The Technological Intensity of Government Demand and Private R&D Activities*

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Abstract

This paper investigates the role of the inter-industry composition of government demand in innovation. We develop an endogenous growth model with quality-improving innovations that incorporates industries with heterogeneous innovation sizes. The model posits that a shift in the composition of government purchases to the benefit of high-tech industries encourages additional private R&D. We empirically test the implications of the model using detailed administrative data on federal procurement in U.S. states. In support of the model, we find that the technological content of public procurement can effectively alter private R&D activities. Instrumental variable results suggest that the estimated effect is indeed causal.

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1 Introduction

Governments purchase everything from airplanes to zucchini. This paper addresses the question whether the technological content of public demand plays a role for private innovation activities. The idea that government purchases can stimulate innovation is grounded in the results of several early studies suggesting that innovation is sensible to general demand conditions (e.g., Gilfillan, 1935; Mill, 1848; Schumpeter, 1942). On the one hand, increasing sales permit the financing of uncertain R&D activities. On the other hand, the size of the (expected) market for an innovation determines its attractiveness for firms, dictating how the firms make practical use of their scientific ideas. Schmookler (1966) uses U.S. patent data to document that inventive activity tended to lag behind the peaks and valleys of the output of a commodity. From this observation, it was inferred that invention responds to profit motives. Griliches (1957) provides evidence that technology adoption is affected by market size as well. Moser (2005) analyzes innovation data from the catalogues of two 19th century world fairs. She finds that market size has an important influence on both, the number of innovations and the distribution of innovative activity across industries. Acemoglu and Linn (2004) and Rosenberg (1969) likewise suggest that demand "steers" firms to address certain problems. The importance of market size and profit incentives in innovation is also acknowledged by endogenous growth theory (Aghion and Howitt, 1992; Romer, 1990; Young, 1998).

In the recent years, public procurement, that is, the purchase by governments of goods and services, 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 (OECD, 2011). 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, and the GPS (Mowery, 2008; Nelson, 1982; Ruttan, 2006).[1] Moreover, Nelson and Langlois (1983) show that the U.S. government was a major driver of the development of industries in which it was an important customer. 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.

However, previous research has mainly focused on a number of highly situational case studies and anecdotal evidence without conclusive results (Cohen and Noll, 1991; Edquist and Hommen, 2000). Only a handful econometric studies examine the relationship between government market

[1] Studying the Canadian public sector, Dalpé, DeBresson and Xiaoping (1992) find that every fourth innovation has its first use in the public sector, as do 13 percent of patents.

size and innovation, all of which are based on firm-level data (Aschhoff and Sofka, 2009; Lichtenberg, 1987, 1988). These studies, however, either rely on doubtful proxies for the existence of procurement contracts in firms (Aschhoff and Sofka, 2009) or refer to a limited set of data on the biggest private contractors (Lichtenberg, 1988).

Moreover, notably absent in the existing literature is a discussion of the innovation effects of government procurement that take into account the types of products bought by the government. This lack of research is surprising because it has been suggested that the stimulus of private R&D and innovation by procurement is especially pronounced for the most advanced technologies (Hart, 1998). Cozzi and Impullitti (2010) argue that an essential part of the realignment of U.S. innovation policy in the late 1970s and 1980s was a shift in the composition of public spending toward industries of significant technological content. Then, the authors present some descriptive evidence indicating that the timings of these shifts are correlated with increases in private R&D spending. However, although suggestive of an association, these studies do not attempt to econometrically establish the link between the dynamics of the inter-industry composition of government purchases and private R&D activities. This paper attempts to fill this gap.

We embed our empirical work in a theoretical model to ensure that we test well-defined hypotheses. The model sheds light on the transition mechanism for government procurement on firms' innovative behavior. We follow the 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), while accounting for the government as an additional source of demand. In the model, industries are heterogeneous in terms of their innovation sizes or quality jumps. Our main theoretical result indicates that when the composition of government purchases changes to the benefit of industries with an above-average quality jump, that is, high-tech industries, the firms' incentives to engage in R&D increase. The mechanism is as follows: A shift in the technological content of public purchases toward high-tech industries translates into a larger flow of 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 reallocation of government procurement from low-tech to high-tech industries stimulates R&D on the level of the aggregate economy as the increased R&D in high-tech industries outweighs the R&D foregone in the remaining industries due to their smaller government market.

The model is closely related to that developed in Cozzi and Impullitti (2010), but deviates from it in a number of important ways. On the one hand, we incorporate recent developments in the endogenous growth literature that elegantly set forth how industries differ in terms of their innovation capacity (Minniti, Parello and Segerstrom, 2008). Imposing a specific assumption on the inter-industry distribution of quality jumps allows a more rigorous analytical treatment of the model as compared to Cozzi and Impullitti (2010). Specifically, we can theoretically derive an explicit expression that links the technological content of government purchases to private R&D activities. On the other hand, Cozzi and Impullitti (2010) are primarily interested in exploring the effects of the inter-industry composition of procurement on the endogenous formation of skills and the skill premium, respectively. To this end, they distinguish between low-skilled and high-skilled labor employed in different sectors of the economy. We, however, focus on the impact of government purchases on firms' R&D decisions, neglecting educational choice and sector-specific skills.

Having theoretically identified the transmission mechanism for the technological content of government procurement on private R&D activities, we analyze the empirical plausibility of the model's predictions 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 1997 to 2009. In particular, we construct a unique panel data set covering the whole universe of federal procurement contracts, cross-classified by state and type of industry. These administrative data are provided by the U.S. General Services Administration. We merge the procurement data with information about private R&D employment, measured as weekly hours worked in R&D-related occupations. 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 OLS estimation of the relationship between the technological intensity of government purchases and private R&D will be biased if there is a systematic relationship between unobserved, state-specific factors and the variable of interest. To identify the causal effect of the technological intensity of government purchases on private R&D, we apply instrumental variable (IV) techniques. We exploit the idea that procurement in high-tech industries is particularly high in states whose governors belong to the majority party in the Congress. The intuition for the instrument is readily accessible: Governors may expect that increases in procurement will stimulate a state's economic performance, positively affecting 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 their constituents, however, governors need support from the Congress, the latter holding 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 empirical analysis provides support for the prediction of the model, namely, that a shift in the composition of procurement toward high-tech industries stimulates private R&D activities.

The OLS results indicate that a doubling of the procurement high-tech share, measured as the proportion of procurement in high-tech industries in a given state, is associated with an increase in R&D employment of approximately 2.6 percent in that state. In terms of the number of hours worked, this represents an increase of approximately 113,000 hours. Our finding is robust under a range of alternative specifications. For instance, in addition to controlling for state and year fixed effects, we include a linear state time trend that allows unobserved state R&D employment patterns to trend linearly over time. Moreover, the results are also robust to excluding influential states, such as California or Florida. The IV models yield point estimates on the technological intensity of government demand of the same magnitude as the OLS coefficients, but are estimated with far less precision. However, exogeneity tests suggest that the IV estimates do not significantly differ from the OLS results. Therefore, we cautiously conclude that our OLS estimates can indeed be interpreted as being of a causal nature.

The remainder of the paper is organized as follows. Section 2 introduces the basic model linking firms' R&D efforts to the technological composition of government purchases. In Section 3, we discuss the specification and estimation issues concerning the empirical assessment of the model's implications. In Section 4, we introduce the data and describe the construction of the key variables. Section 5 presents our findings. Section 6 summarizes and concludes with some policy implications.

2 The Model

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 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, Parello and Segerstrom (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, Scherer and Vopel (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 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.

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:

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

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 of each firm's R&D efforts is a superior quality and to monopolize the market by achieving a patent with infinite patent length.[2] 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:

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

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

[2] 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, Nelson and Walsh, 2000; Mansfield, 1986).

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:

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

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, respectively, 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 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, Parello and Segerstrom, 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 mean 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 $\upsilon^e(\omega,t)$ 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):

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

where $\pi^e(\omega,t)$ denotes the expected profits earned by a successful innovator. In the stock market equilibrium, the expected dividend rate, $\pi^e(\omega,t)/\upsilon^e(\omega,t)$, plus the expected rate of capital gains, $\dot{\upsilon}^e(\omega,t)/\upsilon^e(\omega,t)$, 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 $\upsilon^e(\omega,t)=X(\omega,t)/A$ and recalling that the increase in R&D difficulty is common to all industries in the economy, the dividend rate becomes:

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

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:

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

where

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

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

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

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

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.[3] 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 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.1). 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 A.2) 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 $v^e(\omega, t)$:

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

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,

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

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:

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

while the *resource constraint* of the economy (see Appendix A.3) reads:

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

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

The balanced growth path of the economy (see Appendix A.4) 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.[4]

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 $(\rho - n) > 0$[5], the higher the equilibrium R&D employment is.[6]

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 employment. According to (16), a shift in the structure of government purchases toward industries with an above-average innovation potential stimulates company R&D employ-

[4] Notice that the positive influence of γ on the R&D labor share, $L_I(t)/L(t)$, also holds outside the steady state. From the resource constraint (15), it follows that $L_I(t)/L(t) = 1 - \left[c(t) + \bar{G} - \gamma\kappa\Gamma\right]/(1+\kappa)$.

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

[6] The working paper version of the model (Wiederhold, 2009) presented another prediction of the model, namely that government procurement focused on high-tech industries may also yield beyond some point a negative intertemporal R&D spillover effect (see also Aghion and Howitt, 1992). This effect takes the form of the depletion of the technological opportunities in subsequent periods in a given industry. Thus, procurement expenditures in high-opportunity industries are subject to dynamic diminishing returns for economic growth and social welfare.

ment 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 labor 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. The U.S. is a particularly interesting country to study because the U.S. government is the world's largest purchaser of products and services. Moreover, the U.S. provides detailed procurement data that allow both to determine the value of procurement contracts and to identify to which industries public purchases can be assigned.

The impact of the composition of government sales on private R&D employment 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:

$$\begin{aligned} \log R\&D\_EMPLOYMENT_{i,t} = \;& \beta_1 \log HIGH\_TECH\_SHARE_{i,t-1} + \\ & + \beta_2 X_{i,t} + \xi_i + \nu_t + u_{i,t} \end{aligned} \tag{17}$$

where $R\&D\_EMPLOYMENT_{i,t}$ denotes the number of hours worked in R&D occupations in state i at time t. $HIGH\_TECH\_SHARE_{i,t-1}$ is the empirical approximation of γ from our theoretical model. This variable measures the technological intensity of procurement, defined as federal procurement in high-tech industries as a share of total federal procurement in state i at time $t-1$. To construct $HIGH\_TECH\_SHARE_{i,t-1}$, we exclude government outlays to procure research results (R&D procurement).[7] The procurement high-tech share 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. Moreover, company R&D investment might respond to federal procurement contracts only with a certain lag. A third reason for lagging the technological intensity of procurement is to overcome any reverse causality problems, that is, company R&D funding affecting public procurement.[8]

The vector $X_{i,t}$ contains several control variables. For instance, our model suggests that the size of the market influences private R&D. To proxy for market size, we use the level of the GDP, the population, or the GDP per capita (Moser, 2005; Sokoloff, 1988). Moreover, we control for the total number of hours worked within a state and the state-wide hourly wage of R&D workers.[9] ξ_i

[7] See Section 4.1 for more details on the distinction between R&D and non-R&D procurement and the reasons to exclude the former when constructing $HIGH\_TECH\_SHARE_{i,t-1}$.

[8] However, it has little impact on our results whether we use the lagged or the contemporaneous procurement high-tech share.

[9] In fact, the theoretical model would suggest to use the hours worked in R&D divided by total hours worked as

and ν_t are vectors of state and year 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 decisions. Likewise, ν_t captures the aggregate, macroeconomic factors, such as business cycles, demand shocks, or national policy changes. Accounting for time fixed effects is inevitable in our case because the relevant market for R&D performing companies typically extends well beyond the states in which their R&D is located. The year dummies will pick up the effects of demand when that demand reflects national or global market conditions. Moreover, the year dummies 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. In the presence of serial correlation, the OLS 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 OLS estimator will also be biased. To address the serial correlation concerns, we cluster standard errors by state (Arellano, 1987; Hansen, 2007; White, 1980).[10]

Moreover, it could be objected that drawing causal inferences from (17) about the effect of government procurement composition on private R&D is not foolproof. Specifically, there might be omitted variables that are correlated with both private R&D employment and government procurement or even jointly determine them. For instance, 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 company R&D employment 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 5.3. Before turning to the empirical analysis, we first introduce the data and variables.

the dependent variable. We prefer to control for total hours worked, however, to be able to express our outcome variable as an absolute value instead of a share. We show in Table A.4 that all results are robust to defining the outcome variable as the proportion of hours worked in R&D.

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

4 Data and Variable Construction

4.1 Federal Non-R&D Procurement

Our information on government purchases by state and industry is derived from administrative records of the U.S. government. The data stem from the Federal Procurement Data System – Next Generation (FPDS-NG), provided by the 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. Procurement conducted by state governments and other local public agencies is not included in the data.[11] FPDS-NG reports the federal contracts for each company that is a separate legal entity, independent of the parent company (Goldman, Rocholl and So, 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 share, 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, Hall and Toole, 2000). Therefore, one would expect R&D procurement to directly affect private R&D outlays, while we are interested in the (indirect) effect of government market size on company R&D. Moreover, 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). For these reasons, 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.[12] One should notice, however, that non-R&D procurement might also contain a

[11] It could be objected that by looking only at federal procurement we leave out 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 immediate 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, federal procurement has the important advantage to be rather independent of state-level characteristics, thereby reducing the problem of endogeneity discussed in Section 3.

[12] All regression results are robust to the inclusion of the value of R&D procurement contracts as an additional control. However, we decided against controlling for R&D procurement in our main specification because we lack an appropriate instrument to address the endogeneity concerns associated with R&D procurement (Lichtenberg,

R&D component. Unfortunately, the FPDS-NG data do not allow 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, Scarpetta and Pilat, 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.[13]

To identify high-tech 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).[14] According to this definition, we classify 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),

1988).

[13] Cozzi and Impullitti (2010) also interpret industries with above-average quality jumps as being high-tech industries.

[14] 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).

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 A.5). We use the original NAICS codes and the concordance (if the NAICS code was missing) to classify industries as either high-tech or 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 share, as a measure of the technological content of procurement, as the proportion of procurement in high-tech industries.

4.2 Private R&D Employment and Wages

To proxy R&D labor in the private sector, we draw on the Current Population Survey May Outgoing Rotation Group (May/ORG). The survey is conducted by the U.S. Census Bureau on behalf of the BLS on a monthly basis (BLS, 2011; Bowler and Morisi, 2006). The interviewed households are a scientifically selected sample designed to represent the civilian noninstitutional population. The sample is designed to provide reliable estimates for the U.S. as a whole as well as for the 50 U.S. states and the District of Columbia. It currently includes about 60,000 households. The CPS contains data on various labor force characteristics, such as information about employment status, earnings, hours of work, etc. In addition to that, the CPS collects educational attainment data and a variety of demo-graphic characteristics such as age, sex, race/ethnicity, and marital status.

Following Autor, Katz and Kearney (2008) and Acemoglu and Autor (Forthcoming), we construct our proxy for R&D labor using hours worked in the CPS sample reference week by wage or salary workers (both, part-time and full-time) in the age group 16 to 64.[15] We measure R&D

[15] Alternatively, data on hours worked per week can be obtained from the March CPS. However, March CPS samples rely on retrospective answers by the respondents, while CPS/ORG data provide point-in-time measures of hours worked in the week before the survey. For that reason, May/ORG is typically preferred to the March CPS (Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2008; Lemieux, 2006).

employment as the state-level sum of weekly hours worked in R&D occupations in private-sector firms, excluding employment in the public sector, self-employment, and jobs without payment. Hourly wages are calculated as the reported hourly earnings for those paid by the hour and the usual weekly earnings divided by hours worked last week for non-hourly workers. All calculations are weighted by CPS sampling weights.[16] To identify R&D occupations, we exploit information on detailed occupations in the May/ORG. Occupations are classified as R&D-oriented according to the job descriptions in the Occupational Employment Statistics: Dictionary of Occupations (BLS, 2004).[17]

It is important to note that information in the May/ORG is coded at the place of residence of the surveyed households, while information in the FPDS-NG is geo-coded at the location of the establishment. If there is a substantial amount of employees in the CPS whose working place is in a different state than their home, our analysis will be prone to measurement error. However, the sampling design of the CPS ensures that this is unlikely to be the case. The selection of sample areas in the CPS is based on U.S. labor market areas, so-called Metropolitan Statistical Areas (MSA).[18] Households in the CPS are selected from those MSA that do not cross state borders (BLS, 2011). For this reason, we are confident that the CPS survey respondents rarely show cross-state commuting behavior, which attenuates the problem of different reporting units of the CPS and the FPDS-NG data.

4.3 Population and GDP

Population data are taken from midyear estimates reported by the Bureau of Economic Analysis (BEA). Data on the GDP are also obtained from the BEA, deflated by the GDP deflator.[19] Our final dataset covers 50 U.S. states in the period from 1997 to 2009.

5 Empirical Results

This section reports our empirical findings. We first show how the technological composition of public procurement is related to company R&D employment in the pooled cross section. We then turn to panel estimations that control for time and state specific effects and check the sensitivity

[16] The details of the construction of the labor supply and wage variables are delegated to Appendix A.5.

[17] Our classification of R&D occupations is consistent with, but somewhat more precise, than the definition of technology-oriented workers in Hecker (2005). See Table A.1 for an overview of R&D occupations.

[18] An MSA consists of an urban core plus surrounding territory that is socio-economically linked to the urban core by commuting. See http://www.census.gov/population/www/metroareas/metroarea.html for more details.

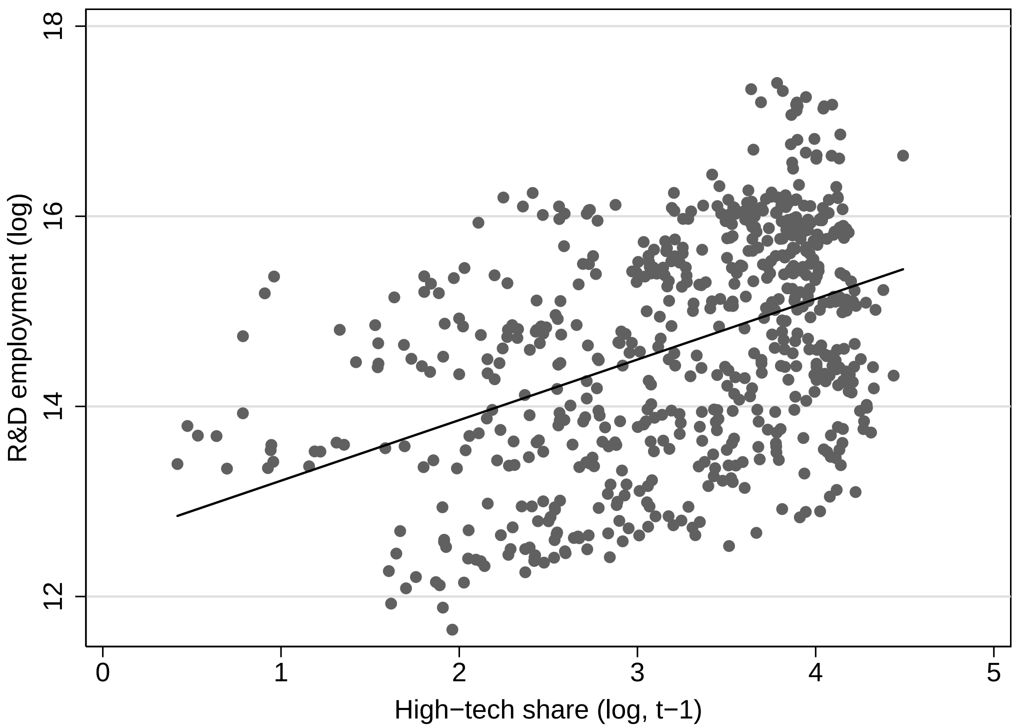
[19] Because the deflator is the same for all states in a given year, it is absorbed by the year dummies in the regressions below.

of our results to various changes in the baseline specification. We close with considering IV estimations to examine the unbiased causal effect of the technological intensity of government procurement on firms' R&D employment decisions.

5.1 Basic Specifications

We begin our empirical investigation by looking at the simple cross-sectional association between the technological intensity of government demand and private R&D. In Figure 1, the procurement high-tech share is plotted against private R&D employment for years from 1997 to 2009 in a pooled cross section. Because the theoretical model's econometric representation in equation (17) is in log-linear terms, the variables are measured in logs. Moreover, for the reasons explained in Section 3, we lag the procurement high-tech share by one year. As indicated by the fitted line, the technological intensity of procurement and privately funded company R&D are positively associated. The correlation between the two variables is equal to 0.43. Below, we more rigorously examine this relationship by controlling for unobserved time-invariant state characteristics and a number of other factors.

Figure 1: Technological intensity of government demand and private R&D: Pooled cross section.



Notes: R&D employment is measured as the number of weekly working hours in R&D occupations. High-tech share is federal non-R&D procurement in high-tech industries as a share of total federal non-R&D procurement. The share variable is lagged by one year. The period of observation is 1997-2009.

Now, we present the results from the OLS estimation of the impact of a reallocation of government purchases in favor of high-tech industries on company R&D employment. Here, identification comes from the within-state (over-time) variation of the variables. The results from the OLS 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 are to be interpreted as elasticities.[20]

The estimation results support the predictions of the theoretical model. In Column (1), we find a positive and statistically significant relationship between the technological intensity of public purchases and private R&D employment. The coefficient, significant at the 1 percent level, shows that a doubling of the procurement high-tech share is associated with a 2.6 percent increase in the weekly working hours of R&D personnel. Evaluated at the respective sample means, our results

[20] Summary statistics and pairwise correlation coefficients of the variables are reported in Tables A.2 and A.3.

imply that if the procurement high-tech share increased from 33 to 66 percent, company R&D employment in the state would rise by approximately 117,000 hours. Put differently, if the high-tech share increased by one standard deviation, private R&D employment would grow by 1.55 percent of a standard deviation. The total size of the market demand, measured as the level of the GDP, is negatively related to private R&D activities and marginally significant. This result appears counterintuitive at first and is, in fact, at odds with the theoretical predictions. However, a likely reason for the negative coefficient on the GDP is that the GDP and total hours worked are highly correlated.[21] Unsurprisingly, total hours worked and hourly wage in R&D occupations are positively associated with hours worked in R&D.

The described pattern remains when using the population (Column (2)) or the GDP per capita (Column (3)) as alternative proxies for total market size. In all specifications, the procurement high-tech share is highly significant and its point estimate is almost unchanged.[22] Further, in Column (4) we show that it is indeed the positive effect of procurement in high-tech industries that drives our results; procurement in high-tech industries and private R&D employment show a significantly positive association, while procurement in the remaining industries fails to capture statistical significance.[23]

[21] In regressions without hours worked, the point estimate on GDP is positive but marginally insignificant.

[22] When estimated without hours worked, both the population and the GDP per capita yield positive yet insignificant effects on private R&D.

[23] The results are virtually identical for the GDP or the population as controls for total market size.

Table 1: Technological intensity of government demand and private R&D: OLS results.

Dependent Variable: R&D Employment (log)	(1)	(2)	(3)	(4)
High-Tech Share (log, t-1)	0.026***	0.025***	0.027***	
	(0.009)	(0.009)	(0.009)	
Procurement High-Tech (log, t-1)				0.022***
				(0.007)
Procurement All Other (log, t-1)				- 0.003
				(0.012)
GDP (log)	-0.142*			
	(0.075)			
Population (log)		-0.225*		
		(0.130)		
GDP Per Capita (log)			-0.048	-0.048
			(0.086)	(0.087)
Total Hours Worked (log)	0.514***	0.509***	0.425***	0.424***
	(0.076)	(0.111)	(0.073)	(0.070)
Hourly Wage R&D (log)	0.760***	0.763***	0.761***	0.763***
	(0.028)	(0.029)	(0.028)	(0.029)
State Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	650	650	650	650
R-squared (overall)	0.995	0.995	0.994	0.994
R-squared (within state)	0.783	0.783	0.782	0.782
F-statistic	261.678	271.371	269.660	233.750

Notes: Results of the OLS estimation of equation (17). The dependent variable is private R&D employment, measured as weekly working hours of employees in R&D occupations (see Section 4). The sample includes 650 observations from 50 states over the period from 1997 to 2009. All variables are log-transformed. High-tech share measures the technological intensity of public purchases. It is defined as federal non-R&D procurement in high-tech industries divided by total federal non-R&D procurement. Gross procurement values are used, that is, de-obligations are not subtracted. High-tech share is lagged by one period, while all control variables are contemporaneous. Total hours worked is measured as the number of weekly hours worked in all occupations. Hourly wage R&D is the state-level sum of per-hour wages earned by workers in R&D occupations. All estimations include year and state fixed effects. Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

5.2 Robustness Tests

Table 2 investigates the robustness of the findings of the baseline specification (Section 5.1). In the remainder of the section, we use the GDP per capita to capture market size because it has the lowest correlation with total hours worked among our various proxies for market size.[24] First, to partly alleviate concerns about the endogeneity of our estimates, we include state-specific time trends, in addition to year and state fixed effects (Column (1)). This specification remedies an omitted variable bias caused by slow-moving R&D employment trends in each state, which, if not properly controlled for, would confound the estimates of the within-state effects (Friedberg, 1998; Kerr and Nanda, 2009). Even in this demanding specification with additional 50 state time trends, the results continue to support our theoretical conjecture that a reshuffling of public purchases in favor of high-tech industries is associated with an increase in company R&D employment.

In Columns (2) and (3), we test whether the results are sensitive to our measurement of government procurement. In Column (2), we use 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 our measure for the technological intensity of procurement. In Column (3), we only consider those procurement contracts for which NAICS information was originally available in the FPDS-NG database, not applying the PSC-NAICS concordances to assign missing industry codes (NAICS) to procurement contracts. The findings are robust to those changes in measuring procurement. However, the coefficient on the high-tech share of procurement somewhat decreases in size in the specification with original NAICS codes. This result reflects the fact that prior to 2001 it is often not possible to identify to which industries public purchases can be assigned, as only little information on the NAICS codes is available in the FPDS-NG data. Thus, effectively, our period of observation shrinks to 2001-2009 in this specification.

One possible source of estimation bias are changes in the within-state industry structure. For instance, the observed positive correlation between high-tech procurement and private R&D employment may simply be an artifact of an increase in the number of firms in high-tech industries in a state. More firms in high-tech industries implies both, more potential contractors for the federal government, potentially leading to an increase in high-tech procurement, and more R&D employment. In Column (4), we address this concern by accounting for the industry-level variation in the GDP within states. The GDP data for 20 industries, approximately at the 2-digit level, are taken from the BEA. The coefficient on the technological intensity of government procurement remains virtually identical to the baseline result.

[24] The GDP per capita is insignificant in all specifications. We obtain qualitatively similar results when the GDP or the population are included in the regressions instead of the GDP per capita. Moreover, total hours worked and hourly wage in R&D occupations are positive and highly significant in all models.

Next, we check whether our results are robust to changes in the construction of the dependent variable. In Column (5), we restrict our sample to full-time employees in R&D occupations, that is, employees who work more than 35 hours per week. We obtain roughly similar results as those in the baseline specification, although the size of the coefficient on the procurement high-tech share somewhat shrinks.

In Column (6), we test whether the basic state-year outcomes are robust to excluding potentially influential states (Kerr and Nanda, 2009). More concretely, we estimate equation (17) for the sample without large states. Following Elis, Malhotra and Meredith (2009), we define large states as those with at least 15 representatives in every Congress since the 1970 apportionment. These states are California, Florida, Illinois, Michigan, New York, Ohio, Pennsylvania, and Texas. Also with this restricted sample our results continue to hold.

Finally, in Column (7), we use an alternative measure of the technological intensity of procurement, calculated as the ratio between federal procurement in high-tech industries and in all other industries. Here, 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 an increase in weekly hours worked in R&D of approximately 1.8 percent. In terms of magnitude, an increase in the procurement high-tech ratio of one standard deviation is associated with an increase in private R&D employment of 1.7 percent of a standard deviation.

Overall, the robustness analysis confirms the findings from the baseline estimation. The positive association between the technological content of public purchases and private R&D employment continues to hold when a linear state time trend is included, when the variables of interest are differently constructed, or when the local industry structure is explicitly controlled for. Moreover, we also perform the analysis using the R&D employment share as outcome variable, measured as the proportion of weekly hours of R&D workers in total weekly hours worked. Table A.4 shows that all above results are robust to this change in the dependent variable.

5.3 Instrumental-Variable Approach

Causal interpretation of the associations reported so far, albeit proving robust under a range of alternative specifications, is apparently hindered by a range of endogeneity concerns. As discussed in Section 3, there might be unobserved factors at the state level not accounted for by the year and state dummies that are correlated with federal procurement or even jointly determine federal procurement and company R&D employment. These omitted variables are a potential source of endogeneity concerns, biasing the OLS estimator in an unknown direction. Moreover, reverse causality might arise if the government perceives a firm's R&D efforts as a signal of its capabilities

Table 2: Robustness tests.

Dependent Variable: R&D Employment (log)	(1) State Trend	(2) With Deob	(3) Original NAICS	(4) Industry Structure	(5) Full-Time Only	(6) Without Large	(7) High-Tech Ratio
High-Tech Share (log, t-1)	0.020**	0.025***	0.010***	0.022***	0.017***	0.029***	
	(0.010)	(0.009)	(0.004)	(0.008)	(0.006)	(0.009)	
High-Tech Ratio (log, t-1)							0.018***
							(0.007)
GDP Per Capita (log)	-0.007	-0.045	-0.029	-0.090	0.066	0.011	-0.049
	(0.173)	(0.085)	(0.088)	(0.093)	(0.064)	(0.100)	(0.087)
Total Hours Worked (log)	0.494***	0.424***	0.403***	0.501***	0.224***	0.493***	0.424***
	(0.130)	(0.073)	(0.066)	(0.115)	(0.051)	(0.072)	(0.072)
Hourly Wage R&D (log)	0.736***	0.761***	0.761***	0.753***	0.838***	0.755***	0.760***
	(0.036)	(0.029)	(0.029)	(0.028)	(0.020)	(0.030)	(0.028)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	646	648	650	546	650
R-squared (overall)	0.008	0.994	0.994	0.987	0.996	0.991	0.994
R-squared (within state)	0.803	0.782	0.785	0.791	0.856	0.778	0.781
F-statistic		269.231	259.773	318.593	526.761	299.690	253.125

Notes: This table provides several robustness tests of the baseline estimation of equation (17) presented in Table 1. In Column (1), we include linear state time trends. In Column (2), the technological intensity is constructed using the net value of the federal non-R&D procurement, that is, dollars obligated minus dollars de-obligated by a contract. In Column (3), the computation of the procurement high-tech share only relies on the NAICS information originally included in the FPDS-NG database. The number of observations shrinks to 646 because no federal procurement in high-tech industries is reported in Maine in 1998, in Vermont in 1996 and 1997, as well as in Wyoming in 1997. Column (4) controls for the local industry structure using the GDP data for 20 NAICS-classified industries obtained from the BEA. In this specification, two observations are missing (Delaware and Maine, both in 2009). In Column (5), weekly working hours in R&D are computed accounting only for workers with at least 36 hours per week. In Column (6), the eight largest states (California, Florida, Illinois, Michigan, New York, Ohio, Pennsylvania, and Texas) are excluded from the sample. In Column (7), the technological intensity of public purchases is measured by the procurement high-tech ratio instead of the high-tech share. The former is calculated as government purchases in high-tech industries relative to purchases in other industries. All variables are log-transformed. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

to perform a procurement contract (Lichtenberg, 1988). Such "signaling R&D" would bias our OLS estimates upwards if it primarily occurred in high-tech industries, that is, the award of high-tech procurement contracts is particularly strongly influenced by the firm's R&D performance. We address these endogeneity concerns in 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 high-tech 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, the state receives more, and in particular high-tech, procurement contracts. 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.). Moreover, 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, that is, either from the House of Representatives, the Senate, or both. 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."[25] The majority party in either chamber of the Congress is entitled to significant agenda control power because it selects the chairmen of committees authorizing and appropriating funds. In fact, the leading party receives a majority on all of the Appropriations subcommittees (Evans, 1991; Fenno, 1973).[26] The party that constitutes a majority in the House or Senate has an incentive to support governors of the same party by means of allocating federal procurement contracts to firms in the respective state because, following 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, Dhillon and Dutta (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, 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 and 0 otherwise.[27] The instrument is lagged by two years behind the endogenous regressor to account for the lag in the budget cycle. Current federal procurement budgets have normally

[25] The president might also play an important role both in the budget process and as chief executive (Larcinese, Rizzo and Testa, 2006).

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

[27] As mentioned above, the Congress consists of two chambers, that is, the House and Senate. The House majority was Democratic in years 1994 to 1995, and Republican in the period thereafter (notice that due to the lag structure we choose for the instrument, which is explained below, our instrument covers the period 1994 to 2006). In principle, the majority party in the Senate has been the same as in the House; only in years 2001 to 2002, Democrats and Republicans provided the same number of Senators. However, according to the U.S. Constitution, the Vice President breaks a tied vote in the Senate. Because the Republican Dick Cheney assumed the position of Vice President from 2001 to 2008, one might regard the Senate as being under the same leadership as the House in our period of observation. In this case, the coincidence of the governor's party and the Senate majority delivers exactly the same results as those reported below.

been appropriated in previous budgetary years (Alvarez and Saving, 1997; Elis, Malhotra and Meredith, 2009; Larcinese, Rizzo and Testa, 2006).[28] Figure A.1 provides an impression of the relationship between the instrument and the high-tech share of federal procurement.

The variation in our instrument comes from two sources, namely, House and governor elections. The identifying assumption of our IV model is that the coincidence of the majority parties at the state and federal level is uncorrelated with changes in the R&D prospects in the state except for the possible indirect effect through the procurement high-tech share. It could be objected that the outcome of gubernatorial elections might be related to state-specific characteristics that also determine private R&D investment. 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, we are confident that our instrument is unrelated to state-specific characteristics that are correlated with company R&D.

We motivated our instrument by assuming that it is particularly attractive for politicians to deliver high-tech procurement to their constituents. Thus, 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. In Table 3, we provide evidence in favor of this assumption. Here, we separately regress our instrument on the level of high-tech procurement and all other procurement, respectively. 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)).

[28] We also experimented with different lag structures, which provided results qualitatively similar to those reported below. First- and second-stage IV results with the instrument being lagged one year behind the procurement high-tech share are shown in Table A.5.

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

	(1) High-Tech Industries	(2) All Other Industries
Coincidence Gov-House (t-2)	0.157**	-0.035
	(0.065)	(0.034)
GDP Per Capita (log)	0.328	0.022
	(0.701)	(0.340)
Total Hours Worked (log)	-0.853	0.101
	(0.810)	(0.405)
Hourly Wage R&D (log)	-0.083	-0.135
	(0.162)	(0.095)
Time fixed effects	Yes	Yes
State fixed effects	Yes	Yes
Observations	650	650
R-squared (overall)	0.305	0.100
R-squared (within state)	0.574	0.810
F-statistic	33.098	82.881

Notes: This table provides the OLS results of regressing our instrument, Coincidence Gov-House, on federal non-R&D procurement in high-tech and all other industries, respectively. The instrument 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 instrument is lagged by two periods to take into account delays between the appropriation of federal funds and the moment when these are actually spent. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

The IV models are presented in Table 4. First, we report the results of the two-stage least squares (2SLS) estimator. The first stage, shown in Column (1), indicates that the instrument is indeed a relevant predictor of the technological intensity of public purchases. States with a governor being member of the majority party in the House experience an increase in the procurement high-tech share of approximately 13 percent. The F-statistic of the excluded instrument equals 6.8, which suggests that the instrument has explanatory power for the potentially endogenous regressor.[29] None of the control variables enter the first-stage model significantly.

[29] As discussed by Staiger and Stock (1997) and Stock, Wright and Yogo (2002) for a single endogenous regressor, the F-statistic typically must exceed 10 for inferences based on the 2SLS estimator to be reliable. However, this threshold value was derived for non-clustered standard errors. If we use Huber-White robust standard errors instead of clustered standard errors, the first-stage F-statistic is 17.51, indicating that there is not a weak instrument problem.

The first-stage fitted values are then plugged into the second-stage equation as regressors to obtain the causal effect of the technological intensity of procurement on private R&D. In Column (2), we show that the estimated coefficient on the technological content of procurement is in line with the OLS results in Table 1. The IV coefficient is positive and in the same order of magnitude as the OLS estimate. At the same time, however, the coefficient on the procurement high-tech share lacks significance, which is due to the relatively large standard error of the IV estimate. A test for exogeneity, implemented through a Durbin-Wu-Hausman χ^2 test, does clearly not reject the null hypothesis of an exogenous regressor ($p = 0.920$). This finding suggests that there is no bias from omitted variables or reverse causality in the OLS regressions, probably because there is not a systematic relationship between the potential omitted variables and the procurement high-tech share. Given this result and taking further into account that IV estimates are less efficient than their OLS counterparts, we cautiously interpret the original uninstrumented estimates to show a positive causal effect of the technological content of procurement on company R&D employment.

To be more confident that we do not suffer from a weak instrument problem, we also perform a Limited Information Maximum Likelihood (LIML) estimation. LIML is preferred to 2SLS when the instruments are weak (Hahn, Hausman and Kuersteiner, 2004).[30] In Columns (3) and (4) in Table 4, 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, while the coefficient on the technological content of procurement is somewhat more precisely estimated.

[30] Weak instruments can lead to inconsistencies in the IV estimates and tend to exacerbate the finite-sample bias that IV approaches suffer from (Bound, Jaeger and Baker, 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, Wright and Yogo, 2002; Temple and Wößmann, 2006).

Table 4: Technological intensity of government demand and private R&D: IV estimates.

	(1) 2SLS First Stage	(2) 2SLS Second Stage	(3) LIML First Stage	(4) LIML Second Stage
Coincidence Gov-House (t-3)	0.129**		0.129**	
	(0.050)		(0.050)	
High-Tech Share (log, t-1)		0.022		0.022
		(0.057)		(0.054)
GDP Per Capita (log)	-0.020	-0.049	-0.020	-0.049
	(0.440)	(0.087)	(0.440)	(0.087)
Total Hours Worked (log)	0.731	0.422***	0.731	0.422***
	(0.591)	(0.084)	(0.591)	(0.083)
Hourly Wage R&D (log)	- 0.028	0.760***	-0.028	0.760***
	(0.131)	(0.029)	(0.131)	(0.029)
Time Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	650	650	650	650
F-statistic (excluded instrument)	6.770		6.770	
R-squared (within state)	0.056	0.180	0.056	0.188
F-statistic	1.620	276.233	1.620	276.643
Durbin-Wu-Hausman test p-value		0.920		0.921

Notes: Results from a 2SLS (Columns (1) and (2)) and LIML (Columns (3) and (4)) estimation of the effect of the technological composition of government procurement on private R&D employment. The first-stage results are presented in the odd columns, while the even columns contain the second-stage results. 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 two periods behind the potentially endogenous regressor 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.

6 Conclusions

The goal of this paper is to analyze the relationship between the inter-industry composition of public purchases 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

(Cozzi and Impullitti, 2010; Minniti, Parello and Segerstrom, 2008). According to the model, a change in the composition of government purchases that relatively favors industries with above-average quality jumps, that is, high-tech industries, stimulates private R&D activities at the level of the economy. The intuition for this result is as follows: The government market 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 efforts increases.

We then compare the implications of the model with observable patterns, using U.S. state-level panel data for the period 1997 to 2009. We exploit administrative procurement data that provide detailed information on all federal procurement contracts above the micropurchase threshold. The technological intensity of procurement is measured as the share of high-tech industry procurement in total procurement. When constructing this measure, we only consider government contracts that are not directly related to R&D work. Our indicator for company R&D is the supply of R&D labor in the private sector, measured as weekly hours worked in R&D occupations. To overcome potential bias in the baseline (OLS) estimation, which could result, in particular, from omitted variables and reverse causality, we apply an IV approach. Our instrument for the composition of federal procurement relies on the idea that federal procurement in high-tech industries is relatively high in states whose governors belong to the House majority party. Previous results in the political science literature suggest that politicians use procurement to reward their voters and to increase their re-election chances. Governors are more able to channel procurement to their states if they belong to the House majority party, which holds the majority in committees authorizing and appropriating funds. Moreover, procurement in high-tech industries is particularly attractive for politicians because, for instance, it typically has a higher publicity effect than other types of procurement (e.g., Cohen and Noll, 1991; Steinberg, 1995).

Our results provide support for the theoretical prediction of a positive effect of a shift in the composition of public purchases to the benefit of high-tech industries on private R&D activities. According to the results of the OLS estimation with state and year fixed effects, doubling the procurement high-tech share is associated, *ceteris paribus*, with an increase in weekly hours worked in R&D of approximately 2.6 percent. This result is robust under a range of alternative specifications. In the IV estimations, the coefficient of interest remains almost unchanged, but is estimated with far less precision. However, tests for exogeneity provide no sign of endogeneity of the technological intensity of procurement, suggesting that we might trust the more efficient OLS estimations. Thus, we argue that we can cautiously interpret the original uninstrumented estimates to show a positive causal effect of the technological content of government procurement on firms' R&D activities.

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 (Cozzi and Impullitti, 2010)? 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. 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 our model suggests that the relationship between R&D and social welfare is 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 may, 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 (e.g., David, Hall and Toole, 2000; Wilson, 2009). Only after having taken into account the potential (opportunity) cost of the deliberate use of public procurement to promote innovation are we able to judge its suitability for furthering the objectives of innovation policy. These are important avenues for future research.

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A Appendix

A.1 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:

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

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 $\varepsilon_1 < \varepsilon_2$.

A.2 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):

$$\pi^e = \int_1^\infty \frac{\lambda - 1}{\lambda} L\,(c + G) g(\lambda) d\lambda. \tag{21}$$

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:

$$\pi^e = \int_1^\infty \frac{L}{\kappa}\frac{\lambda - 1}{\lambda} \lambda^{-\frac{1+\kappa}{\kappa}} \left(c + \bar{G} + \gamma\varepsilon\right) d\lambda. \tag{22}$$

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:

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

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.

A.3 Labor-Market Equilibrium

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:

$$L_Y(t) = \int_0^1 \left[\frac{c(t)L(t)}{\lambda(\omega,t)} + \frac{G(\omega)L(t)}{\lambda(\omega,t)}\right] d\omega$$

$$= \int_0^1 L(t)\left[c(t)\int_1^\infty \lambda^{-1} g(\lambda) d\lambda + \int_1^\infty G(\omega)\lambda^{-1} g(\lambda) d\lambda\right] d\omega.$$

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).

A.4 Existence and Uniqueness of the Steady State

Here, 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:

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

Equation (27) defines a negative linear relationship between the per capita private consumption 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):

$$\log u(t)=\int_{0}^{1}\log\left[\frac{c(t)}{\lambda(\omega,t)}\right]d\omega+\int_{0}^{1}j^{\max}(\omega,t)\log\left[\lambda(\omega,t)\right]d\omega, \tag{31}$$

where $\int_0^1 j^{\max}(\omega,t)d\omega$ 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), $\int_0^1 j^{\max}(\omega,t)d\omega$ 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:[31]

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

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

[31] 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), $\int_0^1\log\left[\lambda(\omega,t)\right]d\omega=\kappa$.

A.5 Data Appendix

Federal Non-R&D Procurement

We use U.S. 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[32], 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.[33] 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 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 Consump-

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

[33] 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, in particular, 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).

tion 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.

Company R&D Employment and Wages

We use data from the Current Population Survey (May/ORG) for years 1997-2009 to construct our sample of employment and wages in R&D occupations by state. CPS collects statistics on the employment status of the labor force as well as educational attainment data and a variety of demographic characteristics such as age, sex, race/ethnicity, and marital status. In addition to that, the data are available by occupation, industry, state, and class of worker. Compared to March CPS, which also contains data on weekly hours worked, May/ORG has the advantage that it asks about working times, wages, etc. at the time of the survey. Instead, March CPS reports employment statistics as retrospective measures, referring to the previous year. As pointed out by Lemieux (2006), another important difference between both surveys is that in May/ORG an individual's probability to be asked in the survey depends on the number of weeks worked during a year. This is because the May/ORG is a point-in-time survey. On the contrary, information in the March CPS can be retrieved irrespective of how many (nonzero) weeks an individual has worked during the year. For more details on variable definitions and sample design of the CPS, see BLS (2011) and Bowler and Morisi (2006).

Our sample includes wage/salary workers ages 16 to 64 who are employed in the private sector (Acemoglu and Autor, Forthcoming; Autor, Katz and Kearney, 2008). We include part-time and full-time workers, but exclude self-employed persons. If employed persons have two or more jobs in the sample reference week, that is, the week before the survey was conducted, we classify them in the job at which they worked the greatest number of hours. To ensure representativeness, weekly hours worked and hourly wages are weighted by CPS sample weights. When constructing our variables for labor supply and hourly wages, we follow closely the calculations described in Acemoglu and Autor (Forthcoming) and Autor, Katz and Kearney (2008).

In principle, May/ORG offers two measures to construct the labor supply variable, hours worked in the week prior to the survey and usual weekly hours. The problem of using the former measure is that, for example, persons who normally work 36 hours a week would be classified as part-time if they were off for one or more days of holiday in the week prior to the survey. However, usual weekly hours has a nonnegligible nonreport rate. As reported by Autor, Katz and Kearney (2008), beginning with the major CPS redesign in 1994, workers whose weekly hours vary are not asked to report usual weekly hours. Therefore, we use hours worked last week to measure labor supply.

We calculate hourly wages as the reported hourly earnings for those paid by the hour and the usual weekly earnings divided by hours worked last week for non-hourly workers. Since earnings are right-censored, we "windsorize" wages by multiplying top-coded earnings observations by 1.5. All earnings are converted to $2000 by the chain-weighted (implicit) price deflator for personal consumption expenditures (PCE).[34]

We identify R&D occupations by using CPS's occupational classification system. Since 1983, the CPS employs the Standard Occupational Classification (SOC) system. In accordance with the Bureau of Labor Statistics, we define as R&D occupations those which are scientific, engineering, and technician occupations (Hecker, 2005). Unless it was an obvious R&D-related occupation, such being the case for scientists (except social scientists) and engineers, we identified workers engaged in R&D by checking the job descriptions in the Dictionary of Occupations (BLS, 2004). We define R&D workers as "increasing scientific knowledge and using it to develop products and production processes" (Hecker, 2005, p. 58). Therefore, we exclude occupations that only have a support function for R&D, such as managers who plan and coordinate R&D. We also exclude social scientists, most health occupations, and (University) teachers.

The above steps were performed for occupations in the 2000 SOC, which is used in the CPS since 2000. For years 1997-1999, occupations in the CPS were classified according to the 1990 Census Occupational Classification System. The comparability of both classifications is somewhat limited, although some occupations are found in both classification systems. For example, both the old 1990 Census Code and the 2000 SOC include the occupation "computer programmers." However, the 2000 SOC contains several computer-related occupations that were not included in the older classification system. Still, workers in these newly classified occupations are likely to have been reported as computer programmers in the past. Moreover, in years 2000-2002, both occupational classification systems were available in the CPS, giving us the opportunity to identify concordances between the two classifications.

According to our definition, 39 out of 503 (7.8 percent) 1990 Census occupations are R&D-related, while 50 out of 449 (11.1 percent) 2000 SOC occupations are R&D occupations.[35] Table A.1 provides an overview of R&D occupations by classification system.

[34] Notice that Acemoglu and Autor (Forthcoming) and Autor, Katz and Kearney (2008) also drop allocated earnings observations and hourly earners above or below certain wage thresholds. As we are not primarily interested in the effects on wages, we keep those observations. However, our results remain qualitatively unchanged when implementing these data adjustments.

[35] In addition to the R&D occupations we have identified, we would have liked to include life scientists, all other (SOC 19-1099); environmental science and protection technicians, including health (SOC 19-4091); forensic science technicians (SOC 19-4092); as well as forest and conservation technicians (SOC 19-4093). Unfortunately, the CPS does not contain these occupations.

Table A.1: R&D occupations in 1990 Census Code and 2000 SOC.

1990 Census Code	Description	2000 SOC	Description
44	Aerospace Engineers	15-1011	Computer and information scientists, research
44	Aerospace Engineers	15-1011	Computer and information scientists, research
45	Metallurgical and Materials Engineers	15-1021	Computer programmers
46	Mining Engineers	15-1031	Computer software engineers, applications
47	Petroleum Engineers	15-1032	Computer software engineers, systems software
48	Chemical Engineers	15-1041	Computer support specialist
49	Nuclear Engineers	15-1051	Computer systems analysts
53	Civil Engineers	15-1081	Network systems and data communications analysts
54	Agricultural Engineers	15-2021	Mathematicians
55	Electrical and Electronic Engineers	15-2031	Operations research analysts
56	Industrial Engineers	15-2090	Miscellaneous mathematical science occupations
57	Mechanical Engineers	17-2011	Aerospace engineers
58	Marine and Naval Architects	17-2021	Agricultural engineers
59	Engineers, n.e.c.	17-2031	Biomedical engineers
63	Surveyors and Mapping Scientists	17-2041	Chemical engineers
64	Computer Systems Analysts and Scientists	17-2051	Civil engineers

1990 Census Code	Description	2000 SOC	Description
65	Operations and Systems Researchers and Analysts	17-2061	Computer hardware engineers
68	Mathematical Scientists, n.e.c.	17-2071	Electrical engineers
69	Physicists and Astronomers	17-2072	Electronics engineers, except computer
73	Chemists, Except Biochemists	17-2081	Environmental engineers
74	Atmospheric and Space Scientists	17-2111	Health and safety engineers, except mining safety engineers and inspectors
75	Geologists and Geodesists	17-2112	Industrial engineers
76	Physical Scientists, n.e.c.	17-2121	Marine engineers and naval architects
77	Agricultural and Food Scientists	17-2131	Materials engineers
78	Biological and Life Scientists	17-2141	Mechanical engineers
79	Forestry and Conservation Scientists	17-2151	Mining and geological engineers, including mining safety engineers
83	Medical Scientists	17-2161	Nuclear engineer
185	Designers	17-2171	Petroleum engineers
213	Electrical and electronic technicians	17-2199	Engineers, all other
214	Industrial engineering technicians	19-1010	Agricultural and food scientists
215	Mechanical engineering technicians	19-1013	Soil and plant scientists
216	Engineering technicians, n.e.c.	19-1021	Biochemists and biophysicists
218	Surveying and mapping technicians	19-1022	Microbiologists
223	Biological technicians	19-1023	Zoologists and wildlife biologists
224	Chemical technicians	19-1029	Biological scientists, all other
225	Science technicians, n.e.c.	19-1031	Conservation scientists
229	Computer programmers	19-1042	Medical scientists, except epidemiologists
233	Tool programmers, numerical control	19-2012	Astronomers and physicists
235	Technicians, n.e.c.	19-2021	Atmospheric and space scientists

1990 Census Code	Description	2000 SOC	Description
		19-2031	Chemists
		19-2041	Environmental scientists and specialists, including health
		19-2042	Geoscientists, except hydrologists and geographers
		19-2099	Physical scientists, all other
		19-4011	Agricultural and food science technicians
		19-4021	Biological technicians
		19-4031	Chemical technicians
		19-4041	Geological and petroleum technicians
		19-4051	Nuclear technician
		19-4099	Life, physical, and social science technicians, all other
		27-1021	Commercial and industrial designers

A.6 Summary Statistics and Further Robustness

Table A.2: Descriptive statistics.

	Mean	**Std. Dev.**	**Min**	**Max**
Company employment R&D	4.339	5.216	0.115	36.113
Company employment total	75.406	81.269	5.608	456.439
Company employment R&D share	5.281	1.703	1.205	10.070
Hourly wage R&D	3.136	4.073	0.577	30.020
Federal non-R&D procurement high-tech	1.500	2.659	0.003	17.708
Federal non-R&D procurement all other	2.077	2.742	0.033	25.894
High-tech share	32.957	19.624	1.520	84.563
GDP	207.531	247.729	15.178	1,576.801
Population	5.793	6.355	0.489	36.962
GDP per capita	34,726	6,639	21,736	59,399

Notes: This table presents summary statistics on our main variables for U.S. states during the period from 1997 to 2009. The total number of state-year observations is 650. Company employment R&D is the number of weekly hours worked in R&D occupations. Company employment total is measured as the number of weekly hours worked in all occupations. Dividing weekly hours of R&D workers by total weekly hours gives the company R&D employment share. Hourly wage R&D is the state-level sum of per-hour wages earned by workers in R&D occupations. The company employment variables, as well as the within-state population, are reported in millions. Hourly wage is measured in millions of constant (2000) dollars. We use CPS sampling weights for all calculations. Federal non-R&D procurement in high-tech industries, federal non-R&D procurement in all other industries, and the GDP are measured in billions of constant (2000) dollars. High-tech share expresses federal non-R&D procurement in high-tech industries as a share of total federal non-R&D procurement. Company employment R&D share and high-tech share are measured in percent. GDP per capita is reported in absolute numbers.

Table A.3: Pairwise correlation coefficients.

	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)
1) Company employment R&D	1									
2) Company employment total	0.966	1								
3) Company employment R&D share	0.612	0.385	1							
4) Hourly wage R&D	0.995	0.952	0.635	1						
5) Federal non-R&D procurement high-tech	0.753	0.743	0.411	0.768	1					
6) Federal non-R&D procurement all other	0.691	0.744	0.191	0.702	0.784	1				
7) High-tech share	0.424	0.354	0.426	0.433	0.702	0.117	1			
8) GDP	0.960	0.986	0.407	0.955	0.768	0.771	0.363			
9) Population	0.954	0.997	0.357	0.941	0.752	0.764	0.345	0.985	1	
10) GDP per capita	0.203	0.124	0.346	0.252	0.231	0.179	0.169	0.267	0.096	1

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

Table A.4: Robustness checks: R&D employment share.

Dependent Variable: R&D Employment Share (log)	(1) Base-line	(2) State Trend	(3) With Deob	(4) Original NAICS	(5) Industry Structure	(6) Full-Time Only	(7) Without Large	(8) High-Tech Ratio
High-Tech Share (log, t-1)	0.031***	0.021**	0.029***	0.009**	0.021**	0.024***	0.033***	
	(0.010)	(0.010)	(0.009)	(0.004)	(0.009)	(0.008)	(0.009)	
High-Tech Ratio (log, t-1)								0.021***
								(0.007)
GDP Per Capita (log)	-0.188*	-0.157	-0.184	-0.177	-0.013	-0.173*	-0.064	-0.189*
	(0.111)	(0.197)	(0.110)	(0.117)	(0.086)	(0.099)	(0.112)	(0.112)
Hourly Wage R&D (log)	0.716***	0.724***	0.716***	0.714***	0.739***	0.763***	0.717***	0.715***
	(0.023)	(0.035)	(0.023)	(0.025)	(0.026)	(0.020)	(0.023)	(0.023)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	646	648	650	546	650
R-squared (overall)	0.411	0.006	0.411	0.412	0.825	0.391	0.489	0.411
R-squared (within state)	0.755	0.793	0.755	0.756	0.779	0.803	0.756	0.754
F-statistic	215.165		220.103	162.512	198.288	370.240	269.99	194.171

Notes: This table uses the share of hours in R&D occupations in total hours as the dependent variable. The data to construct the outcome variable are obtained from May/ORG (see Section 4.2). Column (1) presents estimates analogous to those underlying Column (1) in Table 1. Columns (2)-(8) correspond to Columns (1)-(7) in Table 2. Robust standard errors (clustered by state) in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

Table A.5: Technological intensity of government demand and private R&D: IV estimates with twice-lagged instrument.

	(1) 2SLS First Stage	(2) 2SLS Second Stage	(3) LIML First Stage	(4) LIML Second Stage
Coincidence Gov-House (t-2)	0.093*		0.093*	
	(0.050)		(0.050)	
High-Tech Share (log, t-1)		0.026		0.027
		(0.082)		(0.073)
GDP Per Capita (log)	-0.028	-0.048	-0.028	-0.048
	(0.452)	(0.088)	(0.452)	(0.088)
Total Hours Worked (log)	-0.706	0.425***	-0.706	0.425***
	(0.594)	(0.097)	(0.594)	(0.093)
Hourly Wage R&D (log)	- 0.024	0.761***	- 0.024	0.761***
	(0.134)	(0.028)	(0.131)	(0.134)
Time Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	650	650	650	650
F-statistic (excluded instrument)	3.480		3.480	
R-squared (within state)	0.043	0.180	0.044	0.188
F-statistic	1.420	264.622	1.420	264.754
Durbin-Wu-Hausman test p-value		0.993		0.993

Notes: Results from a 2SLS (Columns (1) and (2)) and LIML (Columns (3) and (4)) estimation of the effect of the technological composition of government procurement on private R&D employment. The first-stage results are presented in the odd columns, while the even columns contain the second-stage results. 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 one period behind the potentially endogenous regressor 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. If Huber-White robust standard errors are used instead of clustered errors, the instrument is significant at the 1 percent level and the F-statistic of the excluded instrument is equal to 8.890. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

Figure A.1: Technological intensity of government demand and state-House coincidence of majority parties (by state, 1996-2009).