&D is eligible for the credit; (ii) incremental with a fixed-period base, where only R&D above a base level, determined by the company’s activity (sales and R&D) in a fixed past period, is eligible; and (iii) incremental with a moving-average base, where the base level is determined by the company’s recent activity.

For nonincremental credits and incremental credits with a fixed-period base, the effective credit rate on a marginal unit of R&D, assuming current R&D is above the base, is \( k_e = k_e (1 - w_e \tau_e) \), where \( k_e \) is the statutory (legislated) credit rate and \( w_e \) is the share of R&D subject to recapture. Similarly, \( k_e = k_e (1 - w_e \tau_e) \).8 For incremental credits with a moving-average base, the base is current sales multiplied by the company’s average R&D-sales ratio over \( n \) previous years. The marginal effective credit rate is then \( k_e = k_e (1 - w_e \tau_e) (1 - \sum_{i=1}^{n} (1 + r_i ...)) \), again assuming that current R&D is above the base.9 As has been pointed out in numerous discussions of R&D tax credits, this moving-average formula drastically reduces the value of the credit, as current R&D spending serves to lower, one-for-one, the amount of R&D that qualifies for the credit in future years.

In the United States, the effective federal and state corporate tax rates generally are lower than the statutory tax rates, \( \tau_p \) and \( \bar{\tau}_p \), because the taxes a firm pays to states are deductible from its federal tax liability, and often vice versa. This makes \( \tau_p \) a function of \( \tau_e: \tau'_p = \tau_p (1 - \bar{\tau}_p); \) and \( \bar{\tau}_p \) a function of \( \tau_e: \bar{\tau}'_p = \tau_p (1 - \lambda_p \bar{\tau}_p) \), where \( \lambda_p \) is the fraction of federal taxes that are deductible from state taxable income. The two equations can be solved in terms of the published statutory tax rates: \( \tau_p = \frac{\tau_p (1 - \bar{\tau}_p)}{1 - \lambda_p \bar{\tau}_p \tau_p} \) and \( \bar{\tau}_p = \tau_p \frac{1 - \lambda_p \bar{\tau}_p}{1 - \lambda_p \tau_p \tau_p} \).

The values of \( k_e, w_e, \tau_p, \) and \( \bar{\tau}_p \) for the fifty states plus the District of Columbia over the period 1981–2006 were compiled from a variety of sources (see Wilson, 2007, for details), with the principal source being online state corporate tax forms.

### III. Empirical Model

In order to analyze the determination of private R&D conducted within a state and, therefore, the impact of R&D tax credits, I begin by modeling the demand for R&D capital by a representative firm in the economy.

First, consider the case where the firm’s output in state \( i \) in year \( t \) is produced via a production function with a constant elasticity of substitution (\( \gamma \)) between R&D services (\( R_{it} \)) and other inputs. The first-order conditions for profit-maximization yield a standard factor demand equation relating R&D services (\( R_{it} \)) to its user cost (\( \rho_{it} \)) and output (\( Y_{it} \): \( R_{it} = \xi Y_{it} \rho_{it}^\gamma \), where \( \xi \) is the CES distribution parameter. Notice that the elasticity of substitution, \( \gamma \), is also the elasticity of R&D with respect to its user cost (in absolute value). This factor demand equation forms the theoretical basis for the estimation of the R&D cost elasticity in most previous studies in this area.

Now consider the case where the R&D capital input into the firm’s state \( i \) production function consists of two subcomponents: in-state R&D services (\( R_{it}^w \)) and out-of-state R&D services (\( R_{it}^o \)). The factor demand equation then becomes

\[
R_{it} = \xi Y_{it} (\rho_{it} - \eta (\rho_{it}^o))^\gamma, \tag{2}
\]

where \( \rho_{it}^o \) is the in-state R&D user cost (that is, the user cost faced by the firm if it conducts R&D within state \( i \)) and \( \rho_{it}^o \) is the out-of-state user cost.

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6 Due to disclosure limitations, R&D spending for small states is often missing. The severity of this problem varies from year to year as the sample size of the underlying survey varies, but generally declines over time. Data are available for nearly all states by the end of the sample. In order to be sure that the data underreporting is not systematically related to any of the analysis variables, I have estimated results (i) based on a balanced panel of eleven large states from 1987 to 2004, and (ii) using a Heckman two-step estimator to allow for potential data-reporting/selection bias. The results from each of these estimations were quite similar to those reported below.

7 This formula assumes that either the credit is refundable or the firm is in a sufficiently positive tax liability position that the credit may be exhausted in the current tax year. This assumption is supported by Hall (1993), who finds that during the 1981–1991 period, over 80% of firms were in a positive tax position in any given year.

8 Note the federal R&D tax credit was not recaptured from 1981 to 1988; in 1989, 50% of the credit was recaptured; since 1989, 100% of the credit has been recaptured. Recapturing in the IRC and in state tax codes is achieved by requiring firms to subtract the credit from expenses that would otherwise be deductible (see IRC Section 280(c)(1)).

9 The assumption that current R&D is above the base level for incremental credits can be justified by the fact that in the Compustat manufacturing sample analyzed by Hall (1993), the percentage of firms with current R&D above their base was 60%–80% depending on year (between 1981 and 1991).
user costs. The sum of the external and internal R&D elasticities, are able to relocate to some extent in response to changes in relative equation becomes

$$Y_{it} = \beta_0 + \beta_1 \log(Y_{it-1}) + \beta_2 \log(R_{it}) + \cdots + \beta_K \log(X_{it}) + \mu_{i,t},$$

where $$Y_t$$ is state output. In this specification, $$-\theta$$ and $$\phi$$ identify the short-run R&D elasticities with respect to the in-state and out-of-state user costs, respectively. The long-run elasticities are given by $$-\theta/ (1 - \lambda)$$ and $$\phi / (1 - \lambda)$$. The use of a lagged-dependent-variable model here is complicated by the fact that the NSF state R&D data are biannual for the early part of the sample. Thus, $$R_{it}$$ is missing for years 1981–1997. Fortunately, the independent variables are observed annually. It can be shown that, under certain reasonable conditions, the model can thus be consistently estimated by simply pooling the biannual and annual samples while allowing the coefficient on the lagged dependent variable to vary across the two periods (see Wilson, 2007).

I employ the standard within-groups estimator, which is simply an OLS regression on mean-differenced data. As a robustness check, I also obtain results based on an R&D stock constructed using the perpetual inventory method assuming a 15% depreciation rate and filling in even-year investment data via interpolation between adjacent years. The results are qualitatively similar (available in Wilson, 2007).

To allow for the possibility of partial adjustment of R&D capital, for example, due to adjustment costs, I extend the above static model by including the lagged dependent variable. Incorporating state and year fixed effects and adding an i.i.d. error term, the estimating equation becomes

$$\log(R_{it}^c) = \lambda \log(R_{it-1}^c) - \theta \log(p_{it}) + \phi \log(p_{it}^c) + \alpha \log(Y_t) + f_i + f_t + \nu_{it},$$

where $$Y_t$$ is state output. In this specification, $$-\theta$$ and $$\phi$$ identify the short-run R&D elasticities with respect to the in-state and out-of-state user costs, respectively. The long-run elasticities are given by $$-\theta/ (1 - \lambda)$$ and $$\phi / (1 - \lambda)$$. The use of a lagged-dependent-variable model here is complicated by the fact that the NSF state R&D data are biannual for the early part of the sample. Thus, $$R_{it}$$ is missing for years 1981–1997. Fortunately, the independent variables are observed annually. It can be shown that, under certain reasonable conditions, the model can thus be consistently estimated by simply pooling the biannual and annual samples while allowing the coefficient on the lagged dependent variable to vary across the two periods (see Wilson, 2007).

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The within estimator is potentially biased in finite samples when the regressor set includes the lagged dependent variable (Nickell, 1981). Fortunately, the bias goes to 0 as $$T \to \infty$$. As a check on the unbiasedness of the estimates in this paper, I additionally estimate the model using the Bias-Corrected Least Squares Dummy Variable (LSDVC) estimator, which is based on adjusting the within estimates using an approximation of the bias term. The results confirm that the original estimates are approximately unbiased (LSDVC results available upon request).
or increase R&D tax credits when current R&D relative to their state average is particularly low. Note, however, that for such reverse causality to cause bias, the link must be contemporaneous: if current R&D affects tax policy only in future periods (as is likely, given the typical lag between the time when tax changes are passed and when they go into effect), then the inclusion of lagged R&D as a regressor will control for this effect. Moreover, if I replace contemporaneous user costs with lagged user costs, which cannot be affected by current R&D spending, I obtain very similar results, suggesting that any bias is negligible.

IV. Results

The main results from estimating the log linear model discussed above are shown in table 1. All regressions include year dummies. The dependent variable in all regressions is the log of company-funded industrial R&D spending, deflated by the GDP deflator.

To facilitate comparisons to previous studies of the R&D cost elasticity, I first estimate an R&D cost elasticity omitting the out-of-state R&D user cost, $\frac{1}{1-e}$. The estimated short-run elasticity of in-state R&D with respect to in-state cost ($-\theta$) is $-1.43$ with a robust standard error of 0.44 (column 1). The long-run elasticity is $-2.18$ (s.e. $= 0.81$). These elasticities are well within the range of R&D cost elasticities found in previous studies. Evaluated at the mean user cost for the sample, these elasticities imply that a 1 percentage point increase in a state’s effective R&D credit rate results in an increase in in-state R&D of around 1.7% in the short run and 3.0% in the long run.11 State GDP is found to be positively and significantly associated with R&D, with a coefficient of 0.73 (0.18). I also control for the state’s federally funded industrial R&D spending (lagged one period to avoid any spurious correlation from contemporaneous company funding affecting federal funding). The estimated coefficient on federally funded industrial R&D is $-0.05$ (0.01). This result of federal R&D funding crowding out private R&D funding is consistent with the industry-level results reported by Mamuneas and Nadiri (1996).

Columns 2–4 of table 1 show the results of explicitly adding the out-of-state cost to the R&D factor demand regression equation. (Note that, to some extent, the out-of-state cost implicitly was taken account of in the previous regression by year effects.) The regression underlying column 2 uses a weighted average of the R&D user costs of the five states closest to state $i$. The weight between state $i$ and some nearby state $j$ is simply the inverse of the distance between their population centroids (from the U.S. Census Bureau). The second regression uses a similarly constructed proximity-weighted average of the user costs of the ten closest states; and the third regression uses a proximity-weighted average of all other states’ user costs.

Adding the out-of-state cost is found to have only a small effect on the estimated in-state elasticity—consistent with the hypothesis that the year effects picked up much of the effect of out-of-state costs in the previous regression. Depending on which measure of out-of-state cost is used, the estimated in-state elasticity is between $-1.26$ and $-1.43$ in the short run, and between $-2.29$ and $-2.58$ in the long run (all significant below the 1% level). The out-of-state elasticity, on the other hand, is estimated to be positive and significant for each of the three measures of out-of-state cost. Using the narrowest measure—a weighted-average of R&D costs in the five closest states, the short-run in-state elasticity is 2.06, and statistically significant at the 5% level. The implied long-run in-state elasticity is 3.72. The implied aggregate-cost elasticity—the sum of the in-state and out-of-state elasticities—is relatively small and statistically insignificant.

As one broadens the measure of out-of-state cost by including more outside states in the weighted average, which reduces cross-sectional variation, the out-of-state elasticity estimate becomes increasingly imprecise. Nonetheless, even with the broader out-of-state cost measures used in the regressions underlying columns 3 and 4, the elasticity is found to be positive and significant at below the 5% level, and in no case is the aggregate-cost elasticity found to be significantly different from 0.

Columns 1–3 of table 2 provide estimates based on regressions analogous to those underlying columns 2–4 of table 1 but replacing the year dummies with a year trend and GDP to capture aggregate macroeconomic shocks to R&D spending.13 I also separately included...
log\(r_t + \delta\) even though this term is already part of log\(\rho^n_t\) and log\(\rho^n_t\) to allow for possible endogeneity of the real interest rate. (Note log\(r_t + \delta\) is absorbed by the year effects in the previous regressions.) The estimated elasticities are quite similar to those in table 1, but are estimated with much greater precision. The in-state elasticity is around \(-1.5\) in the short run while the out-of-state elasticity is around \(+1.6\). The long-run elasticities are somewhat higher, at around \(-2.5\) for the in-state elasticity and \(+2.8\) for the out-of-state elasticity. In both the short and the long run, the aggregate-cost elasticity is essentially \(0\) (and precisely estimated). Moreover, as shown by comparing among columns 1–3, the results are quite consistent across all three measures of out-of-state cost.\(^{14}\)

Alternative weighting schemes for measuring the out-of-state user cost, not based on geographic proximity, yield very similar results. In particular, columns 4 and 5 of table 2 show the results of weighting other states’ user costs by proximity in technology and industry space. Technology proximity is the Euclidean distance between two states’ vectors of patent shares across 401 technology classes (from the U.S. Patent and Trademark Office), while proximity in industry composition is measured by the Euclidean distance between two states’ vectors of employment shares across three-digit industries (from the U.S. Bureau of Labor Statistics).

A number of additional exercises, not shown, confirm the robustness of these regressions (see Wilson, 2007). These robustness checks include verifying that the estimated elasticities are not biased because of the omission of even-year data between 1981 and 1997; replacing the flow (investment) of R&D as the dependent variable with an imputed measure of the stock of R&D; including additional out-of-state factors (constructed as above) such as out-of-state GDP and population; allowing for potential R&D data-reporting/selection bias via a Heckman two-step estimator; and excluding Alaska and Hawaii from the sample.

### Table 2: Within Estimates of R&D Cost Elasticities (without Year Effects) Dependent Variable: Company R&D

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Five closest (1)</th>
<th>Ten closest (2)</th>
<th>All (3)</th>
<th>Patents (4)</th>
<th>Employment (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-state R&amp;D cost</td>
<td>(-1.50*** (0.44))</td>
<td>(-1.48*** (0.43))</td>
<td>(-1.41*** (0.43))</td>
<td>(-1.23*** (0.39))</td>
<td>(-1.13*** (0.40))</td>
</tr>
<tr>
<td>Out-of-state R&amp;D cost</td>
<td>1.64*** (0.50)</td>
<td>1.64*** (0.50)</td>
<td>1.62*** (0.51)</td>
<td>1.42*** (0.48)</td>
<td>1.27** (0.48)</td>
</tr>
<tr>
<td>Fed R&amp;D (-1)</td>
<td>(-0.06*** (0.01))</td>
<td>(-0.06*** (0.01))</td>
<td>(-0.06*** (0.01))</td>
<td>(-0.06*** (0.01))</td>
<td>(-0.06*** (0.01))</td>
</tr>
<tr>
<td>Year</td>
<td>0.03*** (0.01)</td>
<td>0.03*** (0.01)</td>
<td>0.03*** (0.01)</td>
<td>0.03*** (0.01)</td>
<td>0.03*** (0.01)</td>
</tr>
<tr>
<td>State GDP</td>
<td>0.70*** (0.16)</td>
<td>0.72*** (0.15)</td>
<td>0.77*** (0.16)</td>
<td>0.82*** (0.16)</td>
<td>0.83*** (0.16)</td>
</tr>
<tr>
<td>National GDP</td>
<td>(-0.92** (0.46))</td>
<td>(-0.92** (0.46))</td>
<td>(-0.88** (0.49))</td>
<td>(-1.01** (0.49))</td>
<td>(-1.03** (0.48))</td>
</tr>
<tr>
<td>Company R&amp;D (-1)</td>
<td>0.43*** (0.03)</td>
<td>0.44*** (0.03)</td>
<td>0.45*** (0.03)</td>
<td>0.45*** (0.03)</td>
<td>0.45*** (0.03)</td>
</tr>
<tr>
<td>Company R&amp;D (-1)</td>
<td>0.40*** (0.03)</td>
<td>0.40*** (0.03)</td>
<td>0.40*** (0.04)</td>
<td>0.40*** (0.04)</td>
<td>0.30*** (0.04)</td>
</tr>
<tr>
<td>Real interest rate</td>
<td>0.31*** (0.13)</td>
<td>0.28*** (0.13)</td>
<td>0.26** (0.15)</td>
<td>0.27** (0.15)</td>
<td>0.25* (0.15)</td>
</tr>
</tbody>
</table>

**Implied estimates (based on coefficients above):**

- Short-run aggregate-cost elasticity: 0.14 (0.20)
- Long-run in-state elasticity: \(-2.51*** (0.74)\)
- Long-run out-of-state elasticity: 2.75*** (0.82)
- Long-run aggregate-cost elasticity: 0.24 (0.32)
- Year coverage: 1981–2004
- Number of state-year obs.: 365
- Log likelihood: 134.417

**Notes:** All variables are measured in natural logs. Standard errors are shown in parentheses. Standard errors are robust to panel (state) heteroskedasticity and AR(1) within-state autocorrelation. The out-of-state R&D costs are as follows: geographical-proximity-weighted averages of R&D user costs in the five closest states (column 1), ten closest states (column 2), and all other states (column 3); weighted average of R&D user costs in all other states, weighting by similarity between own state’s and other state’s employment composition across three-digit industries (column 4); and weighted average of R&D user costs in all other states, weighting by similarity between own state’s and other state’s employment composition across three-digit industries (column 5).

\(*\) denotes significance at the 95% level.

\(**\) denotes significance at the 99% level.

\(***\) denotes significance at the 99% level.

\(^{14}\) Another finding worthy of note is that holding a state’s own GDP constant, the national GDP has a negative and significant effect on state R&D spending, suggesting that R&D may relocate out of state not just in response to favorable changes in out-of-state costs, but also in response to comparatively faster out-of-state economic growth.

\(^{15}\) Note these are the in-state and out-of-state responses of total R&D. The responses of credit-eligible R&D, which excludes late-stage development, could well be larger, depending on the degree of complementarity between early- and late-stage R&D.
R&D spending by state broken down into these separate margins are not currently available, but may be a fruitful area for research in the future. The result also implies that the net elasticity of R&D—that is, the effect on national R&D of an equiproportional change in all states' R&D user costs—is quite small, suggesting that the setting of R&D tax credits by states is nearly a zero-sum game.

What these findings imply regarding the effectiveness of the U.S. federal R&D tax credit depends on the degree of international mobility of R&D. In the current era of globalization, it seems likely that large foreign and U.S. multinationals, which are responsible for the bulk of U.S. R&D spending, may fairly easily reallocate R&D activity to (from) the U.S. in response to favorable (unfavorable) changes in U.S. policy vis-à-vis foreign policy. Thus, the degree of international R&D mobility remains an important topic for future research.

REFERENCES


