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Abstract

This paper addresses the question of whether government procurement can work as a *de facto* innovation policy tool. We develop an endogenous growth model with quality-improving innovation that incorporates industries with heterogeneous innovation sizes. Government demand in high-tech industries increases the market size in these industries and, with it, the incentives for private firms to invest in R&D. At the economy-wide level, the additional R&D induced in high-tech industries outweighs the R&D foregone

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in all remaining industries. The implications of the model are empirically tested using a unique data set that includes federal procurement in U.S. states. We find evidence that a shift in the composition of government purchases toward high-tech industries indeed stimulates privately funded company R&D.

JEL code: E62, H54, H57, O31, O32, O41

Keywords: public demand, technological change, endogenous growth

1 Introduction

This paper addresses the question whether the inter-industry composition of government purchases (hereafter procurement) works as a *de facto* innovation policy tool inducing additional private R&D in an economy. The idea that government procurement can stimulate innovation is not new. It is grounded in the results of more general studies suggesting that demand can spur private R&D and innovation (e.g., Gilfillan, 1935; Schmookler, 1962, 1966; Sokoloff, 1988). In this type of literature, it is typically assumed that demand (that is, market size) increases the returns on innovative activities and the attractiveness of R&D investment for firms. For instance, Moser (2005) finds that market size has an important influence on both, the number of innovations and the distribution of innovative activity across industries. Similarly, Acemoglu and Linn (2004) and Rosenberg (1969) suggest that demand "steers" firms to address certain problems. Also endogenous growth models acknowledge the importance of market size and profit incentives in innovation (Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b; Romer, 1990). Although it is typically not explicitly discussed in these models, an increase in the size of the market translates into a larger profit flow for each successful innovator and greater incentives to engage in R&D (Young, 1998). Following this line of reasoning, the government, being an important customer, can influence R&D and innovation as well. Empirical evidence at the firm level provides support for the conjecture that public procurement, that is, the purchase by governments of goods and services, can stimulate innovation (Aschhoff and Sofka, 2009; Lichtenberg, 1987, 1988).

In the last years, public procurement has often been advocated as one meaningful way to stimulate innovation (for an overview, see Edler and Georghiou, 2007) Many countries have launched initiatives to foster government purchases of high-tech and innovative solutions

(Edler, 2006; MED, 2005; OGC, 2004). These policies are typically justified by referring to historical examples suggesting that a number of highly influential technologies have been developed in the 20th century with the impetus from government demand, such as computers, semiconductors, or the GPS (Mowery, 2008; Nelson, 1982; Ruttan, 2006). Moreover, Nelson and Langlois (1983) show that the U.S. government was a major driver of the development of technologies in which it was an important customer. Similarly, for Scandinavia, Berggren and Laestadius (2003) and Fridlund (2000) indicate the public sector's major impact on the development of telecommunication technologies. The underlying argument is that the government can create and enlarge markets and thereby induce private R&D investment on a scale that would not have otherwise followed even the most promising research results. It is further suggested that the stimulus of private R&D and innovation by government procurement is especially pronounced for the most advanced products (Cozzi and Impullitti, 2010; Hart, 1998). Despite numerous anecdotes, however, there is little systematic evidence for this reasoning. Moreover, the reallocation of procurement toward certain industries implies that other industries are disadvantaged, with a priori no clear welfare implications. Finally, econometric evidence for the impact of changes in the inter-industry composition of public demand on private R&D in the economy is currently lacking. This paper attempts to fill this gap.

We develop a theoretical model to understand the transmission mechanism for the effect of government procurement on firms' innovative behavior. We follow on stratum of the traditional endogenous growth theory in which long-term growth results from quality-improving innovation (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b), and add the government as an additional source of demand (Cozzi and Impullitti, 2010). In the model,

we account for industry heterogeneity by allowing innovation sizes, that is, quality jumps, to differ between industries (Minniti *et al.*, 2008). Our main theoretical results indicate that when government purchases are relatively in favor of industries with an above-average quality jump, aggregate private R&D activities increase. The mechanism is as follows: A change in the technological composition of public demand spending toward industries with above-average quality jumps causes an increase in the expected profits of firms trying to innovate in these industries. The rewards for successful R&D activities increase because higher innovation size implies higher markups over marginal cost. The shift in the allocation of government demand toward high-tech industries induces more R&D on the level of the aggregate economy because the increased R&D in high-tech industries outweighs the R&D foregone in low-tech industries because of the smaller market there.

We test the predictions of the model regarding the effect of the inter-industry composition of government procurement on private R&D activities for the U.S. To the best of our knowledge, this study is the first to empirically assess the effect of the composition of government purchases, as opposed to their sheer volume, on private R&D behavior. The analysis is performed at the level of U.S. states for the period from 1999 to 2007. In particular, we construct a unique panel data set consisting of federal procurement expenditures provided by the U.S. General Services Administration (GSA), cross-classified by type of industry. We match the procurement data with privately sponsored company R&D spending. For the purposes of the empirical study, industries with quality jumps above the economy-wide average are proxied by high-tech industries using the standard industrial classification developed by the U.S. Bureau of Labor Statistics (Hecker, 2005). The impact of a shift in the composition of federal procurement toward high-tech industries on private R&D is assessed by a fixed-

effects (FE) estimation. However, the FE estimates might be biased because of unobserved, time-variant variables that are correlated with the technological composition of government procurement and company R&D. To instrument the composition of procurement we use the fact that procurement in high-tech industries in particularly high in states whose governors belong to the majority party in Congress. Governors expect that increases in procurement will stimulate a state's economic performance and therefore increase their re-election chances. Procurement in high-tech industries is particularly attractive for politicians because it is more prestigious than procurement in general. To deliver (high-tech industry) procurement to his constituents, however, the governor needs support from the Congress, which holds the "power of the purse." As the party caucus represents a coalition that provides selective benefits to its members, Congressmen are more likely to transfer money to the state level if the state is governed by a "friendly" politician. The respective governor, in turn, invests his political capital to enhance the re-election chances of the Congressman.

The empirical analysis provides support for the prediction of our theoretical model, namely, that a shift in the composition of federal procurement toward high-tech industries stimulates private R&D activities. The results indicate that a doubling of government purchases in high-tech industries relative to purchases in other industries is associated with a 6.8 percent increase in the amount of privately funded company R&D. Evaluated at the respective sample means, our results imply that if the high-tech ratio of government procurement increased from 65 to 130 percent, privately funded company R&D would increase by approximately $255 million (from $3,760 to $4,015 million). This result is robust under a range of alternative specifications. In the instrumental variable (IV) approach, the coefficient on the high-tech ratio of procurement is positive but statistically insignificant. Because there

is indication for a weak instrument problem, which aggravates the "usual" drawbacks of IV estimators, namely, a reduction in efficiency and a large finite-sample bias, we emhasize more the FE results.

The remainder of the paper is organized as follows. Section II introduces the basic model linking firms' R&D efforts to the technological composition of government demand. In Section III, we discuss the specification and estimation issues concerning the empirical assessment of the model's implications. In Section IV, we introduce the data and describe the construction of the key variables. Section V presents our findings. Section VI summarizes and concludes with some policy implications.

2   Theory

To link government procurement to innovation and economic growth, we develop a simple endogenous growth model. The economy in the model is closed and consists of two sectors: a final goods (or manufacturing) sector and a research sector where firms seek innovations. To avoid unnecessary complications and to highlight the basic forces at work, labor is the only input factor used in both sectors and is not further differentiated. Labor supply decisions are treated as being exogenous. There is a continuum of industries in the unit interval indexed by $\omega \in [0, 1]$, with each industry producing exactly one consumption good (or product line). The outputs of the different industries substitute only imperfectly for each other. The set of commodities is fixed in the progress of time. Innovation is vertical, improving the quality of each consumption good, and requires targeted R&D efforts of firms at a respective product line. Let the discrete variable $j \in \{0, 1, 2, ...\}$ denote the quality level. Each innovation in

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industry ω leads to a quality jump from j to $j+1$. The quality increments, denoted by λ, happen independently of each other. Thus, an improvement in one industry does not induce an improvement in any other industry.

Different from previous endogenous growth models with vertical innovation, which treated industries symmetrically (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b; Li, 2001, 2003; Segerstrom, 1998), we assume the size of the quality jump after a successful innovation to be uncertain and industry specific. In line with the more recent work by Minniti *et al.* (2008), the realization of each R&D race is drawn independently from a Pareto distribution. Modeling the size of the quality jump as a Pareto distributed random variable is supported by the patent (including citations) literature. For instance, Scherer (1965) analyzes the patent activities of the 500 largest firms in the U.S. He finds that the distribution of U.S. patent values (measured by profit returns) is highly skewed toward the low-value side and heavy tailed to the high-value side, which comes fairly close to the generic properties of a Pareto distribution. Similarly, in a more recent work, Harhoff *et al.* (2005) ask patent holders in Germany and in the U.S. to estimate the value of their inventions and find a distribution of values that is strikingly close to the Pareto distribution.

On the consumer side, each household is modeled as a dynastic family whose size increases over time at an exogenous rate n. Each household member inelastically supplies labor in exchange for wages. We normalize the total number of individuals at time $t = 0$ to unity by the appropriate choice of unit. Thus, the population of workers at time t equals $L(t) = e^{nt}$. The intertemporal preferences of the representative household are given by:

$$U(t) = \int_0^\infty e^{nt} e^{-\rho t} \log u(t) dt, \tag{1}$$

where ρ denotes the rate of time preference, and $\log u(t)$ represents the flow of utility per household member at time t (see Barro, 1974; Kirman, 1992, for a discussion on infinite-horizon representative agent framework). Any individual's instantaneous utility is represented by:

$$\log u(t) = \int_0^1 \log \left[\sum_{j=0}^{j^{\max}(\omega,t)} \lambda^j(\omega,t) d(j,\omega,t) \right] d\omega. \tag{2}$$

where $d(j,\omega,t)$ is the consumption of quality j in product line ω at time t. The utility derived by an individual from consumption is therefore determined by the quality-weighted amount of consumption integrated over all industries $\omega \in [0,1]$. The preferences in (2) imply that a consumer enjoys one unit of good ω that was improved j times as much as $\lambda^j(\omega,t)$ units of the good if it had never been improved, with $\lambda(\omega,t) > 1$. The logarithmic functional form in (2) was chosen for simplicity and does not affect the main results.

The representative household maximizes lifetime utility (1) subject to the following intertemporal budget constraint:

$$B(0) + \int_0^\infty w(s) e^{-\int_0^t [r(\tau)-n]d\tau} ds - \int_0^\infty e^{-\int_0^t [r(\tau)-n]d\tau} T(s) ds$$
$$= \int_0^\infty e^{-\int_0^t [r(\tau)-n]d\tau} c(s) ds,$$

where $B(0)$ is the ex-ante endowment of asset holdings of the representative household, $w(t)$ is the wage rate earned by each individual, $T(t)$ is a per capita lump-sum tax, and $c(t)$ is the flow of individual consumer expenditures. Under the assumption that when a household member is indifferent between two quality vintages, the higher quality product is bought, the

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household maximization problem yields the following static demand function:

$$
d(j, \omega, t) = \left\{ \begin{array}{cc} \frac{c(t)}{p(j,\omega,t)} & j = j^{max}(\omega, t) \\ 0 & otherwise \end{array} \right\},
\tag{3}
$$

where $p(j, \omega, t)$ is the price of product ω with quality j at time t.

The dynamic optimization problem, that is, the allocation of lifetime expenditures over time, consists of maximizing the discounted utility (1) subject to (2), (3), and the intertemporal budget constraint. The solution of the optimal control problem obeys the Keynes-Ramsey rule:

$$
\frac{\dot{c}(t)}{c(t)} = r(t) - \rho.
\tag{4}
$$

Because preferences are homothetic, the aggregate demand at time t in industry ω is given by $D(j, \omega, t) = d(j, \omega, t)L(t)$.

At any point in time, only one firm possesses the technology to produce the highest quality product using one unit of manufacturing labor to produce one unit of output. The best-practice firm has a quality advantage of λ over the next best quality in the industry. The optimal strategy for the quality leader is to set the *limit price* $p_L(\omega, t)$, preventing any other firm in the industry from offering its product without losses. The quality leader will set a quality-adjusted price below the unit costs of its nearest competitor while that competitor will come up with a price equal to his own marginal cost. The highest price the quality leader can set to capture the entire industry market is his lead over the next best quality follower, implying $p_L(\omega, t) = \lambda(\omega, t)w = \lambda(\omega, t)$. There is no incentive for the quality leader to set a price above the limit price because if he did, he would lose all of his customers.

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Government demand, that is, government procurement, is financed by lump-sum tax revenues and is strictly nonnegative for all industries at any point in time. This assumption allows us to isolate wealth effects from the distortionary effects of taxation. Similarly, the government budget is assumed to be balanced at any time. To avoid unnecessary complications, we abstract from modeling any effects of public demand expenditures on the individual utility or on the marginal productivity of private input factors in manufacturing or research. Denoting per capita public demand spending in industry ω at time t by $G(\omega, t)$, the quality leader in each industry earns a profit flow of:

$$\pi(\omega, t) = [\lambda(\omega, t) - 1] \left\{ \frac{c(t)L(t)}{\lambda(\omega, t)} + \frac{L(t)G(\omega, t)}{\lambda(\omega, t)} \right\}. \tag{5}$$

Here, $\lambda(\omega, t) \left\{ \frac{c(t)L(t)}{\lambda(\omega,t)} + \frac{L(t)G(\omega,t)}{\lambda(\omega,t)} \right\}$ corresponds to market size (sales to private and public customers) for the product being produced in industry ω. The factor $[\lambda(\omega, t) - 1]$ is to be interpreted as the markup over the marginal cost. Thus, the parameter $\lambda(\omega, t)$ describes the degree of monopoly power. Given the preferences in (2), the profits in (5) are independent from the quality level, j.

There is free entry into R&D so that firms may target their research effort at any industry. Labor is the only input used in R&D and can be freely allocated between manufacturing and research. The frictionless nature of the labor market implies that workers earn the same wage in R&D as in manufacturing, $w = 1$. Research is *directed* in the sense that firms can devote their R&D resources to developing state-of-the-art products in any industry (Acemoglu and Linn, 2004). It is important to notice, however, that firms conduct R&D activities in industries in which they are not the current quality leader, to not cannibalize their current monopoly rents (Arrow, 1962; Fudenberg *et al.*, 1983; Fudenberg and Tirole, 1985). The aim

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of each firm's R&D efforts is a superior quality and to monopolize the market by achieving a patent with infinite patent length.[1] All firms have access to the same R&D technology. In industry ω at time t, a firm engaged in R&D that employs $l_i(\omega, t)$ units of labor faces a Poisson arrival rate of innovation, $I_i(\omega, t)$, equal to:

$$I_i(\omega, t) = \frac{Al_i(\omega, t)}{X(\omega, t)},\qquad(6)$$

where $A > 0$ is a given technology parameter, and $X(\omega, t)$ is a function that captures the difficulty of conducting R&D, which is taken as given by each R&D firm.

The R&D technology in (6) reflects the stochastic nature of the innovation process, while $I_i(\omega, t)dt$ is the probability to win the R&D race and become the next quality leader within the time interval $[t, t + dt]$. In (6), the time interval approaches zero. Hence, $I_i(\omega, t)$ is to be interpreted as the instantaneous probability of firm i being successful in finding the next higher quality product per unit of time. Assuming that the probability of winning an R&D race is independent across firms, across industries, and over time, the industry-wide arrival rate of innovation in each industry ω reads:

$$I(\omega, t) = \frac{AL_I(\omega, t)}{X(\omega, t)},\qquad(7)$$

where $L_I(\omega, t) = \sum_i l_{I,i}(\omega, t)$ and $I(\omega, t) = \sum_i I_i(\omega, t)$ denote the R&D labor rate and the accumulated arrival rate of innovation, resepctively, of all firms in industry ω at time t. The specification of the R&D technology in (7) implicitly assumes the existence of intra-industry

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[1] In reality, however, patent protection is often less attractive for firms than keeping new knowledge within the firm (secrecy) or using other means to protect the research results (e.g., Cohen *et al.*, 2000; Mansfield, 1986).

externalities but abstracts from inter-industry knowledge spillovers (Li, 2003).

Different from earlier R&D-driven endogenous growth models (Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b; Romer, 1990), in our model the long-run growth rate of the economy is not influenced by the population size (no "scale effect" property). Following ? and Segerstrom (1998), we assume that the R&D difficulty grows in each industry at a rate proportional to the arrival of innovation:

$$\frac{\dot{X}(\omega, t)}{X(\omega, t)} = \mu I(\omega, t), \tag{8}$$

where $\mu > 0$ is exogenously given, and $X(\omega, 0) = X_0$ for all ω. Similar to A in (6), the parameter μ in (8) captures scientific opportunities in the economy.

Once a firm becomes successful in finding an innovation, the size of that innovation is drawn from a Pareto distribution with a shape parameter $1/\kappa$ and a scale parameter equal to one (Minniti *et al.*, 2008). The probability density function of a Pareto distribution with these properties reads:

$$g(\lambda) = \frac{1}{\kappa}\lambda^{-\frac{1+\kappa}{\kappa}}, \lambda \in [1, \infty), \tag{9}$$

where $\kappa \in (0, 1)$ is a parameter that measures the degree of the dispersion or heterogeneity of the Pareto distribution. The meam of the Pareto distribution equals $1/(1 - \kappa)$.

For analytical tractability, we assume that the initial distribution of λ values is given by $g(\lambda)$ at $t = 0$. Then, as the R&D dynamics start off and successfully innovating firms draw new values of λ, the distribution of λ values does not change over time. Notice further that $X(\omega, t) = X_0$ for all ω implies that $I(\omega, 0) = I_0$ (constant) for all ω. Hence, a symmetric

equilibrium path must exist along which $I(\omega, t) = I(t)$ and $X(\omega, t) = X(t)$ for all ω. We focus on this symmetric equilibrium in the further analysis.

Firms that participate in an R&D race issue securities on a perfect financial market. Let $v^e(\omega, t)$ be the discounted value of expected profits for firms in industry ω at time t. The assumption of no arbitrage on the stock market yields (Blanchard and Fischer, 1989):

$$\frac{\pi^e(\omega, t)}{v^e(\omega, t)} + \frac{\dot{v}^e(\omega, t)}{v^e(\omega, t)} = r(t) + I(t), \tag{10}$$

where $\pi^e(\omega, t)$ denotes the expected profits earned by a successful innovator. In the stock market equilibrium, the expected dividend rate, $\pi^e(\omega, t)/v^e(\omega, t)$, plus the expected rate of capital gains, $\dot{v}^e(\omega, t)/v^e(\omega, t)$, is equal to the rate of return of the risk-free security plus a risk premium. The latter is given by the flow rate of innovation, $I(t)$, because a producer of the latest quality vintage who loses his leadership has a stock value of zero. Taking into account that profit maximization in R&D yields $v^e(\omega, t) = X(\omega, t)/A$ and and recalling that the increase in R&D difficulty is common to all industries in the economy, the dividend rate becomes:

$$\frac{\pi^e(\omega, t)}{v^e(\omega, t)} = r(t) + I(t) - \frac{\dot{X}(t)}{X(t)}. \tag{11}$$

Before we can derive an expression for the expected profits of a firm winning an R&D race, $\pi^e(\omega, t)$, we have to specify how the government allocates its demand expenditures among the various industries in our model economy.

Following Cozzi and Impullitti (2010), the allocation of government procurement across industries is determined as follows:

$$G(\omega, t) = \bar{G} + \gamma\varepsilon, \ 0 \le \gamma \le 1, \tag{12}$$

where

$$\bar{G} \equiv \int_0^1 G(\omega)d(\omega),$$

$$\varepsilon \equiv \begin{cases} -\varepsilon_1 & \text{for } \lambda(\omega, t) < \frac{1}{1-\kappa} \\ \varepsilon_2 & \text{for } \lambda(\omega, t) \ge \frac{1}{1-\kappa} \end{cases},$$

$$0 < \varepsilon_1 < \bar{G},$$

$$0 < \varepsilon_2 < \bar{G}.$$

The first term on the RHS of (12), $\bar{G}$, denotes the average per capita public procurement, that is, the value of public demand spending a quality leader in each industry ω will receive if the government spreads its expenditures $G(\omega)$ evenly across all industries.[2] Such symmetric treatment of industries occurs for $\gamma = 0$. The second term on the RHS of (12) implies that any $\gamma > 0$ corresponds to a public demand policy that more heavily promotes industries with above-average quality jumps. Specifically, if the quality improvement caused by an innovation in industry ω is smaller than the average economy-wide quality increment, public purchases in this industry will be lower than in the symmetric case. However, if an innovator in industry ω draws a value of λ above the average quality jump, he will benefit more from

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[2] Because there is a continuum of industries indexed on the unit interval, average values in the model equal total values.

public spending than under the symmetric demand policy rule. The higher γ is, the more favorable the government treatment of industries is with above-average quality jumps *vis-à-vis* industries with below-average jumps. We make the simplifying assumption that once an industry experiences a quality jump above (below) the economy-wide average and $\gamma \neq 0$ holds, the government spends more (less) in this industry irrespective of how far beyond the average this industry finds itself after the quality jump. It is straightforward to show that the strictly positive values ε_1 and ε_2, which indicate how much government purchases in "low-jump" or "high-jump" industries deviate from average spending, cannot be chosen independently (see Appendix A). As stated above, the distribution of the λ values does not change over time. Thus, although there is uncertainty at the industry level concerning the size of the quality jump that occurs after an innovation arrives, there is always the same share of industries with quality increments above or below the average at the macro level. Moreover, to focus on the effects of the inter-industry composition of government purchases, we assume that $\bar{G}$ is constant (unless otherwise noted).

After solving (see Appendix B) for the expected flow profits of a firm winning an R&D race, $\pi^e(\omega, t)$, using (12), we obtain the following expression for $v^e(\omega, t)$:

$$v^e(\omega, t) = \frac{\frac{\kappa}{1+\kappa} L(t)[c(t) + \bar{G} + \gamma\Gamma]}{r(t) + I(t) - \frac{\dot{x}(t)}{x(t)} - n},$$ (13)

where $\Gamma \equiv \varepsilon_2 \left(1 \big/ \left[1 - (1-\kappa)^{1/\kappa} \right] - 1 \right) > 0$ and $x(t) \equiv X(t)/L(t)$ is a measure of the relative, that is, population-adjusted, R&D difficulty. Because the RHS of (13) does not contain any industry-specific variables, $v^e(\omega, t) = v^e(t)$ is the average market valuation of a successful innovation in the economy. In (13), the effect of "creative destruction" is revealed; the more research that occurs in an industry, the shorter, *ceteris paribus*, the duration of the

accruing monopoly profits is and the smaller the incentives to innovate are. By subtracting the rate of population growth, n, in the denominator of (13), we also take into account that aggregate consumer markets, and thus, profits earned by a successful innovator increase with a growing population.

Equation (13) already highlights the market size effect in innovation: the greater $\bar{G}$ is, that is, the larger the government market is for a new product, the more profitable it is to be the producer of that good. Another important implication of (13) is that the profitability of a successful innovation increases in γ. In other words, it is not only the size of government demand that matters for the valuation of a successful innovator, but also how government expenditures are distributed across industries. Specifically, the more heavily the government promotes industries with relatively high quality jumps, the more attractive an innovation becomes on average. However, although there is a positive effect of the market size on the expected firm value, it is still not clear whether there will also be more research effort to acquire this position. As we will show below, an increase in the size of the government market that affects all industries symmetrically will not stimulate additional R&D in this economy.

To see this, we derive the *R&D equilibrium condition* from the condition for profit maximization in R&D and (13) as:

$$\frac{x(t)}{A} = \frac{\frac{\kappa}{1+\kappa}(c(t) + \bar{G} + \gamma\Gamma)}{r(t) + I(t) - \frac{\dot{x}(t)}{x(t)} - n},$$ (14)

while the *resource constraint* of the economy (see Appendix C) reads:

$$1 = \frac{c(t) + \bar{G} - \gamma\kappa\Gamma}{1 + \kappa} + \frac{I(t)x(t)}{A}.$$ (15)

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The labor-market equilibrium in (15) holds for all t in and outside the equilibrium because factor markets clear instantaneously.

The steady-state growth path of the economy (see Appendix D) is characterized by all endogenous variables growing at a constant (although not necessarily at the same) rate and a common research intensity, $I(t)$, across industries. According to (7), the constant growth rate of the R&D difficulty constrains I to be constant over time and equal to $I^* = n/\mu$. For that reason, $\dot{x}/x = \dot{c}/c = 0$ is implied by (15). Then, $r(t) = \rho$ prevails by (4), meaning that in the steady state the market interest rate must equal the rate of time preference.

Using these results, as well as (7) and (29), the amount of labor devoted to R&D in the steady state can be derived as:

$$\left(\frac{L_I}{L}\right)^* = \frac{\kappa n \left(1 + \gamma \Gamma\right)}{n \left(1 + \kappa - \mu\right) + \mu \rho}. \tag{16}$$

The positive relationship between firms' R&D activities and γ established in this equation is the main result of the model. An increase in γ, the parameter that determines to what extent procurement takes place in industries with above-average quality jumps relative to the remaining industries, instantly raises the expected value of becoming a quality leader [see (13)]. Firms respond by investing more heavily in R&D, so the equilibrium value of the average (and aggregate) R&D employment share increases. Consequently, by varying the composition of its purchases in favor of industries with above-average innovative potential, the government holds a leverage to stimulate private R&D spending.

The steady-state level of labor employed in R&D activities is not affected by the volume of per capita government demand expenditures, $\bar{G}$. This result occurs because when the government increases its demand spending, it takes away resources from the private sector.

From (30) it can be shown that procurement reduces private consumption in equilibrium one-for-one, that is, $dc^*/d\bar{G} = -1$. Therefore, a symmetric increase in government procurement spending that equally affects all industries does not stimulate additional R&D in the economy. Equation (16) indicates a number of further determinants of the equilibrium share of R&D employment. First, it can be easily shown that the growth in the total market size, n, positively affects R&D labor. Moreover, the larger the average size of innovations, that is, the greater κ, and therefore the higher the limit price that a successful innovator can charge, the more that is spent in relative terms on R&D. Finally, equation (16) indicates that investment in R&D is also affected by the technological research opportunities, μ. The smaller μ is, the better the technological research opportunities are [see (8)], and, because $(\rho - n) > 0^3$, the higher the equilibrium R&D employment is.

3 Empirical Specification and Estimation Issues

The theoretical investigation of the industry-level effects of government purchases laid out a potential mechanism through which public demand spending might affect innovative behavior in industries and, with it, the rates of technological change and economic growth. The basis for the empirical analysis is the result that the inter-industry composition of public demand influences private R&D. According to (16), a shift in the structure of government purchases toward industries with an above-average innovation potential stimulates private R&D in the economy. This is due to a market size effect of government procurement in these industries, which raises the returns of successful R&D activities and creates incentives for firms to privately invest in R&D in these industries. The economy-wide amount of private R&D

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[3] This parameter restriction is needed to ensure the convergence of the utility integral in (1).

increases because technological improvements and the R&D intensity in these industries are higher than the economy-wide average. The implications of the theoretical model are tested at the level of U.S. states, mainly because of the availability of detailed procurement data at the industry level.

The impact of the composition of government sales on privately funded company R&D can be empirically assessed by considering (16). Adding other potential determinants, state and time effects, and log-transforming, equation (16) yields the following empirical model:

$$
\log RD_{i,t} = \alpha + \beta_1 \log HIGH\_TECH\_RATIO_{i,t-1} + \beta_2 \triangle \log GDP_{i,t-1}
$$
$$
+ \beta_3 \log GDP_{i,t-1} + \beta_4 \log POP_{i,t-1} + \xi_i + \nu_t + u_{i,t}, \tag{17}
$$

where $RD_{i,t}$ is the amount of privately funded company R&D expenditures in state i at time t. In the theoretical model, the private R&D input is measured in terms of R&D employment. However, for the purposes of empirical analysis, we use the R&D expenditures. To the best of our knowledge, there is no information available that would allow us to distinguish the direct employment effect of public procurement (R&D jobs to accomplish a government contract) from the indirect effect (additional company-funded R&D jobs). $HIGH\_TECH\_RATIO_{i,t-1}$ is the empirical approximation of γ from our theoretical model. This variable is defined as the ratio between non-R&D procurement in high-tech industries and non-R&D procurement in all other industries at time $t-1$.[4] $HIGH\_TECH\_RATIO$ is lagged by one period to account for the fact that procurement contracts appear in our data with the date of contract signature while the effective starting date might be later. Similarly, privately funded company R&D might respond to federal procurement contracts only with a

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[4]   See Section (4.1) for distinction between R&D and non-R&D procurement and the reasons to exclude the former when constructing $HIGH\_TECH\_RATIO$.

certain lag. $\triangle \log GDP_{i,t-1}$ is the GDP growth rate, which proxies for the growth of the total (private and public) market, which is denoted in the theoretical model as n. In addition, to control for the effect of the total market size on private R&D, we use both the level of the GDP, $GDP_{i,t-1}$, and the population size, $POP_{i,t-1}$ (Moser, 2005; Sokoloff, 1988). The population, GDP, and GDP growth are lagged by one period to account for the fact that firms decide on their future R&D investment using current information. The vectors ξ_i and ν_t include the state and time fixed effects, respectively. The state fixed effects, ξ_i, account for all kinds of unobserved time-invariant state-specific factors that might influence private R&D. Similarly, ν_t captures the aggregate, macroeconomic factors, such as demand shocks or policy changes, affecting private R&D spending. Moreover, the time fixed effects also account for the portion of technological opportunities (μ in the theoretical model) that is common to all states. Omitting the state and time fixed effects in the regression will cause biased estimates if these are correlated with any of the regressors. The error term is denoted by $u_{i,t}$.

Despite controlling for state and time fixed effects, the error terms within units may still be correlated over time.[5] In the presence of serial correlation, the fixed-effects (FE) estimator will be inefficient if the unobserved factors that cause the within-state correlation of the residuals are uncorrelated with the included regressors; otherwise, the FE estimator will also be biased. Tackling the problem of inefficiency, we follow previous literature and use standard errors clustered at the state level to ensure valid statistical inferences in the presence of serial correlation (Arellano, 1987; Hansen, 2007; White, 1980).[6]

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[5] Applying Wooldridge's test for serial correlation (Wooldridge, 2002a) , we cannot reject the Null hypothesis of no first-order autocorrelation. However, there is no indication for higher-order autocorrelation.

[6] If both, the AR(1) model for serial correlation and strict exogeneity hold, the FGLS estimator using the Prais-Winsten transformation is asymptotically more efficient than the FE estimator (Wooldridge,

Moreover, it could be objected that drawing causal inferences from (17) about the effect of government procurement composition on private R&D is problematic. Specifically, there might be omitted variables that are correlated with both private R&D and government procurement or even jointly determine them. For instance, because of the local industry structure, we may observe a positive correlation between federal high-tech procurement and private R&D. Changes in the within-state industry structure are not captured in the fixed effects. Moreover, federal procurement contracts might be contingent on certain firm characteristics, such as lobbying activities or management quality that are also systematically related to firm R&D. In other cases, high-tech industry procurement may be used strategically as a policy means to stimulate the local economy. Hence, the estimates of the impact of government procurement on private R&D might be biased while the direction of the bias is not clear. Our strategy for dealing with the various sources of estimation bias is to apply an IV approach. The instrument is discussed in Section 5.4. Before turning to the empirical analysis, we first introduce the data and indicators.

4 Data and Variable Construction

4.1 Federal non-R&D Procurement

Our information on government purchases by state and industry stems from the Federal Procurement Data System – Next Generation (FPDS-NG), provided by the U.S. General Services Administration (GSA). Federal agencies are required by the Federal Acquisition Regulation to report all contract actions of more than \$2,500 directly to the FPDS-NG.

2002b). However, when T is small and strict exogeneity does not hold, FGLS tends to exacerbate the bias (Wooldridge, 2002a).

Procurement conducted by state governments and other local public agencies is not included in the data.[7] FPDS-NG reports the federal contracts for each company that is a separate legal entity, independent of the parent company (Goldman *et al.*, 2008). The information provided contains, *inter alia*, the contract volume, award and completion dates, place of performance, whether a contract is primarily for R&D, Federal Product and Service Code (PSC), and, since 2001, the industry (NAICS) to which a contract can be assigned. The FPDS-NG database contains records of more than 32 million contract actions between 1978 and 2009.

To construct the procurement high-tech ratio, we use only federal non-R&D procurement. Federal R&D procurement reflects the government demand for completely new products, processes, or systems, which essentially means that firms conduct R&D by the order of the government (David *et al.*, 2000). It has been suggested that R&D procurement is often idiosyncratic, and the results of federally funded research are only applicable to the private market to a limited degree (Kanz, 1993; Lichtenberg, 1989). Hence, R&D procurement is less suited to capture the market-size effect of public procurement on private R&D decisions suggested by our theoretical model. One should notice, however, that non-R&D procurement might also contain a R&D component. Unfortunately, the FPDS-NG data do not allow

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[7]   It could be objected that by looking only at federal procurement we miss an important part of general public procurement. The OECD estimates that, in the U.S., the volume of procurement by state and other local agencies is almost twice the volume of federal procurement (Audet, 2002). In particular, the omission of state and local level procurement is problematic if there are systematic differences in the content of procurement by federal and sub-national procurement agencies, for example, with respect to the technological composition of procurement. However, there is no a priori reason to believe that procurement by federal and sub-national agencies differ from each other (see, e.g., Coggburn, 2003). Moreover, to the best of our knowledge, sub-national procurement entities do not provide data at a level of detail necessary for our analysis. However, using only data on federal procurement has an important advantage as it is more likely to be independent of state-level characteristics, thereby reducing the problem of endogeneity discussed in Section 3.

us to discern the R&D portion of non-R&D contracts. However, the primary objective of non-R&D contracts is not to conduct research on behalf of the government (GSA, 2005). Moreover, R&D performed under federal non-R&D contracts is much more likely to also have applications to the private market (Lichtenberg, 1990), thereby creating additional incentives for private investment in R&D.

We classify procurement expenditures according to the date of the contract signature. Moreover, we use the gross contract value, that is, the number of dollars initially obligated by the action. De-obligations are not subtracted because they are typically not foreseeable at the date of the contract signature and, thus, are not factored in by firms in their R&D decisions. However, by not accounting for de-obligations, we implicitly assume that the cancellation, downward adjustment, or deletion of a previously recorded obligation does not affect private R&D decisions.

Testing our model's implications requires identifying procurement in industries with above- and below average quality jumps, respectively. Closest to the theoretical model would be an industry classification according to the average quality jump, measured, for instance, by the average markup of price over marginal cost. However, to the best of our knowledge, estimates of markups for U.S. industries are available only at the 2-digit NAICS level (e.g., Diewert and Fox, 2008; Hall, 1988; Oliveira Martins *et al.*, 1996; Roeger, 1995), which is too broad to meaningfully distinguish industries with respect to their innovation capacity. Thus, for the purposes of the empirical study, we approximate industries in which quality jumps above the economy-wide average by high-tech industries. To identify high-the industries, we refer to the industrial classification provided by the Bureau of Labor Statistics (BLS). The BLS classifies industries as high-tech if the percentage of science, engineering, and technical occupations in

total employment exceeds the average for all industries at least by a factor of five (Hecker, 2005).[8] According to this definition, we classified the following industries as high-tech: Pharmaceutical and medicine manufacturing (NAICS 3254), Computer and peripheral equipment manufacturing (NAICS 3341), Communications equipment manufacturing (NAICS 3342), Semiconductor and other electronic component manufacturing (NAICS 3344), Navigational, measuring, electro-medical, and control instruments manufacturing (NAICS 3345), Aerospace product and parts manufacturing (NAICS 3364), Software publishers (NAICS 5512), Internet publishing and broadcasting (NAICS 5161), Other telecommunications (NAICS 5179), Internet service providers and Web search portals (NAICS 5181), Data processing, hosting, and related services (NAICS 5182), Architectural, engineering, and related services (NAICS 5413), Computer systems design and related services (NAICS 5415), and Scientific research-and-development services (NAICS 5417).

Prior to 2001, the FPDS-NG data contain mainly PSC information, while industry information (NAICS) is only scarcely reported. However, since 2001 the FPDS-NG procurement data contain information on both the PSC and NAICS codes for almost all contracts. We develop a PSC-NAICS concordance based on contract data during the period from 2001 to 2009 for which both the PSC and NAICS were available to assign NAICS codes to contracts with missing industry classification (see Appendix E). We use the original NAICS codes and the concordance (if the NAICS code was missing) to classify industries as either high-tech or

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[8] An alternative classification of high-tech industries, relying on industrial R&D spending, is provided by the Bureau of Economic Analysis in its R&D Satellite Account (Fraumeni and Okubo, 2005). The R&D Satellite Account data are based on the industry-level R&D series collected by the National Science Foundation. However, we do not use this classification because, due to a mistake in the classification methodology, a large part of R&D before 2004 was erroneously attributed to the wholesale trade industry. In reality, this R&D was mostly performed in pharmaceutical and computer manufacturing companies. Despite the fact that since 2004 the NSF has released a revised industry classification, the BEA still uses the unrevised methodology (NSF, 2007; Robbins *et al.*, 2007).

all other.

Finally, we exclude federal purchases from public-sector firms (NAICS 92) from the sample and aggregate the remaining procurement contracts to the state level. We construct the high-tech ratio, as a measure of the technological content of procurement, by computing the ratio between procurement in high-tech industries and procurement in all other industries.

4.2   Privately Funded Company R&D Expenditures

Our data on privately funded company R&D spending are taken from the U.S. Survey of Industrial R&D (SIRD), administered by the National Science Foundation (NSF). The NSF provides estimates of domestically performed R&D expenditures by the source of funding (private and public) for states and industries based on a survey with a stratified representative sample of firms with five or more employees. We focus on data on privately funded company R&D because we want to investigate whether an increase in market size due to government procurement creates incentives for firms to invest their own money in R&D. The SIRD data are biannual from 1981 to 1997 and annual since then. Because of disclosure limitations, the series on privately funded R&D expenditures has a nonnegligible share of missing values. An observation is missing when the number of surveyed firms in a state is low. However, the severity of this problem generally declines over time. Hence, we restrict our analysis to the period from 1999 to 2007. One the one hand, narrowing down the sample period allows us to use annual data with only a few missing values for privately funded R&D. On the other hand, the NSF provides data on the number of surveyed firms by state and year only from 1999 on. We use the number of firms in a Heckman selection model to account for the potential selection bias. In two states (New Hampshire and Rhode Island), however, privately

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funded company R&D is reported only once during our period of observation. These states are dropped from the sample. R&D spending is measured in constant dollars, using the aggregate GDP deflator with the base year 2000.[9]

It could be objected that our R&D and procurement data are not fully compatible because they are based on different reporting units. In particular, the reporting unit for the SIRD data is the company with all subsidiaries while R&D is assigned to firms' headquarters location. The procurement data in the FPDS-NG are reported for the actual place of performance. Thus, if the headquarters and place of performance are not located in the same state, we are likely to underestimate the impact of procurement. Moreover, survey-based SIRD data may not capture R&D spending in small firms well. In fact, firms with less than five employees are even excluded from the survey. It has also been argued that small firms typically do R&D on the job and purchase capital-embodied technology rather than innovate themselves (Kleinknecht *et al.*, 2002). Therefore, the R&D survey data might underestimate R&D efforts within small firms (Patel and Pavitt, 1995). However, small firms are also less likely to be recipients of government contracts.

4.3 Population and GDP

Population data are taken from midyear estimates reported by the Bureau of Economic Analysis (BEA). Data on the GDP (in real terms) are also obtained from the BEA. The GDP is deflated using the state-specific deflator for the year 2000, which better reflects the within-state composition of industries than the aggregate GDP deflator (BEA, 2006). Our

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[9] To the best of our knowledge, reliable output-based R&D deflators, that is, price-deflators that take into account productivity gains in the R&D output, are currently not available. Using the aggregate GDP deflator does not change our results because the deflator is the same for all states and is, thus, controlled away by the year dummies.

final dataset covers 48 U.S. states in the period from 1999 to 2007.

5 Empirical Results

5.1 Federal non-R&D Procurement Composition and Private R&D – A descriptive analysis

In our empirical analysis, we will exploit the within-state (over time) relationship between the technological composition of federal non-R&D procurement spending, that is, the procurement high-tech ratio, and privately funded company R&D. However, our identification strategy rests on the assumption that the procurement high-tech ratio in a state is independent of state characteristics that are not accounted for and that there are no further mechanisms in the background which jointly influence the procurement high-tech ratio and company R&D. This section provides a closer examination of the mechanisms driving the geographic distribution of federal procurement spending. This examination allows us to verify the plausibility of the above assumption and to better understand and interpret the findings of the subsequent econometric analysis.

Figure 1 provides some insights on how the federal government allocates non-R&D procurement (in high-tech industries and in all other industries) across states. Not surprisingly, the total amount of both types of procurement seem to be higher in large (in terms of population), innovative (in terms of privately funded company R&D), and economically powerful (in term of the GDP) states. The respective cross-sectional correlations are between 0.60 and 0.74. However, federal non-R&D procurement relative to privately funded company R&D tends to be higher in smaller, less innovative, and economically less powerful

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states. In these states, the amount of procurement both in high-tech industries and in all other industries typically exceeds company R&D. The cross-state correlations between the procurement-to-private-R&D-ratio and privately funded company R&D, population, and the GDP are between -0.13 and -0.24 for both procurement types.

Figure 1 also reveals significant differences in the development (over time) of federal non-R&D procurement and private R&D in the individual states. Non-R&D procurement in high-tech industries increased in most of the states (38 of 50, or 76 percent), remained virtually unchanged in eleven states (22 percent), and declined only in one state. Procurement in all industries except high-tech industries increased in 48 states and did virtually not change in the other two. Similarly, privately funded company R&D increased or remained constant in the majority of states. For almost all the states, we find a significant positive correlation between both types of federal non-R&D procurement and privately funded company R&D. It also seems that the increase in procurement was relatively strong in periods in which the increase in private R&D was less pronounced. Overall, these first findings suggest that the federal government might allocate procurement so as to support relatively small states that are not performing well.

Figure 2 depicts the procurement high-tech ratio and privately funded company R&D in the U.S. by state. While Figure 1 indicates that the government might strategically use procurement (in general) to stimulate economically weak states, Figure 2 does not provide clear evidence that particularly high-tech procurement is used for this purpose. The procurement high-tech ratio seems slightly (not significantly) higher in large, innovative, and economically powerful states. The correlations between the procurement high-tech ratio and privately funded company R&D, population, and the GDP are positive, but rather weak (0.12-0.15)

Figure 1: Federal non-R&D procurement by industry type and private R&D (by state, 1999-2007).

Billions $2000

Privately funded
company
R&D expenditures

Federal non-R&D
procurement in
other industries

Federal non-R&D
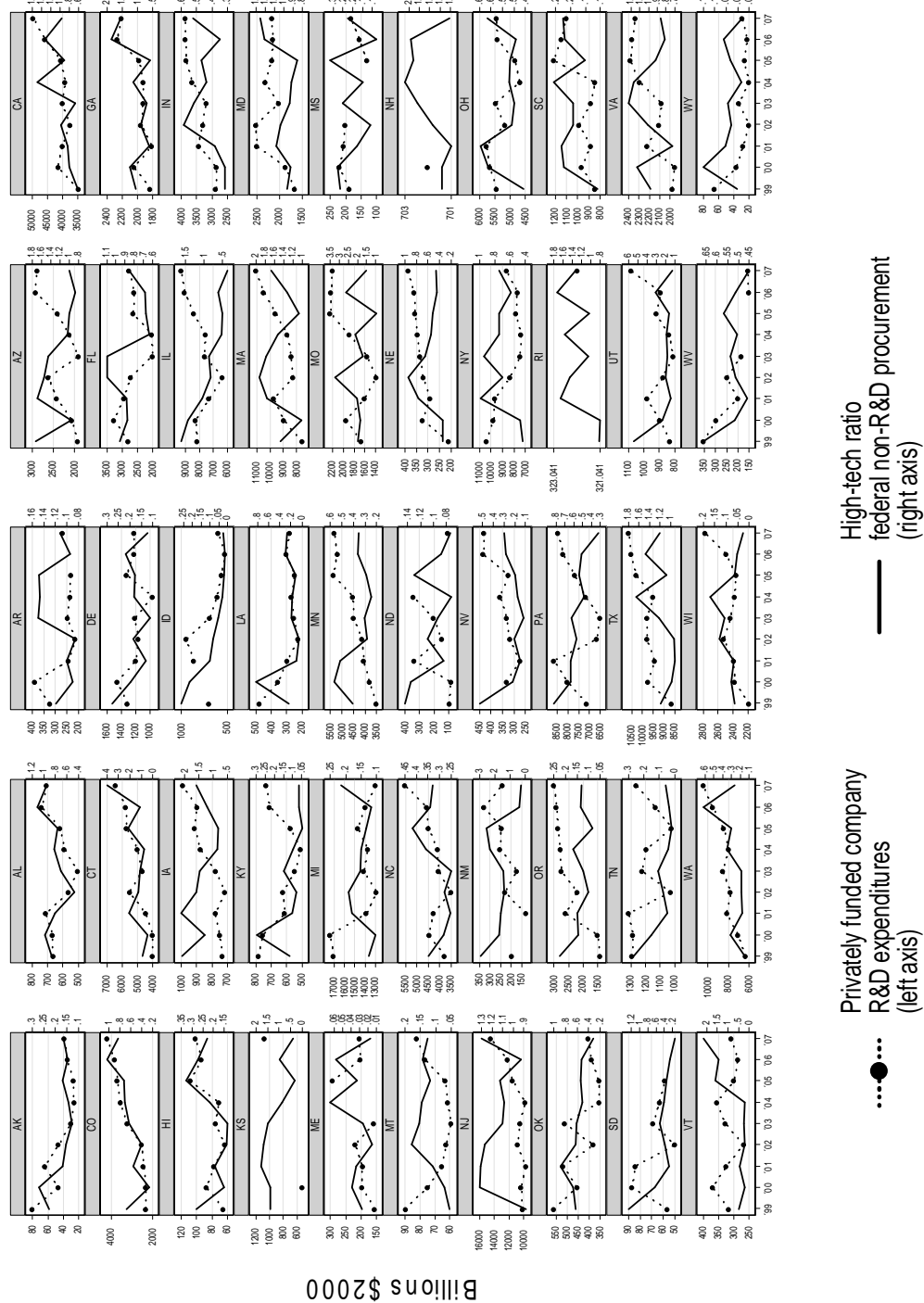procurement in
high-tech industries
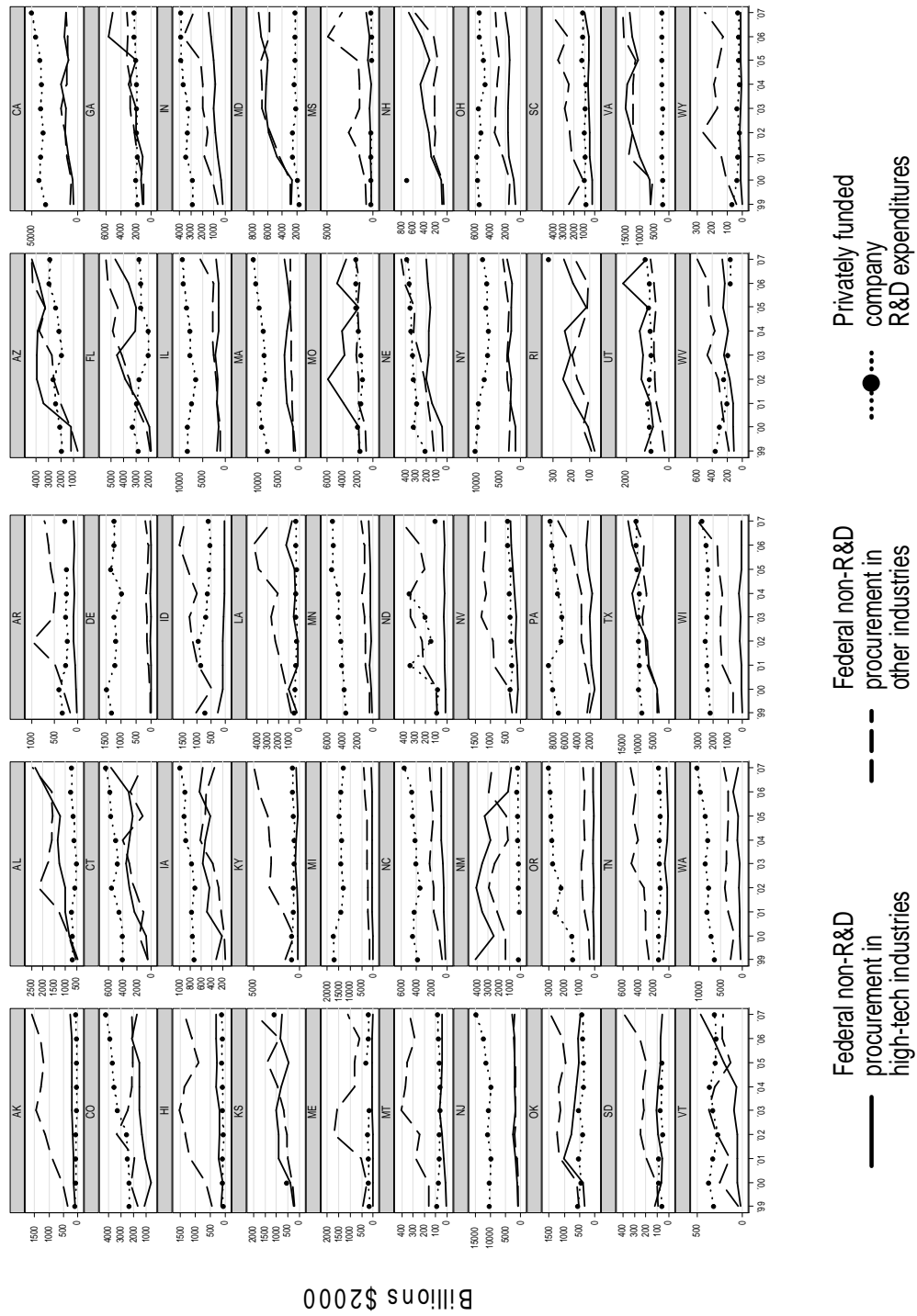
and not significant. However, the procurement high-tech ratio seems to be slightly higher in states in which the federal government is an important customer. The correlation between the procurement high-tech ratio and the share of federal non-R&D procurement in the total GDP is weak but positive (0.21).

Between 1999 and 2007, one can observe an upward shift in the procurement high-tech ratio in 19 states (38 percent) while it remained unchanged in 13 states (26 percent) and decreased in 18 states (36 percent). Within states, on average, we find a weak positive correlation (0.12-0.15) between the procurement high-tech ratio and privately funded company R&D, population, the GDP, share of privately funded company R&D in the GDP, and the share of federal non-R&D procurement in the GDP. In general, the procurement high-tech ratio seems to be a fairly good predictor of privately funded company R&D. Only in a few cases did the procurement high-tech ratio increase in periods when private R&D decreased or stagnated.

Overall, the visual inspection of the data does not reveal clear-cut patterns suggesting that the technological composition of federal non-R&D procurement is contingent on observable state-specific characteristics. However, we cannot rule out that there are further unobserved characteristics that influence the distribution of federal procurement across states and over time.

Figure 2: Technological composition of federal non-R&D procurement and private R&D (by state, 1999-2007).

Finally, in Figure 3, the procurement high-tech ratio as a measure of the technological content of government procurement is plotted against privately funded company R&D for years from 1999 to 2007. Because the econometric representation of the relationship between procurement composition and company R&D from the theoretical model in equation (17) is in log-linear terms, both variables are measured in logs. Moreover, for the reasons explained in Section 3, we lag the procurement high-tech ratio by one year.[10] As indicated by the fitted line, we observe a positive relationship between the technological content of procurement and privately funded company R&D in a pooled cross section. The correlation between the two variables is equal to 0.40. Below, we more rigorously investigate this relationship by controlling for unobserved time-invariant state characteristics and a number of other factors.

Figure 3: Technological composition of federal non-R&D procurement and private R&D in U.S. states (1999-2007, pooled cross section).

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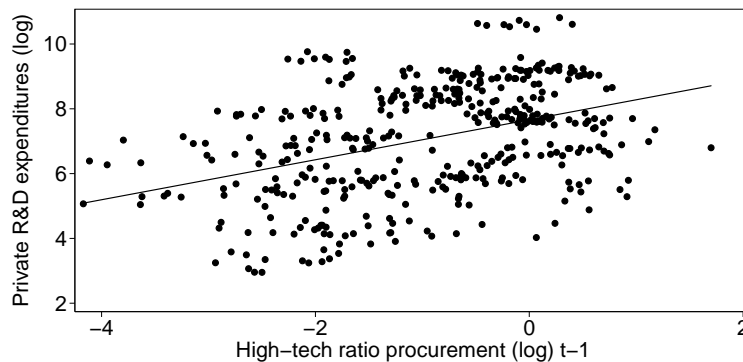
[10] The picture does not change in qualitative terms if we refrain from log-transforming the data and/or from lagging the procurement high-tech ratio.

5.2 Fixed-Effects Results

In this section, we present the results from the baseline econometric analysis of the impact of a reallocation of federal non-R&D procurement in favor of high-tech industries on privately funded company R&D. The results from the FE estimation of equation (17) are reported in Table 1. All models in the remainder of this paper are estimated using cluster robust standard errors, where each state forms one cluster. All variables are measured in natural logs; thus, the coefficients can be interpreted as elasticities.[11]

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[11] Pairwise correlation coefficients of the variables are reported in Appendix F.

Table 1: Technological composition of federal non-R&D procurement and private R&D – Fixed-effects estimation.

	Dependent: Company RandD
High-tech ratio (t-1)	0.068**
	(0.032)
Real GDP Growth (t-1)	-0.434
	(0.843)
Real GDP (t-1)	1.359**
	(0.663)
Population (t-1)	0.081
	(0.889)
Constant	-10.117
	(9.944)
Time fixed effects	Yes
State fixed effects	Yes
Observations	412
States	48
R-squared within	0.139
F	9.752

Notes: Results of FE estimation of equation (17). Because of missing observations for privately funded company R&D (see Section 4), the sample includes 412 observations from 48 states over the period from 1999 to 2007. New Hampshire and Rhode Island are dropped as there is only one non-missing value for the dependent variable in our period of observation for these states. The GDP, privately funded company R&D expenditures, and procurement are originally measured in millions of constant (2000) dollars. The procurement high-tech ratio is defined as the ratio between federal non-R&D procurement in high-tech industries and in all other industries. Gross procurement values are used, that is, de-obligations are not subtracted. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

The estimation results support the predictions of the theoretical model. We find a positive and statistically significant (at 5 percent level) relationship between the technological

content of federal non-R&D procurement and privately funded company R&D. The estimates imply that a doubling of the procurement high-tech ratio, that is, a doubling of government purchases in high-tech industries relative to purchases in other industries, is associated with a 6.8 percent increase in the amount of privately funded company R&D. Evaluated at the respective sample means, our results imply that if the procurement high-tech ratio increased from 65 to 130 percent, privately funded company R&D would increase by approximately $255 million (from $3,760 to $4,015 million).

The total size of the market demand, measured as the level of the GDP, also influences private R&D activities; the estimated coefficient on $GDP_{i,t-1}$ is positive and statistically significant at 5 percent level. The GDP growth rate is not statistically significant, suggesting that a growing market alone might not be sufficient for private companies to invest in R&D. The estimated coefficient for population as an alternative proxy for market size is not statistically significant either. However, it becomes significant if the level of the GDP is excluded from the regression (results not reported). One may interpret this finding as an indication that the GDP is a better proxy for the size of the market than the population.

5.3 Robustness and Sensitivity Analysis

In this section, we test the robustness of the findings in the baseline specification (Section 5.2). First, we apply a Heckman selection model to allow for potential data-reporting/selection bias due to missing values on the dependent variable (see Section 4). Then, we perform the analysis using the net value of the federal non-R&D procurement (dollars de-obligated are subtracted from the dollars originally obligated by a contract) to construct the high-tech ratio of federal non-R&D procurement. Finally, instead of applying the PSC-NAICS

concordances to assign missing industry codes (NAICS) to procurement contracts, we only use those procurement contracts for which NAICS information was originally available in the FPDS-NG database (see Section 4.1). The results are reported in Table 2.

Table 2: Technological composition of federal non-R&D procurement and private R&D – Robustness checks.

	(1) Heckman Selection	(2) With Deobligations	(3) Old NAICS
High-tech ratio (t-1)	0.068** (0.032)	0.067** (0.031)	0.036* (0.020)
Real GDP growth (t-1)	-0.434 (0.829)	-0.428 (0.853)	-0.324 (0.865)
Real GDP (t-1)	1.361** (0.651)	1.372** (0.656)	1.382** (0.649)
Population (t-1)	0.081 (0.873)	0.078 (0.888)	-0.320 (0.868)
Constant	-10.740 (9.907)	-10.233 (9.981)	-4.334 (10.568)
Time fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Observations	450	412	411
States	50	48	48
R-squared within		0.140	0.142
F		10.316	8.813

Notes: Results of robustness analysis of the baseline estimation of equation (17) provided in Table 1. In Column 1, a Heckman selection model is applied to account for any potential data-reporting/selection bias. We use as exclusion restriction the (log of the) number of firms sampled in the SIRD survey (see Section 4.2) as information on private R&D spending is typically missing because of disclosure limitations. This variable is significant at the 1 percent level in the selection equation (results not reported). In Column 2, the net value of the federal non-R&D procurement (dollars de-obligated are subtracted from the dollars originally obligated by a contract) to construct the high-tech ratio of federal non-R&D procurement (see Section 4.1). In Column 3, we only rely on the original NAICS information provided in the FPDS-NG database (see Section 4.1). There are only 411 observations in this specification because no procurement in high-tech industries is reported in Maine in 1998. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

The results of the robustness analysis confirm the findings from the baseline estimation. The results from both, the Heckman model (Column 1) and the FE regression using the net value of procurement (after excluding de-obligations, Column 2) are virtually identical to those from the baseline estimation reported in Table 1. When not applying the PCS-NAICS concordance, that is, using only cases in which NAICS information was originally available in the FPDS-NG data, the estimated coefficient on the procurement high-tech ratio is somewhat smaller but still significant (at the 10 percent level). Overall, these results indicate that the positive association between the technological content of procurement and company R&D found in the baseline specification is robust to a range of alternative specifications. The relationship is neither subject to selection issues, nor particularly dependent on the construction of the variable of main interest (with or without de-obligations) and the implementation of the PSC-NAICS concordance.

5.4   IV Estimation

As discussed in Section 3, one should be careful when drawing a causal inference from the results of the FE estimation. In the baseline estimation of equation (17) presented in Table 1, state and year dummies are included to account for possible confounding factors due to various unobserved state-specific and year (aggregate) effects that do not change over time. However, there might be further unobserved time-variant, unit-specific factors that are correlated with federal procurement or that even jointly determine federal procurement and company R&D. Not accounting for these will cause the FE estimator to be biased. One way to deal with this problem is to apply an IV approach, using an instrument that captures an exogenous part of the variation in the technological content of federal purchases across states

and over time.

Our instrument relies on the idea that politicians can influence the distribution of the high-tech ratio of federal procurement across states and over time. In particular, we argue that if the party holding control of the governorship in a state also has a majority in the Congress, more and primarily high-tech industry procurement is targeted to the state. The assumption underlying our instrument is that politicians channel federal procurement to their constituency in order to "reward" supporters for their votes and to increase their electoral fortune in future elections (Arnold, 1979; Levitt and Snyder, 1997; Shepsle and Weingast, 1981; Stein and Bickers, 1994). As it is generally difficult to deliver direct monetary payback, politicians divert specific investments or procurement contracts to their states (Aghion *et al.*, 2009; Atlas *et al.*, 1995; Cohen and Noll, 1991; Levitt and Snyder, 1997; Mayer, 1995). For instance, there is anecdotal evidence of intervention by members of the House of Representatives to prevent the Department of Defense or the Pentagon from taking away military procurement projects from their constituency (Hoover and Pecorino, 2005). Newspaper accounts also sometimes refer to government procurement as pork barrel spending (e.g., Wheeler, 2004).

However, not all types of procurement spending are equally likely to be strategically distributed to states in the pursuit of political gain. Voters make decisions on the basis of judgments about politicians' contribution to the economy (Arnold, 1979). In this respect, allocating federal procurement to local high-tech industries is likely yielding higher electoral benefits than other types of procurement because promoting high-tech industries is typically assumed to be a promising measure to stimulate the local economy (that is, to secure and/or create jobs, to raise innovativeness and long-term international competitiveness, etc.). More-

over, politicians may tend to support rather risky, technology-intensive procurement projects (Cohen and Noll, 1991). Such high-tech projects usually receive much public attention and are therefore beneficial for the politician's prestige (for a related argument, see Steinberg, 1995).

To channel (high-tech) federal procurement to his state, a governor needs "support" from the Congress. According to Article I of the U.S. Constitution, the Congress holds the "power of the purse" and is the main locus of the "distributive game."[12] The majority party in Congress is entitled to significant agenda control power because it selects the chairmen of committees authorizing and appropriating funds and receives a majority on these committees (Evans, 1991; Fenno, 1973).[13] There is an incentive for the Congress majority party to support governors of the same party by allocating of federal procurement contracts to firms in the respective state because, following Grossman Grossman (1994) and Shor (2005), the party caucus represents a coalition that provides selective benefits to its members. State politicians, in return, invest their political capital to support (the re-election of) the Congressmen in their states.

A number of previous studies provide evidence for policy-related determinants of the distribution of federal spending. Using Indian data, Dasgupta *et al.* (2004) find that states governed by the party that also controls the central government receive more grants. The authors argue that the allocation of federal funds to a governor of the opponent party can generate a "leakage" effect and losses of some of the benefit from spending. In the same vein,

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[12] The president might also play an important role both in the budget process and as chief executive. Studies that investigate the role of the president in the geographic distribution of federal funds are nonetheless sparse (Larcinese *et al.*, 2006).

[13] Aghion *et al.* (2009) provide evidence that House and Senate appropriation committees affect the geographic distribution of educational spending.

Martin (2003) suggests that politicians allocate federal spending strategically to the areas providing them the highest returns on their "investments." Balla *et al.* (2002), in a study of academic earmarks, report that districts represented by majority party House members receive higher funds than those represented by the minority. Alvarez and Saving (1997) generalize this finding to other types of federal funds. Levitt and Snyder (1995) study federal assistance programs in the period from 1984 to 1990 and find that a Democratic majority in Congress is associated with higher spending for districts mainly populated by Democratic voters.

For the purpose of the empirical analysis, we construct our instrument as a dichotomous variable that takes the value of 1 in states whose governors are affiliated with the majority party in the House of Representatives and 0 otherwise.[14] The variation in our instrument comes from two sources, namely, House and governor elections. It could be objected that the outcome of gubernatorial elections might be related to state-specific characteristics. However, the outcome of a Congressional election is exogenous to specific states, and our instrument indicates the party coincidence at the state and federal levels. Moreover, the timing of House and gubernatorial elections is exogenously given. Hence, our instrument should not be related to state-specific characteristics that are correlated with company R&D. . Because of

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[14] Although the Congress consists of two chambers, that is, the House and the Senate, we use political alignment between state governors and the House majority as our main specification. The reason is that there has always been a clear majority in the House in our sample period. The House majority was Republican in all years covered by the dataset. In the Senate, the majority party has not always been unambiguous. From 2001 to 2002 and 2007 to 2008, Democrats and Republicans provided the same number of Senators. However, according to the U.S. Constitution, the Vice President breaks a tied vote in Senate. From 2001 to 2008, the Republican Dick Cheney assumed the position of Vice President. One might therefore regard the Senate as being under Republican leadership in our period of observation as well. In this case, the coincidence of the governor's party and the Senate majority delivers exactly the same results as those reported below. Apparently, if one is willing to accept the assumption of Republican leadership in the Senate during our period of observation, the results also remain in place when the dummy variable indicates that the governor is a member of the majority party in both chambers of Congress.

the relative attractiveness of delivering high-tech procurement for politicians, we expect the instrumental variable to be positively associated with procurement in high-tech industries, and thereby with the high-tech intensity of federal procurement. Put differently, we expect federal procurement in high-tech industries to be relatively high (compared with procurement in other industries) in states whose governors belong to the party holding the majority in the House. The instrument is lagged by one year behind the endogenous regressor to account for the lag in the budget cycle. Current federal procurement budgets have normally been appropriated in previous budgetary years Alvarez and Saving (1997); Elis *et al.* (2009); Larcinese *et al.* (2006).[15]

In Table 3, we explicitly test the assumption that politicians prefer to deliver high-tech procurement to their constituents, thereby changing the technological composition of procurement in a way that is uncorrelated with a state's R&D prospects. To do so, we separately regress our instrument on the level of both high-tech procurement and all other procurement. The results indicate that states with a governor affiliated with the majority party in the House receive relatively more high-tech industry procurement (Column 1). The amount of other types of procurement, however, seems to be unaffected by the coincidence of the governor's party and the majority in the House (Column 2).[16]

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[15] We also experimented with different lag structures, which provided results qualitatively similar to those reported below.

[16] The results do not change if we drop New Hampshire and Rhode Island from the sample.

Table 3: The effect of governor-House majority alignment on the geographic distribution of federal non-R&D procurement by procurement type.

	(1) High-tech	(2) All other
Coincidence Gov-House (t-1)	0.207***	-0.019
	(0.072)	(0.045)
Real GDP Growth	-1.001	1.664**
	(1.867)	(0.768)
Real GDP	-0.879	-0.802
	(1.549)	(0.669)
Population	-1.219	1.021
	(1.794)	(1.167)
Constant	34.035	0.227
	(28.544)	(13.923)
Time fixed effects	Yes	Yes
State fixed effects	Yes	Yes
Observations	450	450
States	50	50
R-squared within	0.450	0.707
F	21.702	57.187

Notes: Fixed-effects results of regressing our instrument on federal procurement in high-tech and all other industries, respectively. Coincidence Gov-House is a binary variable taking the value of 1 if a state governor belongs to the majority party in the House and 0 otherwise. The dummy variable is lagged by one period to take into account delays between the appropriation of federal funds and the moment when these are actually spent. The results remain qualitatively unchanged if we drop New Hampshire and Rhode Island. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

The results of the IV regressions are presented in Table 4. In Column 1, we report the results of the two-stage least squares (2SLS) estimator. We find that the estimated

coefficient on the high-tech ratio of procurement is positive and, compared with the FE results in Table 1, somewhat larger. Assuming correct point estimates, this indicates that the FE results even underestimate the true causal effect of the government procurement composition on private R&D activities, which is consistent with previous findings on total non-R&D procurement (Lichtenberg, 1988). A intuitive explanation for this result is that the distribution of federal procurement is (partly) determined by issues other than efficiency. For instance, federal contracts might be awarded to stimulate firms that are not performing well and, in consequence, do not spend a lot on R&D. However, in the IV approach, the coefficient on the high-tech composition of procurement is not statistically significant. A possible explanation for the stark increase in the standard error is the efficiency loss entailed in the IV estimator compared with the FE estimator. It might be that our instrument explains little of the variation in the potentially endogenous explanatory variable. In the first stage, the instrument has the expected positive sign and is significant at the 5 percent level (p-value: 0.039). However, the F statistic for the excluded instrument, being only equal to 4.49, suggests the weakness of our instrument. As discussed by Staiger and Stock (1997) and Stock *et al.* (2002) for a single endogenous regressor, the F-statistic typically must exceed 10 for inferences based on the 2SLS estimator to be reliable. Weak instruments can lead to inconsistencies in the IV estimates and tend to exacerbate the finite-sample bias that IV approaches suffer from (Bound *et al.*, 1995; Nelson and Startz, 1990). Moreover, in the presence of weak instruments, the conventional asymptotic approximations used for hypothesis tests and confidence intervals are usually unreliable (Stock *et al.*, 2002; Temple and Wößmann, 2006).

The Limited Information Maximum Likelihood (LIML) estimator is preferred to the 2SLS

estimator when the instruments are weak (Hahn *et al.*, 2004). In Column 2, we report the estimates based on Fuller's (1977) modification of the LIML estimator, which ensures that the estimator has finite moments. The Fuller estimation delivers comparable results to those of the 2SLS regressions. The coefficient on the technological content of procurement is somewhat more precisely estimated yet is still not significant.

Table 4: Technological composition of federal non-R&D procurement and private R&D –
Instrumental variable estimates, second-stage results.

	(1) 2SLS	(2) LIML (Fuller)
High-tech ratio (t-1)	0.119 (0.192)	0.113 (0.172)
Real GDP Growth (t-1)	-0.256 (1.165)	-0.275 (1.118)
Real GDP (t-1)	1.412** (0.634)	1.407** (0.631)
Population (t-1)	0.105 (0.907)	0.103 (0.903)
Time fixed effects	Yes	Yes
State fixed effects	Yes	Yes
Observations	412	412
States	48	48
F (excluded instrument)	4.490 (0.039)	4.490 (0.039)
R-squared within (second stage)	0.127	0.129
F (second stage)	7.092	7.043

Notes: Results from a 2SLS (column 1) and LIML (column 2) estimation of the effect of federal procurement composition on private R&D spending. The instrument is a binary variable taking the value of 1 if the state governor belongs to the majority party in the House and 0 otherwise. The instrument is lagged by one period to take into account delays between the appropriation of federal funds and the moment when these funds are actually spent. In the LIML estimation, the user-specified constant (alpha) is set to 1 (see Temple and Wößmann, 2006). Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

Although our instrument has some intuitive appeal, we cannot rule out that the 2SLS
and LIML estimators are biased because of the presence of a weak instrument problem. This

potential bias aggravates the "usual" drawbacks of IV approaches in samples of this size, namely, that both the coefficient estimates and the confidence intervals may be sensitive to small numbers of observations (Bound *et al.*, 1995; Temple and Wößmann, 2006). Taking further into account that IV estimates are less efficient than their FE counterparts, we tend to place more weight on the FE findings earlier in the paper. However, in light of the apparent weakness of our instrument, we are not yet able to convincingly establish a causal effect of federal procurement composition on company R&D at the state level.

6 Conclusions

The goal of this paper is to analyze the relationship between the inter-industrial composition of government demand and firms' R&D decisions both from a theoretical and an empirical perspective. First, we develop a generalized version of a Schumpeterian growth model that incorporates a typical trait of real economies, namely, the presence of industries characterized by different innovation sizes. This asymmetry causes the distribution of monopoly profits from successful innovation to be highly skewed toward the low-value side with a long tail to the high-value side. We use the model to analyze the effects of a change in the technological content of government procurement. Our results indicate a role for public procurement in the debate on innovation and growth policy. According to the theoretical model, a change in the composition of government purchases that relatively favors industries with above-average quality jumps, that is, high-tech industries, stimulates R&D activities at the level of the economy. The intuition for this result is as follows: Government procurement is an additional source of demand, raising the returns from successful R&D activities. Government

demand in industries with an above-average innovation potential increases the market size in these industries, while R&D investment in all other industries becomes less attractive. At the economy-wide level, however, the additional R&D induced in high-tech industries outweighs the R&D foregone in all remaining industries; thus, total private R&D increases.

We empirically test the main prediction of the theoretical model, using U.S. state-level panel data for the period 1999 to 2007. We use federal non-R&D procurement data provided by the Federal Procurement Data System – Next Generation (FPDS-NG) to proxy for the size of the government market. The technological content of procurement is measured as the ratio between federal non-R&D procurement in high-tech industries and in all other industries. Our indicator for private R&D is the amount of privately funded company R&D expenditures. The impact of the technological composition of procurement on company R&D is assessed by means of FE estimation (including several robustness checks). However, to overcome potential bias in the FE estimation, which could result from reverse causality and omitted variables, we additionally apply an IV approach. To instrument for the composition of federal procurement, we rely on the idea that federal procurement in high-tech industries may be relatively high in states whose governors belong to the House majority party. Prior results in the political science literature suggest that politicians use procurement to reward their voters and to increase their re-election chances. Attracting federal procurement contracts increases the re-election chances of the state governor, who, in return, invest his political capital to support the Congressmen in his states. Governors are more able to channel procurement to their states if they belong to the House majority party, which, for instance, holds the majority in committees authorizing and appropriating funds. Moreover, procurement in high-tech industries is particularly attractive for politicians because, for instance, it is typically

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assumed to increase the politicians' prestige (e.g., Cohen and Noll, 1991; Steinberg, 1995).

Our results provide some support for the theoretical prediction of a positive association between an increase in the technological content of public procurement and privately funded company R&D. According to the results of the FE estimation, doubling the high-tech ratio of federal non-R&D procurement is associated, *ceteris paribus*, with an increase in private R&D outlays of approximately 7 percent. Evaluated at the respective sample means, the estimates imply that if the federal government increases the ratio of procurement in high-tech industries relative to all other industries from 65 to 130 percent, then privately funded company R&D expenditures will increase by $255 million. In the IV estimations, the coefficient of interest increases, which indicates that the true causal effect of the technological composition of government procurement on private R&D activities might be underestimated in the FE approach. A possible reason for such underestimation could be that the distribution of federal procurement is (partly) determined by issues other than efficiency, for instance, when federal contracts are awarded to stimulate less innovative and less well performing firms. However, in the IV approach, the coefficient on the technological content of procurement is not statistically significant. The large standard error of the IV coefficient may be the result of the efficiency loss entailed in the IV estimator compared with the FE estimator, which is especially severe in samples of this size. However, we cannot rule out that our instrument explains too little of the variation in the potentially endogenous explanator to ensure the validity of our inferences. Therefore, at the current stage, we tend to place more weight on the FE estimates.

Can a shift in the composition of government purchases in favor of high-tech industries spur firms' R&D investment and work as a *de facto* innovation policy tool? In general, our

results give rise to the idea that the government's purchasing behavior plays an important role in companies' R&D decisions, whether this is actively sought by the government or not. One consequence to be drawn from our analysis is that policy should not be agnostic about the impact of their purchasing behavior on private R&D decisions. If high-tech and low-tech solutions for the same problem are available, public authorities should take into account that purchasing the high-tech solution may come along with the additional benefit of an increase in private R&D. In acknowledging the relevance of the government as a customer on the innovative behavior of firms, we complement earlier studies on the role of profit incentives and market size in innovation (e.g., Acemoglu and Linn, 2004; Schmookler, 1966).

We believe that the research question addressed in this paper possesses a substantial degree of policy relevance. Some major initiatives have recently been launched to encourage public authorities to take into account the technological content of products and services in their purchasing decisions (Edler and Georghiou, 2007, and the references cited therein). However, it is important to note that the fundamental procurement function is to deliver quality goods and services in a timely fashion and at a reasonable price. The deliberate use of public procurement as a tool for R&D and innovation policy implies distorting this demand and may come at substantial social costs. First, there is less transparency in the procurement process when factors other than the price are the main decision criteria. Second, the government procurement in certain industries might signal, from companies' point of view, that certain technological paradigms in economic development are perceived to have greater potential than others. Consequently, firms might be more likely to invest in certain technologies than they would have in the absence of the government demand signal. This presents the government with the burden of selecting very carefully which technologies to back to avoid

potential lock-ins into inferior technologies (Arthur, 1989; Cowan, 1990). Third, because of the existence of negative externalities associated with private R&D (see, e.g., Aghion and Howitt, 1992) the relationship between R&D and social welfare might be nonlinear. In other words, from a social point of view, there could also be "too many" productive resources employed in the R&D process. If this was the case, a procurement policy to induce additional R&D would not be desirable from a social viewpoint. We have not yet accounted for such welfare considerations in the empirical analysis. Fourth, procedural aspects of awarding federal procurement contracts (for example, competitive versus non-competitive procedures) are neglected in this paper but might, in general, play an important role (Lichtenberg, 1988). Finally, giving reasonable policy advice requires a cost-benefit comparison of procurement with other innovation policy tools, such as R&D subsidies or R&D tax credits etc (e.g., David *et al.*, 2000; Wilson, 2009). Only after having taken into account the potential (opportunity) cost of government procurement are we able to judge its suitability as a tool for innovation policy. This is an important avenue for future research.

References

Acemoglu, D. and J. Linn (2004). Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry. *Quarterly Journal of Economics* **119**, 1049–1090.

Aghion, P. and P. Howitt (1992). A Model of Growth Through Creative Destruction. *Econometrica* **60**, 323–351.

Aghion, P., L. Boustan, C. Hoxby and J. Vandenbussche (2009). The Causal Impact of Education on Economic Growth: Evidence from US. Harvard University.

Alvarez, R. M. and J. L. Saving (1997). Congressional committees and the political economy of federal outlays. *Public Choice* **92**, 55–73.

Arellano, M. (1987). Computing Robust Standard Errors with Within-Groups Estimators. *Oxford Bulletin of Economics and Statistics* **49**, 431–434.

Arnold, D. (1979). *Congres and the Bureaucracy: A Theory of Influence*. New Haven: Yale University Press.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for inventions. In: *The Rate and Direction of Inventive Activity* (R. R. Nelson, Ed.). pp. 609–625. Princeton: Princeton University Press.

Arthur, B. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *Economic Journal* **99**, 116–131.

Aschhoff, B. and W. Sofka (2009). Innovation on demand - Can public procurement drive market success of innovations?. *Research Policy* **38**, 1235–1247.

Atlas, C. M., T. A. Gilligan, R. J. Hendershott and M. A. Zupan (1995). Slicing the federal government net spending pie: Who wins, who loses, and why. *American Economic Review* **85**, 624–629.

Audet, D. (2002). Government procurement: A synthesis Report. *OECD Journal of Budgeting* **2**, 149–194.

Balla, S. J., E. D. Lawrence, F. Maltzman and L. Sigelman (2002). Partisanship, Blame Avoidance, and the Distribution of Legislative Pork. *American Journal of Political Science* **46**, 515–525.

Barro, R. J. (1974). Are Government Bonds Net Wealth?. *Journal of Political Economy* **82**, 1095–1117.

BEA (2006). Gross Domestic Product by State Estimation Methodology. Bureau of Economic Analysis.

Berggren, C. and S. Laestadius (2003). Co-Development and Composite Clusters - The Secular Strength of Nordic Telecommunication. *Industrial and Corporate Change* **12**, 91–114.

Blanchard, O. and S. Fischer (1989). *Lectures on Macroeconomics*. Cambridge: MIT Press.

Bound, J., D. A. Jaeger and R. M. Baker (1995). Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak. *Journal of the American Stastistical Association* **90**, 443–450.

Coggburn, J. D. (2003). Exploring differences in the American states' procurement practices. *Journal of Public Procurement* **3**, 3–28.

Cohen, L. R. and R. G. Noll (1991). *The Technology Pork Barrel.* Washington, DC: The Brookings Institution.

Cohen, W. M., R. R. Nelson and J. P. Walsh (2000). Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). NBER Working Paper No. 7552.

Cowan, R. (1990). Nuclear Power Reactors: A Study of Technological Lock-In. *Journal of Economic History* **50**, 541–566.

Cozzi, G. and G. Impullitti (2010). Government Spending Composition, Technical Change and Wage Inequality. *Journal of the European Economic Association* **8**, 1325–1358.

Dasgupta, S., A. Dhillon and B. Dutta (2004). Electoral Goals and Centre-State Transfers in India. Unpublished manuscript, University of Warwick.

David, P. A., B. H. Hall and A. A. Toole (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy* **29**, 497–529.

Davidson, C. and P. S. Segerstrom (1998). R&D Subsidies and Economic Growth. *RAND Journal of Economics* **29**, 548–577.

Diewert, E. W. and K. J. Fox (2008). On the estimation of returns to scale, technical progress and monopolistic markups. *Journal of Econometrics* **145**, 174–193.

Edler, J. (2006). *Nachfrageorientierte Innovationspolitik.* Büro für Technologiefolgenabschätzung im Deutschen Bundestag.

55

Edler, J. and L. Georghiou (2007). Public Procurement and Innovation - Resurrecting the Demand Side. *Research Policy* **36**, 949–963.

Elis, R., N. Malhotra and M. Meredith (2009). Apportionment cycles as natural experiments. *Political Analysis* **17**, 358–376.

Evans, C. L. (1991). *Leadership in Committee: A Comparative Analysis of Leadership Behavior in the U.S. Senate.* Ann Arbor, MI: University of Michigan Press.

Fenno, R. F. (1973). *Congressmen in Committees.* Boston: Little, Brown and Company, Inc.

Fraumeni, B. M. and S. Okubo (2005). R&D in the National Income and Product Accounts: A First Look at its Effect on GDP. In: *Measuring Capital in the New Economy* (C. Corrado, J. Haltiwanger and D. Sichel, Eds.). pp. 275–321. Chicago: University of Chicago Press.

Fridlund, M. (2000). Switching Relations and Trajectories: The Development Procurement of the Swedish AXE Switching Technology. In: *Public Technology Procurement and Innovation* (C. Edquist, L. Hommen and L. Tsipouri, Eds.). pp. 143–165. Norwell, MA: Kluwer Academic Publishers.

Fudenberg, D. and J. Tirole (1985). Preemption and Rent Equalization in the Adoption of New Technology. *American Economic Review* **52**, 383–401.

Fudenberg, D., R. J. Gilbert, J. E. Stiglitz and J. Tirole (1983). Preemption, Leapfrogging, and Competition in Patent Races. *European Economic Review* **22**, 3–31.

Fuller, W. A. (1977). Some properties of a modification of the limited information estimator. *Econometrica* **45**, 939–954.

Gilfillan, S. C. (1935). *The Sociology of Invention.* Chicago: Follett Publishing Company.

Goldman, E., J. Rocholl and J. So (2008). Political Connections and the Allocation of Procurement Contracts. Indiana University.

Grossman, G. M. and E. Helpman (1991a). Quality Ladders in the Theory of Growth. *Review of Economic Studies* **58**, 43–61.

Grossman, G. M. and E. Helpman (1991b). *Innovation and Growth in the Global Economy.* Cambridge, MA, London: MIT Press.

Grossman, P. J. (1994). A Political Theory of Intergovernmental Grants. *Public Choice* **78**, 295–303.

GSA (2005). Federal Acquisition Regulation. General Services Administration.

GSA (2008). Federal Procurement Data System-Next Generation (FPDS-NG) Government User's Manual. General Services Administration.

Hahn, J., J. Hausman and G. Kuersteiner (2004). Estimation with weak-instruments: accuracy of higher order bias and MSE approximations. *Econometrics Journal* **7**, 272–306.

Hall, R. E. (1988). The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy* **96**, 921–947.

Hansen, C. (2007). Asymptotic properties of a robust variance matrix estimator for panel data when T is large. *Journal of Econometrics* **141**, 597–620.

Harhoff, D., F. Scherer and K. Vopel (2005). Exploring the Tail of Patented Invention Value Distributions. In: *Patents: Economics, Policy and Measurement* (O. Granstrand, Ed.). pp. 251–281. Cheltenham, UK and Northampton, MA: Elgar.

Hart, D. M. (1998). U.S. Technology Policy: New Tools for New Times. *NIRA Review* **Summer 1998**, 3–6.

Hecker, D. E. (2005). High-technology employment: a NAICS-based update. *Monthly Labor Review* **July 2005**, 57–72.

Hoover, G. A. and P. Pecorino (2005). The political determinants of federal expenditure at the state level. *Public Choice* **123**, 95–113.

Kanz, J. W. (1993). Technology, globalization and defence: Military electronics strategies in a changing world. *International Journal of Technology Management* **8**, 59–76.

Kirman, A. P. (1992). Whom or what does the representative individual represent?. *Journal of Economic Perspectives* **6**, 117–136.

Kleinknecht, A., K. Van Montfort and E. Brouwer (2002). The non-trivial choice between innovation indicators. *Economics of Innovation and New Technology* **11**, 109–121.

Larcinese, V., L. Rizzo and C. Testa (2006). Allocating the US federal budget to the states: the impact of the President. *Journal of Politics* **68**, 447–456.

Levitt, S. D. and J. M. Snyder (1995). Political parties and the distribution of federal outlays. *American Journal of Political Science* **39**, 958–980.

Levitt, S. D. and J. M. Snyder (1997). The impact of federal spending on house election outcomes. *Journal of Political Economy* **105**, 30–53.

Li, C. W. (2001). On the Policy Implications of Endogenous Technological Progress. *Economic Journal* **111**, 164–179.

Li, C. W. (2003). Endogenous Growth without Scale Effects: Comment. *American Economic Review* **93**, 1009–1017.

Lichtenberg, F. R. (1987). The Effect of Government Funding on Private Industrial Research and Development: A Re-Assessment. *Journal of Industrial Economics* **36**, 97–104.

Lichtenberg, F. R. (1988). The Private R&D Investment Pesponse to Federal Design and Technical Competitions. *American Economic Review* **78**, 550–559.

Lichtenberg, F. R. (1989). The Impact of the Strategic Defense Initiative on US Civilian R&D Investment and Industrial Competitiveness. *Social Studies of Science* **19**, 265–282.

Lichtenberg, F. R. (1990). Issues in measuring industrial R&D. *Research Policy* **19**, 157–163.

Mansfield, E. (1986). Patents and Innovation: An Empirical Study. *Management Science* **32**, 173–181.

Martin, P. S. (2003). Voting's Rewards: Voter Turnout, Attentive Publics, and Congressional Allocation of Federal Money. *American Journal of Political Science* **47**, 110–127.

Mayer, K. R (1995). Electoral Cycles in Federal Government Prime Contract Awards State-Level Evidence from the 1988 and 1992 Presidential Elections. *American Journal of Political Science* **39**, 162–185.

MED (2005). *New Zealand Government Procurement Policy Review*. New Zealand Ministry of Economic Development.

Minniti, A., C. A. Parello and P. S. Segerstrom (2008). A Schumpeterian Growth Model with Heterogenous Firms. MPRA Working Paper.

Moser, P. (2005). How to patent laws influence innovation? Evidence from 19th-century world's fairs. *American Economic Review* **95**, 1215–1236.

Mowery, D. C. (2008). National security and national innovation systems. *Journal of Technology Transfers* **34**, 455–473.

Nelson, C. R. and R. Startz (1990). Some Further Results on the Exact Small-Sample Properties of the Instrumental Variable Estimator. *Econometrica* **58**, 967–976.

Nelson, R. R. (1982). *Government and Technical Progress - A Cross-Industry Analysis*. New York: Pergamon Press.

Nelson, R. R. and R. N. Langlois (1983). Industrial innovation policy: lessons from American history. *Science* **219**, 814–818.

NSF (2007). Revised Industry Classification Better Reflects Structure of Business R&D in the United States. National Science Foundation.

OGC (2004). *Capturing Innovation. Nurturing Supplier's Ideas in the Public Sector*. UK Office of Government Commerce.

Oliveira Martins, J., S. Scarpetta and D. Pilat (1996). Mark- Up Ratios in Manufactoring

Industries: Estimates for 14 OECD Countries. OECD Economics Department Working Papers, No. 162, OECD Publishing.

Patel, P. and K. Pavitt (1995). Patterns of technological activity: their measurement and interpretation. In: *Handbook of the Economics of Innovation and Technological Change* (P. Stoneman, Ed.). pp. 14–51. Oxford: Blackwell.

Robbins, C. A., F. V. Candela, M. Fahim-Nader and G. W. Medeiros (2007). Methodology for the Industry Estimates in the 2007 R&D Satellite Account. Bureau of Economic Analysis/National Science Foundation 2007 R&D Satellite Account Background Paper.

Roeger, W. (1995). Can Imperfect Competition Explain the Difference between Primal an Dual Productivity Measures? Estimates for US Manufacturing. *Journal of Political Economy* **103**, 316–330.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy* **98**, 71–102.

Rosenberg, N. (1969). Direction of technological change- inducement mechanism and focusing devices. *Economic Development and Cultural Change* **18**, 1–24.

Ruttan, V. W. (2006). *Is War Necessary for Economic Growth? Military Procurement and Technology Development.* New York: Oxford University Press.

Scherer, F. M. (1965). Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. *American Economic Review* **55**, 1097–1123.

Schmookler, J. (1962). Economic Sources of Inventive Activity. *Journal of Economic History* **XXII**, 1–20.

Schmookler, J. (1966). *Invention and Economic Growth.* Cambridge, MA: Harvard University Press.

Segerstrom, P. S. (1998). Endogenous Growth without Scale Effects. *American Economic Review* **88**, 1290–1310.

Shepsle, K. A. and B. Weingast (1981). Political Preferences For the Pork Barrel: A Generalization. *American Journal of Political Science* **25**, 96–111.

Shor, B. (2005). The Weak Leviathon? Testing Partisan Theories of Political Influence on Defense Procurement in Congressional Districts: 98th-102nd Congress. Princeton University.

Sokoloff, K. (1988). Inventive Activity in Early Industrial America: Evidence from Patent Records, 1790-1846. *Journal of Economic History* **48**, 813–850.

Staiger, D. and J. H. Stock (1997). Instrumental Variables Regressions with Weak Instruments. *Econometrica* **65**, 557–586.

Stein, R. M. and K. N. Bickers (1994). Congressional Elections and the Pork Barrel. *Journal of Politics* **56**, 377–399.

Steinberg, G. M. (1995). Comparing Technological Risks in Large Scale National Projects. *Policy Sciences* **18**, 79–83.

Stock, J. H., J. H. Wright and M. Yogo (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics* **20**, 518–529.

Temple, J. and L. Wößmann (2006). Dualism and cross-country growth regressions. *Journal of Economic Growth* **11**, 187–228.

Wheeler, W. T. (2004). Don't Mind if I Do. The Washington Post, 08/22/2004.

White, H. (1980). *Asymptotic Theory for Econometricians.* San Diego: Academic Press.

Wilson, D. J. (2009). Beggar Thy Neighbor? The In- State, Out- of- State, and Aggregate Effects of R&D Tax Credits. *Review of Economics and Statistics* **91**, 431–436.

Wooldridge, J. M. (2002a). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Wooldridge, J. M. (2002b). *Introductory Econometrics – A Modern Approach.* Cambridge, MA: MIT Press.

Young, A. (1998). Growth Without Scale Effects. *Journal of Political Economy* **106**, 41–63.

A   Determining the Unique Ratio Between ε_1 and ε_2

In this appendix, we derive the relation between ε_1 and ε_2 for the public demand in (12) rule to be feasible. Recall that, by definition, the following holds: $\int_0^1 G(\omega)d\omega \equiv \bar{G}$. Substituting the public demand rule for $G(\omega)$ yields:

$$\int_0^1 \int_1^\infty \left(\bar{G} + \gamma \varepsilon \right) d\lambda d\omega$$

$$= \int_0^1 \left\{ \int_1^\infty \bar{G}g(\lambda)d\lambda + \gamma \left[\int_1^{\frac{1}{1-\kappa}} -\varepsilon_1 g(\lambda)d\lambda + \int_{\frac{1}{1-\kappa}}^\infty \varepsilon_2 g(\lambda)d\lambda \right] \right\} d\omega, \tag{18}$$

where $g(\lambda)$ is the Pareto density function with a scale parameter equal to one and a share parameter equal to $1/\kappa$. According to (9), we can express $g(\lambda)$ as $1/\kappa \lambda^{-(1+\kappa)/\kappa}$, which allows us to rewrite (18) as:

$$\int_0^1 \left\{ \frac{1}{\kappa}\bar{G} \int_1^\infty \lambda^{-\frac{1}{1-\kappa}}d\lambda + \frac{\gamma}{\kappa} \left[\int_1^{\frac{1}{1-\kappa}} -\varepsilon_1 \lambda^{-\frac{1}{1-\kappa}}d\lambda + \int_{\frac{1}{1-\kappa}}^\infty \varepsilon_2 \lambda^{-\frac{1}{1-\kappa}}d\lambda \right] \right\} d\omega.$$

Solving the integral above gives:

$$\int_0^1 G(\omega)d\omega = \bar{G} + \gamma \left\{ \varepsilon_1 \left(\left(-1 + (1-\kappa)^{\frac{1}{\kappa}}\right) + \varepsilon_2 \left(1-\kappa\right)^{\frac{1}{\kappa}} \right) \right\}. \tag{19}$$

By definition, the expression on the RHS of (19) is equal to $\bar{G}$. It is now straightforward to show that this relationship determines the unique ratio between ε_1 and ε_2, which is equal to:

$$\frac{\varepsilon_1}{\varepsilon_2} = \frac{(1-\kappa)^{\frac{1}{\kappa}}}{1-(1-\kappa)^{\frac{1}{\kappa}}}. \tag{20}$$

Because the RHS of (20) is strictly positive, but smaller than one, it follows that $\varepsilon_1 < \varepsilon_2$.

B   Expected Profit Stream of an Industry Leader

When we take into account (5), the expected value of the profit flow that accrues to the winner of an R&D race in industry ω at time t can be written as (suppressing time and industry arguments for notational convenience):

$$\pi^e = \int\limits_{1}^{\infty} \frac{\lambda - 1}{\lambda} L\,(c + G)g(\lambda)d\lambda. \tag{21}$$

We substitute for the Pareto density function, $g(\lambda)$, and for public demand spending, $G(\omega)$, by using (9) and (12). Equation (21) then becomes:

$$\pi^e = \int\limits_{1}^{\infty} \frac{L}{\kappa}\frac{\lambda - 1}{\lambda}\lambda^{-\frac{1+\kappa}{\kappa}}\left(c + \bar{G} + \gamma\varepsilon\right)d\lambda. \tag{22}$$

The term $(\lambda - 1)\,(1/\lambda)\,\lambda^{-(1+\kappa)/\kappa}$ can be simplified to $(\lambda - 1)\,\lambda^{-2-1/\kappa}$. Keeping this in mind, we can compute the integral (22) as being equal to:

$$\pi^e = \frac{\kappa}{1 + \kappa}L\left(c + \bar{G} + \gamma\left[\varepsilon_1\left\{-1 + 2\left(1 - \kappa\right)^{\frac{1}{\kappa}}\right\} + \varepsilon_2 2\left(1 - \kappa\right)^{\frac{1}{\kappa}}\right]\right). \tag{23}$$

In Appendix A, we showed that there exists a specific relationship between ε_1 and ε_2, given by (20). We now make use of this result to eliminate ε_1. Using (20), the integral above boils down to:

$$\pi^e = \frac{\kappa}{1 + \kappa}L\left(c + \bar{G} + \gamma\varepsilon_2\left[\frac{1}{1 - (1 - \kappa)^{\frac{1}{\kappa}}} - 1\right]\right). \tag{24}$$

Notice that $0 < 1 - (1 - \kappa)^{1/\kappa} < 1$ for all $\kappa \in (0, 1)$ and, thus, $1\big/\left[1 - (1 - \kappa)^{1/\kappa}\right] > 1$,

leaving the term in round brackets on the RHS of (24) positive. Rearranging (24) eventually allows us to write the expected profit stream as:

$$\pi^e = \frac{\kappa}{1+\kappa} L \left(c + \bar{G} + \gamma \Gamma \right), \tag{25}$$

where $\Gamma \equiv \varepsilon_2 \left(1 \big/ \left[1 - (1-\kappa)^{1/\kappa} \right] - 1 \right) > 0,$ defined for notational simplicity, is completely determined by parameter values. Because the RHS of (25) does not depend on industry-specific variables, π^e is to be interpreted as the average value of profits that an industry leader in this economy expects.

C Labor Market

Labor demand in manufacturing equals the aggregate demand from both private and public consumers (recall that the production function in manufacturing reads $Y = L_y$ and that we assume market clearing). The total employment in manufacturing is then given by:

$$L_Y(t) = \int\limits_0^1 \left\{ \frac{c(t)L(t)}{\lambda(\omega,t)} + \frac{G(\omega)L(t)}{\lambda(\omega,t)} \right\} d\omega$$

$$= \int\limits_0^1 L(t) \left\{ c(t) \int\limits_1^\infty \lambda^{-1} g(\lambda) d\lambda + \int\limits_1^\infty G(\omega) \lambda^{-1} g(\lambda) d\lambda \right\} d\omega.$$

Using the Pareto density function given in (9), as well as the public demand rule as specified in (12) and (20), the total employment necessary to satisfy private and public consumers' demand for the consumption good can be calculated as:

$$L_Y(t) = L(t) \frac{c(t) + \bar{G} - \gamma\kappa\Gamma}{1 + \kappa}.$$

An equation for the R&D labor can be derived from solving (7) for the R&D input of a firm in industry ω and then aggregating over the continuum of industries $\omega \in [0, 1]$. Further taking into account that we assume symmetric behavior, that is, the industry-level innovation rate $I(\omega, t)$ is the same across industries at each point in time, we obtain:

$$L_I(t) = \frac{I(t)X(t)}{A}.$$

Labor-market clearing implies that $L(t) = L_Y(t) + L_I(t)$ is always fulfilled, which, when slightly rewritten, gives (15).

D   Existence and uniqueness of the steady state

In this appendix, we solve for the steady state of this economy, in which all endogenous variables grow at a constant (although not necessarily at the same) rate and research intensity $I(t)$ is common across industries. We already established in the main text that a constant growth rate constrains constrains I, $\dot{x}/x$, and $\dot{c}/c$ to be constant over time, while the latter implies $r(t) = \rho$. Equations (8), (14), and (15) represent a system of three equations in three unknowns x, c, and I. Solving this system of equations allows us to uniquely determine the steady-state values for all endogenous variables.

We first derive an expression for the equilibrium research intensity, I^*. Taking the logarithm of the expression on the RHS of (7) and differentiating with respect to time yields, using (8):

$$I^* = \frac{n}{\mu}. \tag{26}$$

According to equation (26), the steady-state value of the research intensity is completely pinned down by the population growth rate, n, and the parameter governing the R&D difficulty, μ.

Having determined the equilibrium value of I, we are now in the position to solve for the steady-state values of x and c. Given (26) and that $r = \rho$ holds along the steady state, the R&D equilibrium condition (14) can be written as:

$$\frac{x(t)}{A} = \frac{\frac{\kappa}{1+\kappa}(c(t) + \bar{G} + \gamma\Gamma)}{\rho + n(\frac{1}{\mu} - 1)}. \tag{27}$$

Equation (27) defines a negative linear relationship between the per capita private con-

sumption expenditures, c, and the relative R&D difficulty, x. The resource constraint (15) becomes:

$$1 = \frac{c(t) + \bar{G} - \gamma\kappa\Gamma}{1 + \kappa} + \frac{n}{\eta A}x(t), \tag{28}$$

defining a positive linear relationship between c and x. Equation (27) is an upward sloping line in the (c, x) space while (28) is a downward sloping linear function in the (c, x) space. The necessary and sufficient condition for both lines to have a unique and positive intersection is given by $\bar{G} < 1$. Solving the system of linear equations in (27) and (28) by applying Cramer's rule uniquely determines the steady-state values of x and c as:

$$x^* = \frac{A\kappa\mu(1 + \gamma\Gamma)}{n(1 + \kappa - \mu) + \mu\rho}, \tag{29}$$

$$c^* = \frac{\mu\rho(1 + \kappa + \gamma\kappa\Gamma - \bar{G}) - n[\bar{G}(1 + \kappa - \mu) + (1 + \kappa)(\mu - 1) + \gamma\kappa\mu\Gamma]}{n(1 + \kappa - \mu) + \mu\rho}. \tag{30}$$

Finally, we calculate the steady-state growth rate of the economy. Because we refrain from capital accumulation, the concept of growth in the model relates to growth in each individual's utility. This property is shared by all Schumpeterian growth models in which firms' R&D efforts are directed toward increasing the product quality, and the per capita consumption does not change in equilibrium. However, even if the amount of goods consumed per person remains constant, the individual utility in (2) augments when R&D turns out to be successful. To obtain an explicit expression for the utility growth rate, we substitute for consumer demand in (2) by using (3):

$$\log u(t) = \int\limits_0^1 \log \left[\frac{c(t)}{\lambda\left(\omega, t\right)} \right] d\omega + \int\limits_0^1 j^{\max}\left(\omega, t\right) \log \left[\lambda\left(\omega, t\right)\right] d\omega, \tag{31}$$

where $\int_0^1 j^{\max}\left(\omega, t\right) d\omega$ is a measure of the number of quality improvements aggregated over all industries, $\omega \in [0, 1]$. The index j^{max} increases when firms are successful in innovating and engage in R&D in all industries throughout time in any steady-state equilibrium. In each industry ω, the (Poisson distributed) probability of exactly m improvements within a time interval of length τ can be calculated as:

$$f(m, \tau) = \frac{(I\tau)^m e^{-I\tau}}{m!},$$

where $f(m, \tau)$ represents the measure of products that are improved exactly m times in an interval of length τ. Following Davidson and Segerstrom (1998), $\int_0^1 j^{\max}\left(\omega, t\right) d\omega$ then equals tI. Taking this and (26) into account, differentiating (31) with respect to time yields the following steady-state growth rate of the per capita utility:[17]

$$\frac{\dot{u}(t)}{u(t)} \equiv g^* = \frac{n}{\mu}\kappa. \tag{32}$$

This completes the characterization of the steady state of this economy.

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[17] Notice that the first integral on the RHS of (31) is constant along the balanced-growth path. We further exploit the fact that quality jumps follow a Pareto distribution, so, using (9), $\int_0^1 \log \left[\lambda\left(\omega, t\right)\right] d\omega = \kappa$.

E Data Appendix: U.S. Federal Procurement

We use federal procurement data provided by FPDS-NG in the period from 1997 to 2007. During the import of the raw data from the FPDS-NG data archives[18], we performed data corrections to accommodate changes in the industry code from the 1997 and 2002 NAICS to the 2007 NAICS system. Although most federal statistical agencies adopted NAICS codes already in 1997 to replace the Standard Industrial Classification (SIC) system, only a small fraction of contracts in the FPDS-NG database are assigned a NAICS code in the years before 2001.

To be able to properly identify high-tech industries also in the years before 2001, we exploit the fact that we have information on the PSC for almost all contracts. The FPDS-NG user's manual reports that the PSC is required to correlate to the selected NAICS code (GSA, 2008). Moreover, according to the Federal Acquisition Regulation, the NAICS code "best describes the principal nature of the product or service being acquired" GSA (2005, p. 19.1-3). Therefore, we develop a PSC-NAICS concordance based on contract data for 2001 to 2009 for which both code categories are available. Using this concordance table, we assign NAICS codes to all contracts for which an industry classification had previously been missing.[19] If more than one NAICS code applies to a PSC, each of the respective industries receives a share of the contract's total value with the share being equal to the relative frequency

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[18] The raw data files are available at www.fpds.gov.

[19] A further virtue of using the PSC-NAICS concordance to assign an industry classification code to contracts without a NAICS code is that we can take into account contracts for which a NAICS code has not been reported by the contracting agency for strategic reasons, for example, to circumvent size standards for certain contracts. The FPDS-NG data show that the Department of Defense, especially, does often not report NAICS codes associated with its contract actions. An analysis conducted by the consultant Aronson LLC suggests that this is mainly due to bypass size limitations for certain contracts (http://www.aronsonblogs.com/gcsg/?p=135).

of occurrence of the respective PSC-NAICS concordance. This procedure circumvents that part of a contract's value that gets "lost" during the aggregation of contracts to the industry level. After having identified to which industries public purchases can be assigned, we exclude federal procurement within the public sector (NAICS 92). For the reasons mentioned in the main text, we also drop R&D procurement contracts, which can be identified using the PSC.

We obtain state-level procurement data by using information on the state where the contract was performed, which is mandatory for the procurement officers to report in the FPDS-NG database (GSA, 2008). Moreover, information on the place of performance allows us to focus on domestic federal procurement, excluding all government contracts performed outside the U.S. We also exclude procurement contracts performed in the District of Columbia. The deflator used for the conversion of current to constant contract value (base year 2000) is the Government Consumption Expenditures and Gross Investment Index (GCEGII). We prefer GCEGII over the Consumer Price Index because the "market basket of goods" purchased by the federal government may be significantly different from the purchases of the typical household.

F   Summary Statistics

Table 5: Pairwise correlation coefficients.

	1)	2)	3)	4)	5)	6)	7)
1) Company R&D	1						
2) Procurement high-tech	0.65	1					
3) Procurement all other	0.60	0.78	1				
4) High-tech ratio	0.41	0.77	0.21	1			
5) Real GDP	0.89	0.77	0.77	0.42	1		
6) Real GDP growth	-0.02	-0.05	-0.09	0.01	-0.03	1	
7) Population	0.86	0.77	0.78	0.41	0.99	-0.05	1

Notes: See main text for further details on the construction of the variables. All variables are log-transformed.