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Technological Intensity of Government Demand and Innovation

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Abstract

Governments purchase everything from airplanes to zucchini. This paper investigates whether the technological intensity of government demand affects corporate R&D activities. In a quality-ladder model of endogenous growth, we show that an increase in the share of government purchases in high-tech industries increases the rewards for innovation, and stimulates private-sector R&D at the aggregate level. We test this prediction using administrative data on federal procurement performed in US states. Both panel fixed effects and instrumental variable estimations provide results in line with the model. Our findings bring public procurement within the realm of the innovation policy debate.

JEL Classification: E62, H57, O31, O33, O38.
Keywords: Government demand, technological change, endogenous growth, innovation policy.

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1 Introduction

Nowadays, there is intense discussion among researchers and policymakers on whether public procurement can be used as an innovation policy tool (for overviews, see Edler and Georghiou, 2007; OECD, 2011). For instance, some major initiatives have been launched at the European level to encourage public authorities to focus their procurement spending on innovative products and services (EU, 2010). It is argued that such an increase in the size of innovative procurement markets can 'fill half of the EU-US R&D investment gap' (EU, 2011, p. 3). Several European Member States already set aside part of their procurement budget for purchasing innovative solutions from the private sector (for example, Belgium, United Kingdom, the Netherlands), or—such as Germany—plan to do so in the near future (BMWi, 2012).

The idea that demand can affect innovation is not new. John Stuart Mill pointed out the link between market opportunities and innovation: 'The labor of Watt in contriving the steam-engine was as essential a part of production as that of the mechanics who build or the engineers who work the instrument; and was undergone, no less than theirs, in the prospect of a remuneration from the produce' (Mill, 1848, p. 41). On the one hand, sales play important role in financing R&D. On the other hand, the size of the (expected) market encourages private R&D and the commercialization of new ideas (for instance, Gilfillan, 1935; Schumpeter, 1942).

The first comprehensive empirical evidence for the role of demand in innovation, which led to the so-called the demand-pull hypothesis, was provided by Schmookler (1966). Using US data, he showed that patents tend to lag behind real output. From this observation it was inferred that inventive activities are driven by profit motives. Similarly, Griliches (1957) provides evidence that technology adoption depends on market size. Moser (2005) analyzes innovation data from catalogs of two 19th century World Fairs and finds that market size influences both the total number of innovations and their distribution across industries. Acemoglu and Linn (2004) and Rosenberg (1969) suggest that demand 'steers' firms to address certain problems. Also, endogenous-growth theory acknowledges the importance of profit incentives and market size for innovation (Aghion and Howitt, 1992; Romer, 1990; Young, 1998).

Yet, most of the experience concerning the influence of *government* demand on innovation stems from US defense and space programs, often in so-called 'big science initiatives.' The argument is that the US government guaranteed a market for products such as semiconductors, large passenger jets, the Internet, and the GPS and thereby induced private-sector R&D investment on a large scale (for instance, Cohen and Noll, 1991; Mowery, 2008; Nelson, 1982; Ruttan, 2006). Edquist and Hommen (2000) report several cases of public procurement creating the initial market for a number of products and services in Europe. This case-study evidence is complemented by econometric studies at the firm level that point toward a positive impact of government purchases on corporate R&D (Draca, 2012; Lichtenberg, 1987, 1988) and firms' sales with new products (Aschhoff and Sofka, 2009).

Notably absent in the existing literature, however, is a discussion how the types of products and services purchased by the government, and especially their technological content, affect firms' innovative behavior. This lack of research reporting is surprising for a number of reasons. On the one hand, there is evidence that public purchases are unevenly distributed across industries (Marron, 2003; Nekarda and Ramey, 2010; Ramey and Shapiro, 1998). At the same time, Dalpé, DeBresson and Xiaoping (1992), Geroski (1990), and Mazzucato (2011) indicate that the government has often been a main (and early) customer of technology-intensive products, while Hart (1998) argues that these products bear the greatest potential for the innovation stimulus of procurement. On the other hand, Dalpé, DeBresson and Xiaoping (1992) and Nelson and Langlois (1983) show that the government is a major driver of the development of industries in which it is an important customer. Related to this, Cozzi and Impullitti (2010) provide descriptive evidence that shifts in the composition of US public investment toward Equipment and Software are correlated with the share of corporate R&D in the US GDP. However, although previous research suggests that the technological content of public demand might influence the amount of R&D undertaken in the economy, the existing evidence is rather anecdotal and the underlying mechanisms are largely unclear.

In this paper, we econometrically establish a robust causal link between the technological content of public procurement and private-sector R&D at the aggregate level. We embed our empirical work in a theoretical model thats highlights the mechanism through which the allocation of government purchases across industries affects firms' R&D activities. The model builds upon the traditional literature on endogenous growth with quality-improving innovation (Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b). However, it additionally incorporates the government as a source of demand and explicitly allow government purchases to vary across heterogeneous industries, differing in their technological content. In the theoretical analysis, technology-intensive industries (hereafter high-tech industries) are modeled as industries in which the size of technological improvement (that is, quality jump) is higher than the economy-wide average (Cozzi and Impullitti, 2010).

Our main theoretical result indicates that an increase in the share of public purchases in high-tech industries stimulates private-sector R&D in the whole economy. The underlying mechanism is as follows: In the model, higher quality jumps imply higher markups over marginal cost and, thus, higher innovation rewards. Hence, a shift in government procurement toward high-tech industries translates into larger expected profits for successful innovators in these industries, and firms respond by devoting relatively more resources to R&D. The increase in R&D is permanent, because the marginal productivity in the R&D sector is decreasing, so that relatively more research efforts are needed to innovate after the government increased the technological intensity of its purchases.

Our model is related to that developed in Cozzi and Impullitti (2010), but is novel in several regards. While Cozzi and Impullitti (2010) analyze the effects of the technological content of public procurement on the formation of skills and the skill premium, we focus on its impact on private-sector R&D. Moreover, we follow recent developments in the endogenous-growth literature by explicitly modeling the heterogeneity of industries in their technological intensity (Minniti, Parello and Segerstrom, Forthcoming). This allows us to derive an analytical expression for the relationship between the technological content of government demand and private-sector R&D that provides the basis for our empirical analysis.

We test the predictions of the theoretical model at the level of the US states for the period 1997–2009. In particular, we relate corporate R&D in a state to the share of procurement contracts in high-tech industries allocated by the federal government to that state. Using administrative data provided by the US General Services Administration (GSA), we construct a unique panel dataset that contains all federal procurement prime contracts above the micropurchase threshold, cross-classified by year, state, and type of industry (high-tech versus all others). Our measure of corporate R&D is weekly hours worked in R&D-related occupations in the private sector, obtained from the Current Population Survey.

To assess the relationship between the technological intensity of government purchases and private-sector R&D, we apply both panel fixed effects (FE) and instrumental variable (IV) techniques, the latter accounting for potential biases due to omitted variables and reverse causality. In the IV approach, we use (changes in) the coincidence between a state governor's party and the party holding a majority in the Congress as a source of exogenous variation in the technological content of federal procurement in a state. The instrument is based on the well-established result that local politicians use federal funds to reward their voters and to increase their re-election chances (for instance, Aghion et al., 2009; Cohen, Coval and Malloy, 2011). Attracting procurement contracts in high-tech industries is particularly appealing when seeking to maximize electoral support, because these contracts receive more public attention than procurement in general does (Cohen and Noll, 1991; Dalpé, 1994). However, to divert federal procurement contracts to their states, governors need support from a 'friendly' party that holds the majority in the Congress and, thus, in the committees authorizing and appropriating funds. Since both the timing and the outcome of a Congressional election are exogenous to a specific state, the positive shock to the amount of federal procurement in high-tech industries that a state experiences when its governor's party and the party in control of the Congress become aligned is independent of private-sector R&D investment decisions in that state.

The results of the empirical analysis support the predictions of the theoretical model. The FE estimates indicate an elasticity of private R&D with respect to the share of federal procurement in high-tech industries of approximately 0.026. Put differently, an increase by 1 standard deviation of the high-tech share of procurement in an average state corresponds to an increase of approximately 81 thousand hours weekly worked in R&D in the private sector, which is equivalent to 1800 full-time R&D employees. The results of the FE estimation are robust under a range of specifications. For instance, we include detailed industry controls to account for changes in the within-state industry composition. We also show that the observed pattern is not driven by influential outliers.

The IV approach yields point estimates of the procurement high-tech share of the same magnitude as the FE coefficients, but with far larger standard errors. Taking into account that exogeneity tests provide no evidence for endogeneity of the technological content of procurement and the loss in efficiency that IV estimates typically entail, we conclude that the FE results provide unbiased estimates of the impact of the technological intensity of public procurement on corporate R&D.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical model that illustrates the mechanisms through which the technological content of government purchases influences corporate R&D investment. In Section 3, we discuss the specification and estimation issues in the empirical assessment of the model's implications. In Section 4, we describe the data and the construction of the key variables. Section 5 presents our empirical findings. Section 6 summarizes, and concludes with implications for policy and research.

2 The Model

We develop a quality-ladder model of endogenous growth to link the technological intensity of public procurement to corporate R&D at the aggregate level. We extend earlier models in this tradition (for instance, Aghion and Howitt, 1992; Grossman and Helpman, 1991a,b) by explicitly accounting for both the government as an additional source of demand, and the heterogeneity of industries in terms of their quality jumps (see Cozzi and Impullitti, 2010, for a similar approach). In particular, to overcome the symmetric treatment of industries, we assume the size of the quality jump after a successful innovation to be probabilistic and industry-specific. In line with recent work by Minniti, Parello and Segerstrom (Forthcoming), the realization of each R&D race is drawn independently from a Pareto distribution. Modeling the size of the quality jump to obey a Pareto distribution is supported by the empirical literature on the distribution of patent values (Harhoff, Scherer and Vopel, 2005; Scherer, 1965).[1]

The economy in the model is closed and consists of two sectors: a final goods (or manufacturing) sector and a research sector. 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. 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 over time. Innovation is vertical, improving the quality of a consumption good, which requires the R&D efforts of firms targeted at that particular product. Let the discrete variable $j \in \{0, 1, 2, ...\}$ denote the quality level. An innovation in industry ω leads to a quality jump from j to $j + 1$. The quality increments, denoted by λ, are independent of each other. Thus, an improvement in one industry does not induce an improvement in another industry.

On the consumer side, each household is modeled as a dynastic family whose size grows at an exogenous rate n. Household members' labour supply is inelastic with respect to their wage. The total number of individuals at time $t = 0$ is normalized to unity. Thus, the working population at time t equals $L(t) = e^{nt}$. The inter-temporal preferences of a 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. An 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. Therefore, the utility derived by an individual from consumption equals the sum of the quality-weighted amounts of consumption in all industries $\omega \in [0, 1]$. The preferences in (2) imply that a consumer enjoys 1 unit of good ω that was improved j times as much as $\lambda^j(\omega, t)$ units of the same good as if it had never been improved; $\lambda(\omega, t) > 1$. The logarithmic functional form in (2) is chosen for simplicity and does not affect the main results.

The representative household maximizes lifetime utility (1) subject to the following inter-

[1] These results are very applicable to our model, because we assume that a patent is granted for each successful innovation. In a methodological framework related to ours, Jones (2005) and Kortum (1997) model the realization of new ideas (interpreted as productivity levels or production techniques) to be Pareto-distributed.

temporal 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 a representative household, $w(t)$ is the individual wage rate, $T(t)$ 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, then 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 inter-temporal 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, aggregate demand in industry ω at time t 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 1 unit of the highest-quality product using 1 unit of manufacturing labor, $Y = L_Y$. The best-practice firm has a quality advantage of λ over the next best firm in the industry. The optimal strategy for the quality leader is to set a limit price $p_L(\omega, t)$ that prevents any other firm in the industry from offering its product without losses. The highest price the quality leader can set to capture the entire industry market is their lead over the next best quality follower, implying $p_L(\omega, t) = \lambda(\omega, t)w = \lambda(\omega, t)$. If the quality leader sets a price above the limit price, they will immediately lose all of their customers.

Government procurement is financed by lump-sum tax revenues and is strictly non-negative in all industries at any point in time. The government budget is assumed always to be balanced. Denoting per capita public demand in industry ω at time t by $G(\omega, t)$, the quality leader in each industry earns a profit flow:

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

where $\lambda(\omega,t)\left[\frac{c(t)L(t)}{\lambda(\omega,t)}+\frac{L(t)G(\omega,t)}{\lambda(\omega,t)}\right]$ corresponds to the total demand (sales to private and public customers) in industry ω. The factor $[\lambda(\omega,t)-1]$ is the markup over the marginal cost, with $\lambda(\omega,t)$ being the degree of monopoly power.

There is free entry into R&D, so firms can devote their research effort to developing products in any industry. It is important to notice, however, that firms target their R&D resources only to industries in which they are not the current quality leader; this is so that they do not cannibalize their current monopoly rents (Arrow, 1962). Labor is the only input used in R&D, and it can be freely allocated between manufacturing and research, implying that all workers earn the same wage $w=1$. The aim of each firm's R&D efforts is superior quality and to monopolize the market by achieving a patent of infinite patent length. All firms have access to the same R&D technology. In industry ω at time t, a firm employing $l_i(\omega,t)$ units of labor in R&D 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 exogenously given industry-wide difficulty of conducting R&D.

The innovation process in (6) is stochastic, with $I_i(\omega,t)dt$ being the instantaneous probability of winning the R&D race and thus becoming the next quality leader. We follow Jones (1995) and Segerstrom (1998) in assuming that the R&D difficulty in an industry grows at a rate proportional to the arrival of innovation ('no scale effect' property):

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

where $I(\omega,t)=\sum_i I_i(\omega,t)$ denotes the industry-wide instantaneous arrival rate of the innovation, $\mu>0$ is an exogenously given parameter that captures the scientific opportunities in the economy, and $X(\omega,0)=X_0$ for all ω.

Once a firm succeeds in finding an innovation, the size of that innovation is drawn from a Pareto distribution with a shape parameter of $1/\kappa$, $\kappa\in(0,1)$, and a scale parameter equal to 1 (Minniti, Parello and Segerstrom, Forthcoming). The probability density function of a Pareto distribution with these properties reads:

$$g(\lambda) = \frac{1}{\kappa}\lambda^{-\frac{1+\kappa}{\kappa}}, \lambda \in [1, \infty). \tag{8}$$

For analytical tractability, we assume that the initial distribution of λ values is given by $g(\lambda)$ at $t = 0$, and it does not change over time as the R&D dynamics start and successfully innovating firms draw new values of λ. Notice further that $X(\omega, t) = X_0$ for all ω implies that $I(\omega, 0) = I_0$. Hence, a symmetric equilibrium path must exist along which $I(\omega, t) = I(t)$ and $X(\omega, t) = X(t)$ for all ω. As is common in the literature on quality-improving innovation and growth, in the further analysis we focus on this symmetric equilibrium.

The government allocates procurement across industries according to the following rule (Cozzi and Impullitti, 2010):

$$G(\omega, t) = \bar{G} + \gamma\varepsilon(\omega, t),\ 0 \le \gamma \le 1, \tag{9}$$

where

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

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

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

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

In (9), $\bar{G}$ denotes the average per capita public procurement, that is, the amount of public demand a quality leader in industry ω will receive if the government spreads its expenditures $G(\omega)$ evenly across industries.[2] The parameter γ determines the technological content of procurement. In particular, γ indicates the portion of government demand in industries with quality jumps above or below the average in the economy. An equal treatment of all industries occurs for $\gamma = 0$. $\gamma > 0$ implies that public purchases in industry ω will be higher (lower) than in the symmetric case if the quality improvement in this industry is greater (smaller) than the average economy-wide quality increment. For simplicity, we assume 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 above (below) the average the quality jump is in this industry.

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

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 the average, cannot be chosen independently (see Appendix A.1). As the distribution of the λ values does not change over time, there is always the same share of industries with quality increments above or below the average. Moreover, to highlight the effects of the technological content of government purchases, we assume that $\bar{G}$ is constant (unless otherwise noted).

Under the assumption of no arbitrage on the stock market, and using (9) to solve for the expected profits earned by a successful innovator (see Appendix A.2), we obtain the following expression for the discounted value of the expected profit flow of a firm winning an R&D race:

$$v^e(\omega, t) = \frac{\frac{\kappa}{1+\kappa} L(t)[c(t) + \bar{G} + \gamma\Gamma]}{r(t) + I(t) - \frac{\dot{x}(t)}{x(t)} - n}, \tag{10}$$

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 (10) 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 (10), the effect of 'creative destruction' is revealed; the more research that occurs in an industry, the shorter, *ceteris paribus*, is the duration of the accruing monopoly profits and the smaller are the incentives to innovate. By subtracting the rate of population growth, n, in the denominator of (10), we also take into account that aggregate consumer markets and, thus, profits earned by a successful innovator increase with a growing population.

Equation (10) 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 (10) is that the profitability of a successful innovation in the economy 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 that the government purchases in industries with relatively high quality jumps, the higher the rewards for successful innovation activities become on average. However, although there is a positive effect of the market size on 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.

The R&D equilibrium condition can be derived from the condition for profit maximization in R&D and (10) as:

$$\frac{x(t)}{A} = \frac{\frac{\kappa}{1+\kappa}\left[c(t) + \bar{G} + \gamma\Gamma\right]}{r(t) + I(t) - \frac{\dot{x}(t)}{x(t)} - n}, \tag{11}$$

while the resource constraint (that is, the labor-market clearing condition) of the economy reads (see Appendix A.3):

$$1 = \frac{c(t) + \bar{G} - \gamma\kappa\Gamma}{1+\kappa} + \frac{I(t)x(t)}{A}. \tag{12}$$

The labor-market equilibrium in (12) holds for all t in and outside the equilibrium, because factor markets clear instantaneously.

Along the balanced-growth path (see Appendix A.4), all endogenous variables develop at a constant (although not necessarily at the same) rate and the research intensity, $I(t)$, is common across industries. Using these results, as well as (6) and (A.12), the amount of labor devoted to R&D in the steady state can be derived as:

$$\left(\frac{L_I}{L}\right)^* = \frac{\kappa n\,(1+\gamma\Gamma)}{n\,(1+\kappa-\mu)+\mu\rho}. \tag{13}$$

Equation (13) reveals the main result of the model; namely, that a positive relationship exists between the technological content of government procurement, measured by γ, and the relative amount of private-sector R&D in the economy.[3] An increase in the share of procurement in industries with above-average quality jumps, γ, instantly raises the expected value of becoming a quality leader. This occurs because higher quality jumps imply higher markups over marginal cost and, thus, higher rewards for successful innovation activities (see (10) and (A.8)). Firms respond by investing more heavily in R&D, and the economy-wide corporate R&D increases. Since the returns to knowledge in the R&D technology in (6) are diminishing, the increase in private R&D leveraged by a shift in the composition of government purchases toward high-tech industries must be permanent to maintain constant rates of technological change and economic growth along the balanced-growth path.[4]

The steady-state level of aggregate corporate R&D is not affected by the absolute amount of per capita government demand expenditures $\bar{G}$. This is because when the government increases

[3] Since economic growth in our model is entirely driven by firms' R&D investment, a positive relationship between γ and the macroeconomic growth rate is trivially established. However, as we are interested in the question of whether government market size affects innovation, we focus on the impact of an increase of γ on private-sector R&D.

[4] It is important to notice, however, 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 (12), it follows that $L_I(t)/L(t) = 1 - \left[c(t) + \bar{G} - \gamma\kappa\Gamma\right]/(1+\kappa)$.

its demand, it takes away resources from the private sector. From (A.13) it follows that, in the equilibrium, procurement reduces private-sector consumption 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 (13) indicates a number of further determinants of the equilibrium share of R&D employment. First, it can easily be shown that the growth in total market size, n, positively affects R&D. Moreover, the larger the average size of innovations is, that is, the greater is κ, and therefore the higher the limit price that a successful innovator can charge, the more is spent, in relative terms, on R&D. Finally, equation (13) 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 (7)),[5] the higher is the equilibrium R&D employment.

3 Empirical Specification and Estimation Issues

The main result of our theoretical analysis in Section 2 is that an increase in the technological content of public procurement, measured as the share of procurement in high-tech industries, increases the economy-wide returns to successful R&D, and, consequently, the incentives to invest in R&D. Ideally, we would like to test the implications of the model in a cross-country setting over time. However, reliable international data on government purchases by industry are not widely available. To the best of our knowledge, only the United States provides high-quality administrative data on federal procurement, cross-classified by year, industry, and place of performance.[6] Using these data, we construct a unique panel dataset that allows us to test our model's predictions at the level of the US states in the period 1997–2009.

The empirical model used to assess the impact of the technological content of government procurement on private R&D is derived from equation (13). Adding other potential determinants of private-sector R&D, state and time fixed effects, and log-transforming, equation (13) yields:

$$\log R\&D\_EMPL_{i,t} = \beta_1 \log HIGH\_TECH\_SHARE_{i,t-1} + \beta_2 X_{i,t} + \xi_i + \nu_t + u_{i,t}, \tag{14}$$

where $R\&D\_EMPL_{i,t}$, measured as the number of weekly hours worked in R&D occupations in

[5] Note that $(\rho - n) > 0$ is needed to ensure the convergence in (1).

[6] For a number of European countries, public procurement data can be obtained from tender information published in the Official Journal of the European Union. However, there only exists a compulsory requirement to publish tenders in this journal for procurements being tendered on a Europe-wide scale. Since the share of Europe-wide tenders greatly differs across Member States, these data are not suitable for cross-country comparisons.

the private sector in state i in year t, is our indicator for corporate R&D. In fact, in the theoretical model (see equation (13)), an increase in the technological content of public procurement causes an increase in the share of resources that private firms allocate to R&D. However, to not impose a specific structure on the error term, $u_{i,t}$, we use the absolute value of state-wide weekly hours worked in R&D occupations in the private sector as our outcome variable. To be consistent with the model, we include the number of hours worked in all private-sector occupations (that is, the denominator in equation (13)) on the RHS of equation (14).[7]

$HIGH\_TECH\_SHARE_{i,t-1}$, defined as federal procurement in high-tech industries as a share of total federal procurement in the private sector in state i at time $t-1$, measures the technological intensity of procurement (γ in equation (9)). The procurement indicator is lagged by one period to account for the fact that contracts might effectively start some time after they have been signed, and also to avoid immediate feedback effects (Draca, 2012).

The vector $X_{i,t}$ contains a set of state-level control variables. For instance, the theoretical model suggests that the size of the total market (that is, private and public demand) affects corporate R&D. To proxy total market size, we use three alternative indicators: the level of the GDP, the population, and the GDP per capita (Moser, 2005; Sokoloff, 1988). Additionally, we include the state-wide hourly earnings of R&D workers to rule out the possibility that any positive correlation between the high-tech intensity of procurement and private-sector R&D is an artifact of unobserved wage dynamics. Moreover, adding an earnings control allows us to account for possible confounding effects of government policies affecting the wages of R&D workers (Goolsbee, 1998). The state fixed effects, ξ_i, pick up all kinds of unobserved time-invariant state-specific factors that might influence private-sector R&D. Likewise, the year fixed effects, ν_t capture macroeconomic conditions that equally affect all states. These include factors such as business cycles, changes in (national and global) demand and market conditions, or national policy changes. The year dummies also account for the proportion of technological opportunities (μ in the theoretical model) that is common to all states.

A straightforward way to assess the impact of the technological content of public procurement on private-sector R&D employment is to estimate equation (14) by OLS; because we account for state and time fixed effects, we will refer to this specification as panel fixed-effects (FE) estimation. However, drawing causal inferences on the basis of a simple FE estimation of equation (14) is not foolproof. Specifically, there might be further unobserved factors that are correlated with both private-sector R&D and the technological intensity of government procurement, or that may even jointly determine them. For instance, the amount of federal procurement contracts in high-

[7] In Section 5.2, we show that all our results continue to hold when corporate R&D employment is expressed as a share of total employment.

tech industries might depend on a variety of unobserved time-variant state-specific characteristics (for example, state-specific policy changes and regulations, taxes, subsidies, and so on) that are also systematically related to private-sector R&D. Moreover, reverse causality problems arise if, for example, the government perceives a firm's R&D intensity as a signal of its capabilities to perform a procurement contract (Lichtenberg, 1988). If these confounding factors are not captured by the included control variables—or by the fixed effects—the FE estimates on the impact of the technological content of public procurement on corporate R&D might be biased, while the direction of the bias is not clear. To address these endogeneity concerns, we additionally apply an instrumental variable (IV) approach that uses an exogenous variation in the share of federal procurement in high-tech industries over time, and across states, to identify its effect of private-sector R&D (see Section 5.3 for the details). In both approaches, FE and IV, standard errors are clustered by state to address potential serial correlation problems.[8]

4 Data and Variable Construction

4.1 Technological Intensity of Public Procurement

Our indicator for the technological content of government procurement is constructed as the share of federal non-R&D procurement in high-tech industries in total federal non-R&D procurement in a state and year. We obtain administrative data on US federal procurement from the Federal Procurement Data System—Next Generation (FPDS-NG), provided by the GSA. In the United States, federal agencies are required, by the Federal Acquisition Regulation, to report directly to the FPDS—NG all prime contract actions above the micropurchase threshold of $2,500[9] for companies that are separate legal entities (Goldman, Rocholl and So, 2010). Procurement contracts awarded by non-federal public entities (for example, state and local agencies) are not included in the data.[10]

[8] In case of AR(1) serial correlation and if strict exogeneity holds, the FGLS estimator using the Prais-Winsten transformation is asymptotically more efficient than the FE estimator (Wooldridge, 2002b). However, when T is small and strict exogeneity does not hold, FGLS tends to exacerbate a potential bias in the FE estimator (Wooldridge, 2002a). Hence, we prefer the FE estimator with clustered standard errors.

[9] The threshold was $25,000 before 2004. To check whether this change in the reporting obligations affects our results, we created a dummy variable taking the value of 1 after the new reporting threshold came into force. The inclusion of the dummy variable—entering the regressions separately and interacted with all other variables—leaves the results reported below unaffected. Thus, we decided not to include a control for the change in the reporting threshold in our main specifications.

[10] Procurement by non-federal public agencies (that is, state and local agencies) may constitute a significant part of total public procurement (Audet, 2002). However, non-federal public procurement data are not provided at a level of detail necessary for our analysis. Moreover, there is no evidence of systematic differences in the technological content of purchases by federal and non-federal public agencies (Coggburn, 2003). Finally, federal procurement is more likely to be independent of state-level characteristics than non-federal procurement, thereby

The information contained in the FPDS-NG procurement data covers, *inter alia*, the contract volume (in current USD), award and completion dates, the place of performance, whether or not a contract is primarily for R&D, Federal Product and Service Code (PSC), and, since 2001, the NAICS-classified industry to which a contract can be assigned. The FPDS-NG database contains more than 32 million contract actions between 1978 and 2009.[11]

We only use federal non-R&D procurement contracts to construct the indicator for the technological content of procurement, because we are interested in the effect of demand created by the government on the R&D decisions of private companies. Federal R&D procurement, instead, essentially means that firms conduct R&D by the order of the government (David, Hall and Toole, 2000; GSA, 2005). Moreover, R&D procurement is typically idiosyncratic and the results of federally funded research are not always applicable to the private market (Kanz, 1993; Lichtenberg, 1989, 1990). For these reasons, R&D procurement is less suited to capturing the market-size effect of public demand on private R&D.

To assign procurement contracts to high-tech and all other industries, respectively, we use the NAICS information available in the FPDS-NG data. According to the Federal Acquisition Regulation, the NAICS codes best describe the principal nature of the product or service being acquired (GSA, 2005, p. 19.1-3). As mentioned above, the FPDS-NG database contains information on the PSC and NAICS codes to which each procurement contract can be assigned. However, while PSC information is available for the entire observation period, NAICS codes are not fully available for contracts prior to 2001. To assign procurement to NAICS-classified industries in cases where NAICS codes were originally not reported, and, on that basis, to obtain a consistent time series also for the years before 2001, we developed a PSC-NAICS concordance based on contract data from 2001 to 2009 for which both classifications are consistently provided. If more than one NAICS code corresponds to a PSC, each of the respective NAICS industries receives a share of the contract's gross value that equals its frequency of occurrence.

We use the gross value of procurement contracts, that is, the number of dollars initially obligated by an action. Deobligations are not subtracted because it seems reasonable to assume that they were not foreseeable at the date of the contract signature, and, thus, are not factored in by firms in their R&D decisions. Contract values are converted from current into constant USD using the Government Consumption Expenditures and Gross Investment Price Index, with base year 2000, as a deflator. The price-index data are provided by the Bureau of Economic Analysis (BEA).

reducing the problem of endogeneity discussed in Section 3.

[11] Although the US federal procurement data have been used before (for instance, Draca, 2012; Lichtenberg, 1988), this is the first study that does not focus on a specific sub-sample of the data but considers all administrative procurement records.

Finally, to identify high-tech industries, we apply the definition of the Bureau of Labor Statistics (BLS) (Hecker, 2005).[12] Table A.1 provides an overview of the NAICS-classified high-tech industries. All remaining private sector industries are classified as non-high-tech. Since our analysis focuses on private sector industries only, we exclude federal procurement in the public sector (NAICS 92).

Geographically, federal procurement is assigned to the state in which a contract is performed. We restrict our analysis to the 50 US states; federal procurement contracts performed outside the United States and in the District of Columbia are excluded.[13] Moreover, procurement contracts are assigned to the year of the contract award. Our analysis covers the period 1997–2009 because the NAICS classification applied to distinguish between high-tech and all other industries was introduced in 1997.

4.2 Private-Sector R&D

To measure corporate R&D by state and year, we use data from the Current Population Survey May and Outgoing Rotation Group samples (May/ORG CPS). The CPS contains comprehensive information on various individual and labor-market characteristics, and is representative of the civilian non-institutional population at the US state level (BLS, 2011; Bowler and Morisi, 2006). We construct our measure of corporate R&D as the state-level sum of hours worked in the CPS sample reference week (that is, the week before the survey) in R&D occupations in the private sector. Following Autor, Katz and Kearney (2008) and Acemoglu and Autor (Forthcoming), we restrict our sample to workers aged 16 to 64 who participate in the labor force on a full-time or part-time basis, excluding self-employed persons. If workers have two or more jobs in the sample reference week, we classify them in the job at which they worked the greatest number of hours (Autor, Katz and Kearney, 2008).

[12] 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 5 (Hecker, 2005). An alternative classification of high-tech industries, based on R&D-expenditures, is provided by the BEA in its R&D Satellite Account (Fraumeni and Okubo, 2005). However, due to a mistake in the classification methodology, a large part of R&D before 2004 was erroneously attributed to the wholesale trade industry sector. In reality, this R&D was mostly undertaken 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).

[13] We also exclude two individual contracts that clearly appear as outliers. One of these contracts was awarded in Illinois in 2006, with a contract value of more than $68 billion, which is about 16 times the yearly average value of *all* contracts awarded in that state between 1997 and 2009. The other outlier contract appeared in Pennsylvania, also in 2006, being worth more than $55 billion. This is approximately 8 times the yearly average of all contracts awarded in Pennsylvania in our period of observation. However, keeping both contracts in our sample leaves all results unaffected. Results are available on request,

Prior to 2000, occupations in the May/ORG CPS samples were classified according to the 1990 Census Occupational Classification System (COCS), while since 2000 the Standard Occupational Classification (SOC) is used. However, in the years 2000–2002, both occupational classification systems are reported in the May/ORG CPS. To obtain a consistent time series, we use this overlap to develop a concordance between the two systems, translating the 1990 COCS into the 2000 SOC system. On that basis, we identify R&D occupations according to the job descriptions of detailed occupations in the BLS *Dictionary of Occupations* (BLS, 2004).[14] Table A.2 provides an overview of R&D occupations used in the empirical analysis. To ensure representativeness, we use CPS sampling weights for all calculations.[15]

4.3 Control Variables

Population data stem from BEA's mid-year estimates. Data on the GDP—deflated by the GDP deflator with base year 2000—are also provided by the BEA. Hourly wages of R&D workers are calculated as the state-level sum of earnings of all wage and salary workers aged 16 to 64 in the private sector. For workers paid by the hour, hourly wages are directly reported in the May/ORG CPS. For non-hourly workers, the usual weekly earnings in the May/ORG CPS are divided by hours worked in the survey reference week. Top-coded earnings observations are multiplied by 1.5 (Acemoglu and Autor, Forthcoming; Autor, Katz and Kearney, 2008). Wages are converted into constant dollars, for the year 2000, by applying the chain-weighted (implicit) price deflator for personal consumption expenditures (PCE). Finally, total hours worked in a state is measured as the state-level sum of weekly hours worked by wage and salary workers, aged 16 to 64, in all private-sector occupations, as reported in the May/ORG CPS.

5 Empirical Results

This section reports the results of our empirical investigation. In Section 5.1, we provide a graphical impression of the relationship between the technological content of federal procurement and

[14] Our classification of R&D occupations is closely related to the definition of technology-oriented workers provided by the BLS (Hecker, 2005). However, we exclude occupations that only have a supporting function for R&D (for example, managers who plan and coordinate R&D), social scientists, most health occupations, and (university) teachers.

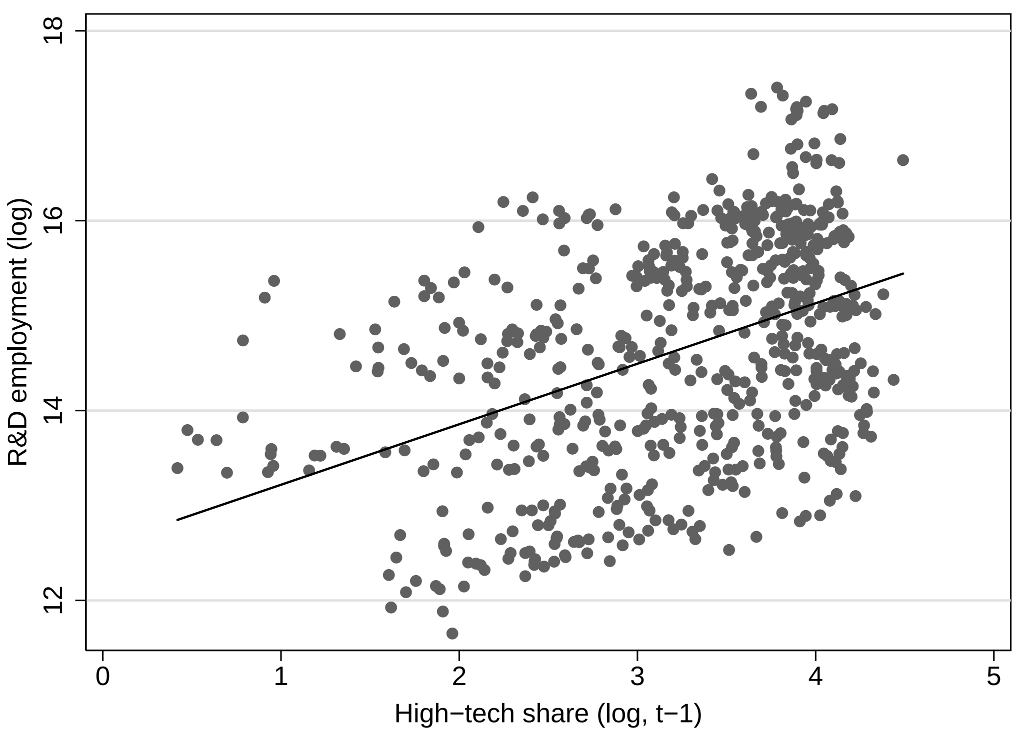
[15] It is important to note that our analysis is unlikely to suffer from a measurement error resulting from the fact that information in the May/ORG CPS is geo-coded at the place of residence of the surveyed households, while information in the FPDS-NG is geo-coded at the location of the establishment performing the contract. The selection of sample areas in the CPS is based on Metropolitan Statistical Areas (MSA), and only households in MSAs are surveyed 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.

corporate R&D and perform our baseline regressions. In Section 5.2, we show the results of several robustness checks. For instance, we check whether the observed pattern is robust to including detailed industry controls and changes in the definitions of the variables of main interest. Finally, in Section 5.3, we address potential endogeneity issues by instrumenting for the technological content of public procurement, using changes in political conditions.

5.1 Basic Specifications

Figure 1 plots the share of federal procurement in high-tech industries against private-sector R&D, using a pooled sample of all state-year observations. The slope of the fitted line provides a first indication that a positive association between the two variables exists. The correlation between the technological intensity of procurement and corporate R&D is 0.43, being statistically significant at the 1 percent level.

Figure 1: Technological intensity of government demand and private-sector R&D



Notes: Pooled cross section: 50 US states, 1997–2009. *R&D employment* is measured as the number of hours worked per week in R&D occupations in the private sector. *High-tech share* is the share of federal non-R&D procurement in high-tech industries in total federal non-R&D procurement performed in a state.

Table 1 presents the results of an OLS estimation of equation (14).[16] In Column (1), in addition to accounting for state and year dummies, we include as control variables total hours worked in a state and hourly earnings in R&D occupations. In line with the predictions of the theoretical model, we find a positive and statistically significant relationship between the technological intensity of federal procurement and private-sector R&D. The coefficient estimate indicates an elasticity of private R&D with respect to the share of federal procurement in high-tech industries of 0.027. Put differently, a 1 standard deviation increase in the share of federal procurement in high-tech industries is associated with an increase in corporate R&D of approximately 81 thousand hours, which corresponds to about 1800 full-time R&D workers.[17]

In Columns (2) to (4), we include three alternative control variables to capture the effect of total market size in a state on private-sector R&D: the GDP, population, and the GDP per capita. Since the correlation between total hours worked on the one hand, and the GDP, or population, on the other is close to unity (see Table A.3), total hours worked are excluded from the regressions in Columns (2) and (3) to avoid multicollinearity. Accounting for total market-size effects in Columns (2) to (4) does not change our main result: the coefficient on the high-tech share of federal procurement is virtually identical to that in Column (1) and remains highly significant.

In Column (5), we decompose the procurement high-tech share into federal procurement in high-tech industries and in all other industries to rule out the possibility that our results are simply an artifact of a negative relationship between low- and medium-tech procurement and corporate R&D. This is clearly not the case. The estimated coefficient on federal procurement in high-tech industries is positive and significant; the estimate for procurement in the remaining industries is essentially 0 in magnitude and statistically insignificant. Thus, in accordance with the mechanism identified in the model, the positive association between the high-tech share of procurement and corporate R&D is driven by increases in procurement in high-tech industries. In total, the results of the baseline estimations in Table 1 indicate that the technological content of federal procurement performed in a state and private-sector R&D in that state are positively associated.

[16] Summary statistics and pairwise correlation of the variables are reported in Table A.3.
[17] In our period of analysis, an average full-time R&D employee works 44.42 hours per week.

Table 1: Technological intensity of government demand and private-sector R&D: Baseline results

Dependent Variable: R&D Employment (log)	(1)	(2)	(3)	(4)	(5)
High-Tech Share (log, t-1)	0.027***	0.026***	0.026***	0.027***	
	(0.009)	(0.009)	(0.009)	(0.009)	
Total Hours Worked (log)	0.411***			0.425***	0.410***
	(0.083)			(0.073)	(0.081)
GDP (log)		0.124			
		(0.092)			
Population (log)			0.216		
			(0.131)		
GDP Per Capita (log)				-0.048	
				(0.086)	
Procurement High-Tech (log, t-1)					0.022***
					(0.007)
Procurement All Other (log, t-1)					-0.003
					(0.012)
Hourly Earnings R&D (log)	0.761***	0.788***	0.785***	0.761***	0.764***
	(0.029)	(0.031)	(0.029)	(0.028)	(0.029)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	650	650
R-squared (within state)	0.782	0.771	0.771	0.782	0.782
F-statistic	285.049	207.805	219.190	269.660	242.940

Notes: Results of an OLS estimation of equation (14). The sample consists of 650 observations, covering 50 US states in the period 1997–2009. The dependent variable, *R&D employment*, is measured as the state-level sum of weekly working hours in R&D occupations in the private sector (see Section 4). *High-Tech Share*, indicating the technological intensity of procurement, is defined as the share of federal non-R&D procurement in high-tech industries in total federal non-R&D procurement in a state. *Total Hours Worked* is measured as the state-level sum of weekly hours worked in all occupations in the private sector. *Hourly Earnings R&D* is the state-level sum of per-hour wages of workers in R&D occupations in the private sector. 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

In Table 2, we report the results from several robustness checks, verifying that the baseline findings in Section 5.1 hold under a variety of alternative specifications and for changes in the definitions of the main variables. In Column (1), we add linear time trends for each of the 50 states to eliminate various factors potentially responsible for a spurious correlation between the high-tech share of procurement and corporate R&D. For instance, the above results might simply reflect a general increase of the R&D intensity in a state's economy. In fact, an increasing number of firms in high-tech industries may imply both more potential contractors for the federal high-tech procurement, and more private-sector R&D. However, the results in Column (1) indicate that the positive association between the technological intensity of federal procurement and corporate R&D is robust to the inclusion of state-specific time trends. The estimate remains highly significant, although its magnitude decreases somewhat compared to the baseline in Table 1.[18] In Column (2), we account more specifically for changes of a state's industry structure as a potential source of estimation bias. In particular, we include the GDP data for 53 different industries, obtained from the BEA, as additional control variables. The results in Column (2) show that the positive association between the procurement high-tech share and private-sector R&D is not driven by unobserved sectoral dynamics.

In Columns (3) and (4), we test the robustness of the baseline outcomes with respect to the measurement of procurement. In Column (3), we subtract the deobligations from the gross federal contract values and use these net procurement values to construct our indicator for the technological content of procurement. By doing so, we explicitly account for cancellation or downward adjustment of procurement contracts. In Column (4), we only consider those procurement contracts for which NAICS information was originally available in the FPDS-NG data; that is, we do not apply our PSC-NAICS concordance to assign missing NAICS codes to procurement contracts. Overall, the results are robust to these changes for measuring procurement. In Column (3), the results are virtually identical to those obtained in the baseline specifications in Table 1. In Column (4), the estimated coefficient on the high-tech share of procurement, although remaining highly significant, decreases considerably in size. The latter may be due to the fact that all observations without original NAICS information are dropped in this specification. Thus, for the period 1997–2000, the measure for the high-tech share of federal procurement relies on far fewer observations than the measure based on assigned NAICS codes and thus is, presumably, less precise.

In Column (5), we restrict our sample to full-time R&D employees (that is, workers with more than 35 hours per week) to check whether the baseline results are sensitive to changes in

[18] The state-specific trends are jointly significant.

the measurement of the dependent variable, corporate R&D. The estimated coefficient on the share of federal procurement in high-tech industries is somewhat smaller in magnitude than in the basic specification in Table 1, but it remains statistically significant. This decrease in the coefficient suggests that firms react to an increase in public demand by mainly hiring part-time R&D workers.[19]

[19] In unreported regressions, we provide support for this conjecture. The elasticity of corporate R&D with respect to the procurement high-tech share is about 4 times higher for part-time R&D workers than for full-time R&D employees.

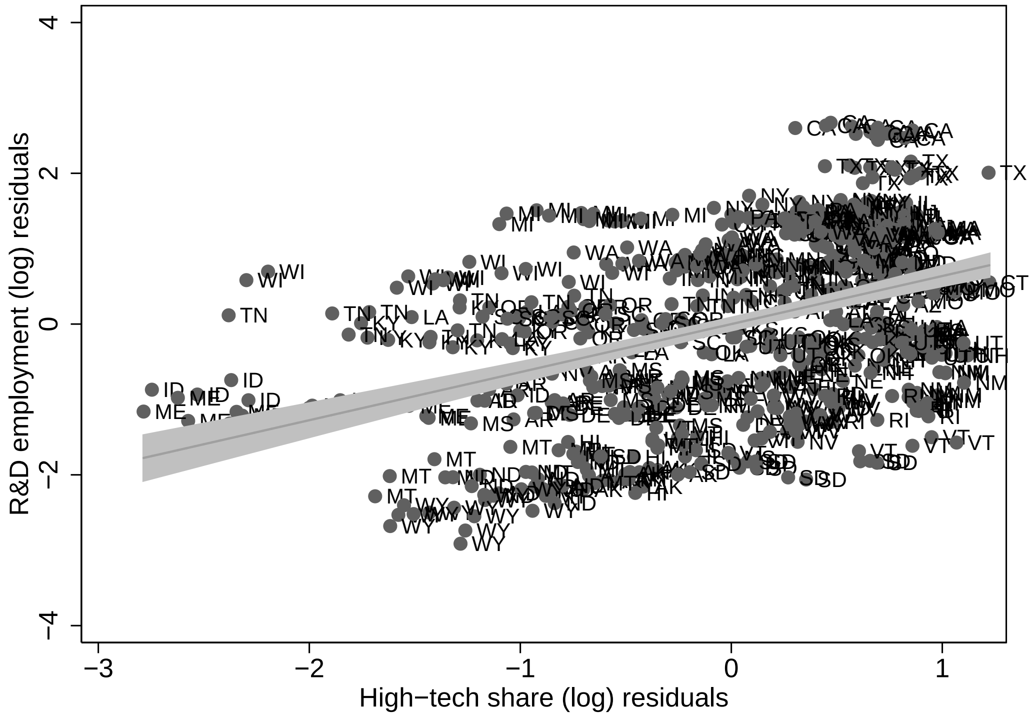
Table 2: Technological intensity of government demand and private-sector R&D: Robustness checks

Dependent Variable: R&D Employment (log)	(1) State Trend	(2) Industry Structure	(3) With Deob	(4) Original NAICS	(5) Full-Time Only
High-Tech Share (log, t-1)	0.020**	0.023***	0.026***	0.010***	0.017**
	(0.010)	(0.008)	(0.008)	(0.003)	(0.006)
Total Hours Worked (log)	0.492***	0.524***	0.411***	0.394***	0.244***
	(0.130)	(0.123)	(0.084)	(0.078)	(0.055)
Hourly Earnings R&D (log)	0.736***	0.753***	0.761***	0.762***	0.836***
	(0.036)	(0.029)	(0.029)	(0.030)	(0.020)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	646	650
R-squared (within state)	0.803	0.804	0.781	0.785	0.856
F-statistic			284.232	276.659	557.982

Notes: Robustness tests of the baseline estimation of equation (14) are presented in Table 1. In Column (1), linear state-specific time trends are included to eliminate sources of spurious correlations between the procurement high-tech share and private-sector R&D. In Column (2), we add the GDP of 53 detailed industries, obtained from the BEA, to control more rigorously for changes in the local industry structure. If possible, we use GDP data at the 3-digit NAICS level. When the BEA does not provide GDP data at this level of detail, we consider the 2-digit classification instead. From this sample, we drop eight industries with missing values due to disclosure limitations. GDP data are deflated by the GDP deflator (base year: 2000). In Column (3), we construct our measure for the high-tech intensity of procurement using the net value of the federal procurement contracts; that is, we subtract deobligations from the initial gross value of contracts. In Column (4), the measure of the high-tech intensity of procurement is based on contracts for which NAICS information was originally available in the FPDS-NG data; we do not apply the PCS-NAICS concordance to assign missing NAICS codes to procurement contracts. In this specification, the number of observations reduces to 646 because the raw data do not contain any of the NAICS codes classified as high-tech in Maine in 1998, in Vermont in 1996 and 1997, and in Wyoming in 1997. In Column (5), we only use information on working hours and wages for full-time employees (that is, wage and salary workers with at least 35 hours per week). Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

We also test whether the observed pattern is driven by influential outliers. Figure 2 plots the residuals of private-sector R&D against the residuals of the share of federal procurement in high-tech industries, after removing state and year fixed effects (see also Acemoglu and Linn, 2004). The figure suggests that there are no specific observations strongly influencing the relationship between corporate R&D and the technological content of federal procurement.

Figure 2: Outlier detection



Notes: Sample: 50 US states, 1997–2009. Residuals are obtained from OLS regressions of the log of private-sector R&D and the log of the share of federal procurement in high-tech industries on state and year dummies. The fitted line maps a log-linear relationship between the R&D residuals and procurement's technological content residuals; the shaded area represents 95 percent confidence bound.

Finally, one may object that our results are simply picking up differences between high-tech and other procurement with respect to procedural aspects associated with awarding federal procurement contracts. For instance, Lichtenberg (1988) provides evidence that competitively awarded procurement contracts elicit substantial firm R&D investment, while procurement contracts not being exposed to competition have no or even a negative effect on corporate R&D. Our results, however, are unlikely to be driven by differences in the competitive nature of high-tech vis-à-vis other procurement contracts. A two-sided t-test reveals that the quantity of competitively awarded procurement, relative to procurement being awarded in non-competitive procedures, does not differ between high-tech and other industries ($p = 0.564$).[20] In fact, the ratio of competitively to

[20] If a procurement contract in the FPDS-NG data was awarded using one of the following procedures, we classify it as competitive: Full and Open Competition; Full and Open Competition after Exclusion of Sources; Follow On

non-competitively awarded procurement is approximately 5:1 for both procurement types.

In sum, the robustness analysis provides added confidence in our baseline results in Table 1. The positive association between the technological content of public procurement and private-sector R&D holds across different model specifications with respect to changes in the definitions of the variables of interest, and is not influenced by high-leverage observations.[21]

5.3 Instrumental Variable Estimation

To be able to draw causal inferences from the results in sections 5.1 and 5.2 about the impact of the technological content of federal procurement on private-sector R&D, changes in the share of government purchases in high-tech industries must be truly exogenous. Although we account for permanent differences between states, and for spurious correlations between federal high-tech procurement and corporate R&D resulting from similar trends, a state's economic strength, and its industry structure, our results might still be subject to omitted-variable bias or reverse causality. Omitted-variable bias might arise if there are unobserved, time-variant factors that are correlated with both federal procurement and corporate R&D, or that even jointly determine them. For instance, there might be (changes in) regulations that affect both private-sector R&D and high-tech procurement. Moreover, reverse causality will confound our estimates if the number of government contracts in high-tech industries that a state receives is influenced by the amount of private-sector R&D undertaken in that state. In fact, there is some evidence that the government perceives a firm's R&D efforts as a signal of its capabilities to perform procurement contracts (Lichtenberg, 1988). Overall, given the large number of potentially confounding factors, both the strength and the direction of the bias are not clear *a priori*.

To assess the unbiased effect of the technological content of federal procurement on corporate R&D, we apply an IV approach that uses an exogenous part of the variation in the technological content of federal procurement across states and over time. Following the literature that uses political conditions to isolate exogenous variation in the distribution of government spending (among others, Aghion et al., 2009; Cohen, Coval and Malloy, 2011; Draca, 2012; Fishback and Kachanovskaya, 2010), our instrument relies on the idea that local politicians can influence the number of federal high-tech procurement contracts performed in their states. We argue that if a

to Competed Action; Competed under Simplified Acquisition Threshold; and Competitive Delivery Order. Accordingly, non-competitive award procedures are: Not Available for Competition; Not Competed; Not Competed under Simplified Acquisition Threshold; and Non-Competitive Delivery Order.

[21] We also performed the above analysis using the share of hours worked in R&D occupations in total weekly hours worked as dependent variable (see Table A.4) and using hours worked in non-R&D occupations as a control variable instead for total hours worked (Table A.5). The results indicate that our findings are robust to these changes.

governor is affiliated with the same party that has a majority in the Congress, the state receives more procurement contracts, particularly in high-tech industries.

Our instrument is based on the well-established result that politicians channel federal procurement to their constituency in order to 'reward' voters for their support and to increase their chances in future elections (Arnold, 1979; Levitt and Snyder, 1997; Shepsle and Weingast, 1981; Stein and Bickers, 1994). As it is generally difficult to deliver a direct monetary payback, politicians attempt to divert specific investments or procurement contracts for their states (for instance, Aghion et al., 2009; Atlas et al., 1995; Cohen, Coval and Malloy, 2011; Levitt and Snyder, 1997; Mayer, 1995).[22] For instance, Hoover and Pecorino (2005) report interventions 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. Newspaper accounts also refer to government procurement as 'pork barrel' spending (Wheeler, 2004).

To channel federal procurement to their own state, a governor needs support from the party in control of the Congress (the House, the Senate, or both), which, according to Article I of the US Constitution, holds the 'power of the purse' and is the main locus of the 'distributive game' (Larcinese, Rizzo and Testa, 2006). The party controlling the Congress is entitled to significant agenda-control power, as it receives a majority in committees authorizing and appropriating funds, and it selects their chairmen (Fenno, 1973). Following Grossman (1994) and Shor (2005), a party can be seen as a coalition of individuals who collectively contribute to the achievement of a common goal and then distribute the benefits to the coalition members. In this line of reasoning, the party that constitutes a majority in the Congress has an incentive to be well-disposed toward governors of the same party, for example, by shaping a procurement solicitation in such a way that the likelihood to be awarded the contract increases for companies in friendly governors' states. These governors, in return, invest their political capital to support (the re-election of) the providing Congressmen. The allocation of federal funds to a governor of the opponent party, in contrast, generates a 'leakage' effect, entailing reduced benefits from procurement spending (Dasgupta, Dhillon and Dutta, 2004).

However, not all types of procurement spending are equally well-suited to satisfy the strategic considerations of politicians. We argue that the gains from which politicians hope to benefit when diverting federal procurement to local high-tech industries are higher than those provided by other types of procurement, because the former yield higher perceived electoral profits. In fact, as voters consider the contribution of politicians to the local economy in their election decisions (Arnold,

[22] Dalpé (1994) argues that gaining electoral support through procurement is considered as particularly promising by policymakers, because procurement decisions are more often publicized than are other types of government spending.

1979), measures to stimulate the local economy receive much public attention and contribute to the politicians' prestige. Promoting high-tech industries appears promising in this respect, because it is regarded by the general public as raising the economy's long-term international competitiveness, which secures or creates jobs. This implies that politicians favor technology-intensive procurement projects to be undertaken in their states (Cohen and Noll, 1991; Dalpé, 1994).

A number of previous studies show that the distribution of federal spending is indeed influenced by political factors. Using Indian data, Dasgupta, Dhillon and Dutta (2004) find that states governed by the party that also controls the federal government receive more grants. Similarly, Martin (2003) suggests that politicians strategically allocate federal spending 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 members of the majority party in the House receive more funds than those represented by members of the minority party do. Alvarez and Saving (1997) generalize this finding to other types of federal funds. Levitt and Snyder (1995) study federal assistance programs and find that a Democratic majority in Congress is associated with higher spending for districts mainly populated by Democratic voters. Goldman, Rocholl and So (2010) show that a firm's likelihood of being awarded a government contract is influenced by its connection to the party in control of the House or the Senate.

Our instrument is constructed as a dichotomous variable that takes the value of 1 in states whose governors are affiliated with the majority party in the Congress and 0 otherwise.[23] We relate the share of federal procurement in high-tech industries in a state at time t to the coincidence between the state governor's party and the majority party in the Congress two years earlier (that is, at time t-2); this is to account for the fact that current federal procurement budgets have normally been appropriated in previous budgetary years (Alvarez and Saving, 1997; Elis, Malhotra and Meredith, 2009; Larcinese, Rizzo and Testa, 2006).[24]

To be a valid instrument, the coincidence between the governor's party and the party holding the majority in the Congress has to meet two conditions. First, the instrument must not itself be related to (past and future) private-sector R&D in the state. One concern is that the outcome of gubernatorial elections is related to the state's economic conditions and, thus, private-sector R&D. However, the outcome of a Congressional election can be considered independent of the characteristics of specific states, and our instrument indicates the party coincidence at the state and federal level. Moreover, the timing of Congress and gubernatorial elections is exogenous. Still,

[23] In our period of analysis, the majority party in the Senate was the same as in the House, given that the Vice President breaks a tied vote in the Senate.

[24] Assuming different time lags between party coincidence and the high-tech share of procurement leads to qualitatively similar results as those reported below. See Table A.6 for results with one-year and three-year lagged instruments.

one may voice the objection that the instrument is invalid because it simply reflects the geographical distribution of firms' lobbying activities, as a consequence of firms expecting a higher impact of their lobbying if they are backed by a governor whose requests are met with great interest in the Congress. However, using data from the Center for Public Integrity on lobbying spending by state in the period 1997–2006,[25] we find no evidence for a relationship between lobbying expenditures and the instrument.[26] This result provides added support for the exogeneity of the instrument.

Second, the instrument has to explain (part of) the supposedly endogenous explanator, that is, it must be relevant. To provide evidence in favor of our instrument's relevance, we separately regress the levels of federal procurement in high-tech industries and all other industries, respectively, on our instrument. The results are reported in Table 3. In Column (1), we show that when a governor's party and the Congress majority party become aligned, the state receives more federal procurement in high-tech industries. At the same time, the amount of procurement in industries other than high-tech is unaffected by the coincidence of the governor's party and the party holding majority in the Congress (Column (2)).

[25] Unfortunately, we were not able to obtain state lobbying data for years after 2006. Moreover, some states do not publish information on their firms' lobbying spending throughout the entire observation period, and five states (Alabama, Arkansas, New Hampshire, New Mexico, and Rhode Island) do not publish any spending data related to lobbying. In total, we use 365 observations.

[26] Results are available on request.

Table 3: Coincidence between the governor's party and the Congress majority and the distribution of federal procurement

	(1) High-Tech Industries	(2) All Other Industries
Coincidence Gov-Congress (t-2)	0.172**	-0.039
	(0.068)	(0.034)
Total Hours Worked (log)	-1.081	0.204
	(0.800)	(0.393)
Hourly Earnings R&D (log)	-0.080	-0.155
	(0.185)	(0.093)
Time fixed effects	Yes	Yes
State fixed effects	Yes	Yes
Observations	650	650
R-squared (within state)	0.608	0.828
F-statistic	36.060	101.066

Notes: Results of OLS regressions with state and year fixed effects (50 US states). The period of analysis is 1996–2008 because *High-Tech Share* itself enters equation (14) with a one-year lag. *Coincidence Gov-Congress* is a binary variable taking the value of 1 if a state governor belongs to the majority party in the Congress and 0 otherwise. *Coincidence Gov-Congress* is measured two years before *High-Tech Share* to account for delays between the appropriation of federal funds and actual procurement spending. Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

The results of the IV estimation of the impact of the technological content of federal procurement on corporate R&D are presented in Table 4. In Columns (1) and (2), we report the results of the first and second stage of a two-stage least squares (2SLS) estimation. Columns (3) and (4) contain the results of Fuller's (1977) version of the Limited Information Maximum Likelihood (LIML) estimator, which is more robust than 2SLS in the presence of potentially weak instruments.[27]

As shown in Column (1), the share of federal procurement in high-tech industries increases by approximately 13 percent when a state governor's party coincides with the party holding majority in the Congress. The F-statistic of the excluded instrument equals 7.2, which indicates that the instrument is indeed a relevant predictor of the technological content of federal procurement.[28]

[27] Weak instruments can lead to inconsistencies in the IV estimates and tend to exacerbate the finite-sample bias from which IV approaches suffer (Bound, Jaeger and Baker, 1995). 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).

[28] In case of a single endogenous regressor, an F-statistic larger than 10 is typically required for inferences based

In Column (2), the IV coefficient on the high-tech share of federal procurement is quantitatively similar to the FE estimate reported in Table 1, but it is no longer significant because the standard error is considerably larger than in the baseline. However, a Durbin-Wu- Hausman χ^2 test for exogeneity provides no sign of endogeneity for the high-tech share of federal procurement ($p = 0.960$), implying that there is no bias from omitted variables or reverse causality in the FE regressions. Taking further into account that the IV estimator is generally less efficient than the FE estimator, we conclude that the FE results in Table 1 provide unbiased estimates for the effect of the technological content of procurement on company R&D.

Finally, there is no indication that the 2SLS results suffer from a weak-instrument problem. On the one hand, the LIML estimation, presented in Columns (3) and (4), delivers similar results as the 2SLS regressions. On the other hand, we construct the Moreira (2003) conditional likelihood ratio 95% confidence interval, which is robust to weak instruments. This confidence interval is reasonably close to those obtained from 2SLS and LIML estimations, respectively, which indicates that the confidence intervals in Table 4 are not biased.'s

on the 2SLS estimator to be considered as reliable (for a discussion, see Staiger and Stock, 1997 and Stock, Wright and Yogo, 2002). 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 18.10.

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

	(1) 2SLS First Stage	(2) 2SLS Second Stage	(3) LIML First Stage	(4) LIML Second Stage
Coincidence Gov-Congress (t-3)	0.129**		0.129**	
	(0.048)		(0.048)	
High-Tech Share (log, t-1)		0.025		0.025
		(0.057)		(0.053)
Total Hours Worked (log)	-0.736	0.410***	-0.736	0.410***
	(0.546)	(0.095)	(0.546)	(0.094)
Hourly Earnings R&D (log)	- 0.028	0.761***	-0.028	0.761***
	(0.130)	(0.029)	(0.130)	(0.029)
Robust 95% Confidence Interval		(-0.067, 0.191)		(-0.067, 0.191)
Time Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	650	650	650	650
F-statistic (excluded instrument)	7.200		7.200	
R-squared (within state)	0.056	0.782	0.056	0.782
F-statistic	1.590	290.030	1.590	290.140
Durbin-Wu-Hausman test p-value		0.960		0.960

Notes: Results from 2SLS and LIML estimation of the effect of the technological content of federal procurement on private-sector R&D. The instrument is a binary variable taking the value of 1 if the state governor belongs to the party holding majority in the Congress and 0 otherwise. The instrument measures the coincidence between the governor's party and the party holding a majority in the Congress two years before procurement contracts are awarded, taking into account delays between the appropriation of federal funds and actual procurement spending. In the LIML estimation, the user-specified constant (alpha) is set to 1. Fuller's (1977) modification of the LIML estimator is used, which ensures that the estimator has finite moments. Robust confidence intervals are calculated using conditional likelihood ratio tests developed by Moreira (2003), in which iid error terms are assumed. Robust standard errors (clustered by state) are in parentheses. Small-sample adjustment of the standard errors has been made. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

6 Conclusions

This paper addresses the question of whether the technological content of government purchases can stimulate private-sector R&D at the aggregate level. We first develop a theoretical model that aids our understanding of the mechanisms through which the composition of public demand may stimulate corporate R&D, and then we test the model's predictions empirically. The model builds upon the traditional literature on endogenous growth with quality-improving innovation but, additionally, it incorporates the government as a source of demand, and it explicitly allows for the government purchases to vary across industries that differ with respect to their technological intensity. The main result of the model is that an increase in the share of government purchases in high-tech industries stimulates corporate R&D activities in the economy. This is because a shift in government procurement toward high-tech industries translates into larger expected profits for successful innovators and higher incentives for firms to invest in R&D.

We test the predictions of the model at the level of the US states for the period 1997–2009. We exploit administrative data provided by the US GSA to construct a unique panel dataset that contains all federal non-R&D procurement prime contracts above the micropurchase threshold, cross-classified by year, state, and type of industry (high-tech versus all other). The technological intensity of procurement is measured as the state-level share of federal non-R&D procurement in high-tech industries in total federal non-R&D procurement. Our indicator for corporate R&D is the number of weekly hours worked in R&D occupations in the private sector. To assess the impact of the technological content of federal procurement on corporate R&D, we apply both FE and IV estimation, the latter accounting for potential endogeneity problems due to omitted variables and reverse causality.

The results of the empirical analysis indicate a positive impact of the technological content of government purchases on corporate R&D, which supports the main insight from the theoretical model. According to the results of the FE estimation, a 1 standard deviation increase in the share of federal procurement in high-tech industries is associated with an increase of approximately 81 thousand weekly working hours in R&D occupations in the private sector; this is equivalent to 1800 full-time R&D workers. The results are robust under a range of different specifications, including additional control variables (for example, linear state-specific time trends, or detailed controls for the local industry structure), and alternative definitions of the dependent and independent variables. The results of the IV approach support the findings from the FE estimation. The IV coefficient is of similar magnitude to the FE result, but the standard errors are considerably larger, reflecting the lower efficiency of the IV estimates as compared to our baseline estimates. Since tests for exogeneity provide no sign of endogeneity of the procurement high-tech share, we conclude that the FE findings provide unbiased estimates of the effect of the technological content of government purchases on private-sector R&D.

Can changes in the technological content of government procurement be used by policymakers to stimulate private R&D? This research question has a substantial degree of policy relevance, since there is an intense discussion among researchers and policymakers on whether public procurement can be utilized as an innovation policy tool (Edler and Georghiou, 2007, and the references cited therein). Our results give rise to the idea that the government, as a customer, indeed plays an important role for the innovative behavior of firms, whether this is actively sought or not. In particular, one consequence to be drawn from our analysis is that policymakers and public administration should not be agnostic about the impact of public purchases 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 yield the additional benefit of an increase in corporate R&D. Hence, not only through procurement contracts dedicated to R&D a government can influence private-sector innovation activities, but also through its allocation of non-R&D procurement across industries.

However, is the responsiveness of private-sector R&D to changes in the technological intensity of government demand sufficient to advise policymakers to co-opt procurement into the innovation policy portfolio? First and foremost, the fundamental aim of public procurement is to ensure that the government can sustain, or even improve, its core functions. The deliberate use of public procurement as an innovation policy tool implies that public demand is distorted, which may come at substantial social costs. On the one hand, there is less transparency in the procurement process when factors other than the (quality-adjusted) price are the main decision criteria. On the other hand, changes in the technological content of government demand, by affecting the relative attractiveness of private-sector R&D investment in different fields, may well guide the direction of search away from socially beneficial technologies, or may even contribute to a lock-in into inferior technologies (Arthur, 1989; Cowan, 1990). No less important is the fact that reasonable policy advice requires a comparison of procurement with other innovation policy tools, such as R&D subsidies, or R&D tax credits (for instance, David, Hall and Toole, 2000; Wilson, 2009). These issues need to be resolved before the suitability of public procurement for furthering the objectives of innovation policy can be definitely judged.

References

Acemoglu, D., and D. H. Autor. Forthcoming. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics.* , ed. O. Ashenfelter and D. E. Card. Amsterdam: Elsevier.

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

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

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

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

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

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

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

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

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

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

Autor, D. H., L. F. Katz, and M. S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, 90: 300–323.

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

BLS. 2004. "Occupational Employment Statistics. Dictionary of Occupations. 2004 Survey." Bureau of Labor Statistics. Washington, DC.

BLS. 2011. "Handbook of Methods." Bureau of Labor Statistics. Washington, DC.

BMWi. 2012. "Innovationskonzept: 'Lust auf Technik'–Neues wagen, Wachstum stärken, Zukunft gestalten." German Federal Ministry of Economics and Technology. Berlin.

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

Bowler, M., and T. L. Morisi. 2006. "Understanding the employment measures from the CPS and CES survey." *Monthly Labor Review*, February: 23–38.

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

Cohen, L., J. Coval, and C. J. Malloy. 2011. "Do Powerful Politicians Cause Corporate Downsizing?" *Journal of Political Economy*, 119: 1015–1060.

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

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

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

Dalpé, R. 1994. "Effects of government procurement on industrial innovation." *Technology in Society*, 16: 65–83.

Dalpé, R., C. DeBresson, and H. Xiaoping. 1992. "The Public Sector as First User of Innovations." *Research Policy*, 21: 251–263.

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

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

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

Draca, M. 2012. "Reagan's Innovation Dividend? Technological Impacts of the 1980s US Defense Build-Up." London School of Economics. Unpublished manuscript.

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

Edquist, C., and L. Hommen. 2000. "Public Technology Procurement and Innovation Theory." In *Public Technology Procurement and Innovation.* , ed. C. Edquist, L. Hommen and L. Tsipouri, 5–70. Norwell, MA: Kluwer Academic Publishers.

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

EU. 2010. *Europe 2020 Flagship Initiative: Innovation Union.* European Union, Brussels.

EU. 2011. *FP7-ICT-2011-12: Pre-Commercial Procurement (PCP) Actions.* European Union, Brussels.

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

Fishback, P. V., and V. Kachanovskaya. 2010. "In Search of the Multiplier for Federal Spending in the States During the Great Depression." *NBER Working Paper No. w16561.*

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

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

Geroski, P. A. 1990. "Procurement Policy as a Tool of Industrial Policy." *International Review of Applied Economics*, 4: 182–198.

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

Goldman, E., J. Rocholl, and J. So. 2010. "Political Connections and the Allocation of Procurement Contracts." Indiana University. Unpublished manuscript.

Goolsbee, A. 1998. "Does Government R&D Policy Mainly Benefit Scientists and Engineers?" *American Economic Review*, 88: 298–302.

Griliches, Z. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, XXV: 501–522.

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

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

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

GSA. 2005. "Federal Acquisition Regulation." General Services Administration. Washington, DC.

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

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

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

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

Jones, C. I. 1995. "R&D- Based Models of Economic Growth." *Journal of Political Economy*, 103: 759–784.

Jones, C. I. 2005. "The Shape of Production Functions and the Direction of Technological Change." *Quarterly Journal of Economics*, 120: 517–549.

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

Kortum, S. 1997. "Research, Patenting, and Technological Change." *Econometrica*, 65: 1389–1419.

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

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

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

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

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

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

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

Marron, D. 2003. "Greener Public Purchasing as an Environmental Policy Instrument." In *The Environmental Performance of Public Procurement: Issues of Policy Coherence.* , ed. OECD, 21–49. Paris: OECD.

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

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

Mazzucato, M. 2011. *The Entrepreneurial State.* London: Demos.

Mill, J. S. 1848. *Principles of Political Economy - Vol. 1.* New York: The Colonial Press.

Minniti, A., C. A. Parello, and P. S. Segerstrom. Forthcoming. “A Schumpetreian growth model with random quality improvements.” *Economic Theory.*

Moreira, M. J. 2003. “A conditional likelihood ratio test for structural models.” *Econometrica*, 71: 1027–1048.

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

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

Nekarda, C. J., and V. A. Ramey. 2010. “Industry Evidence on the Effects of Government Spending.” *NBER Working Paper No. 15754.*

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

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

NSF. 2007. “Revised Industry Classification Better Reflects Structure of Business R&D in the United States.” National Science Foundation. Arlington, VA.

OECD. 2011. *Demand-side Innovation Policies.* OECD Publishing, Paris.

Ramey, V., and M. Shapiro. 1998. “Costly Capital Reallocation and the Effects of Government Spending.” *Carnegie-Rochester Conference Series on Public Policy*, 48: 145–194.

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

Romer, P. M. 1990. “Endogenous Technological Change.” *Journal of Political Economy*, 98: 71–102.

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

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

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

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

Schumpeter, J. A. 1942. *Capitalism, Socialism, and Democracy.* New York: Harper and Brothers.

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

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

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

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

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

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

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

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

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

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

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

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

A 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 rule in (9) 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:

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

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

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 (8), we can express $g(\lambda)$ as $1/\kappa\lambda^{-(1+\kappa)/\kappa}$, which allows us to rewrite (A.1) 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:

$$\int_0^1 G(\omega)d\omega = \bar{G} + \gamma \left\{ \varepsilon_1 \left[-1 + (1-\kappa)^{\frac{1}{\kappa}} \right] + \varepsilon_2 (1-\kappa)^{\frac{1}{\kappa}} \right\}. \tag{A.2}$$

By definition, the RHS of (A.2) 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:

$$\frac{\varepsilon_1}{\varepsilon_2} = \frac{(1-\kappa)^{\frac{1}{\kappa}}}{1-(1-\kappa)^{\frac{1}{\kappa}}}. \tag{A.3}$$

Because the RHS of (A.3) is strictly positive, but smaller than one, it follows that $\varepsilon_1 < \varepsilon_2$.

A.2 Expected Profit Stream of an Industry Leader

Taking into account (5), the expected value of the profit flow 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):

$$\pi^e = \int_1^\infty \frac{\lambda - 1}{\lambda} L\,(c + G) g(\lambda) d\lambda. \tag{A.4}$$

Substituting for the Pareto density function, $g(\lambda)$, and for public demand spending, $G(\omega)$, by using (8) and (9), equation (A.4) becomes:

$$\pi^e = \int_1^\infty \frac{L}{\kappa} \frac{\lambda - 1}{\lambda} \lambda^{-\frac{1+\kappa}{\kappa}} \left(c + \bar{G} + \gamma\varepsilon\right) d\lambda. \tag{A.5}$$

The term $(\lambda - 1)(1/\lambda)\,\lambda^{-(1+\kappa)/\kappa}$ can be simplified to $(\lambda - 1)\,\lambda^{-2-1/\kappa}$. Hence, solving the integral (A.5) yields:

$$\pi^e = \frac{\kappa}{1+\kappa} L \left\{ c + \bar{G} + \gamma \left[\varepsilon_1 \left(-1 + 2\,(1-\kappa)^{\frac{1}{\kappa}} \right) + \varepsilon_2 2\,(1-\kappa)^{\frac{1}{\kappa}} \right] \right\}. \tag{A.6}$$

Using (A.3) in Appendix A.1 to eliminate ε_1, the integral above boils down to:

$$\pi^e = \frac{\kappa}{1+\kappa} L \left[c + \bar{G} + \gamma\varepsilon_2 \left(\frac{1}{1-(1-\kappa)^{\frac{1}{\kappa}}} - 1 \right) \right]. \tag{A.7}$$

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 (A.7) positive. Rearranging (A.7) eventually allows us to write the expected profit stream as:

$$\pi^e = \frac{\kappa}{1+\kappa} L \left(c + \bar{G} + \gamma\Gamma \right), \tag{A.8}$$

where $\Gamma \equiv \varepsilon_2 \left(1 \Big/ \left[1 - (1-\kappa)^{1/\kappa}\right] - 1 \right) > 0$. Because the RHS of (A.8) does not depend on industry-specific variables, π^e is to be interpreted as the average expected profits of an industry leader.

A.3 Labor-Market Equilibrium

Labor demand in manufacturing equals 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 (8), as well as the public demand rule as specified in (9) and (A.3), the total employment necessary to satisfy private and public demand 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 (6) for the R&D input of a firm in industry ω and then aggregating over the continuum of industries $\omega \in [0, 1]$. Noting further that the industry-level innovation rate $I(\omega, t)$ is the same across industries at each point in time, R&D labor becomes:

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

Labor-market clearing implies that $L(t) = L_Y(t) + L_I(t)$ is always fulfilled, which, when slightly rewritten, gives (12).

A.4 Existence and Uniqueness of the Steady State

Here, we solve for the steady state of the 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 I, $\dot{x}/x$, and $\dot{c}/c$ to be constant over time, while the latter implies $r(t) = \rho$. Equations (7), (11), and (12) 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 RHS of (6) and differentiating with respect to time while using (7) yields:

$$I^* = \frac{n}{\mu}. \tag{A.9}$$

According to equation (A.9), the research intensity in the steady-state is completely pinned down by the population growth rate, n, and the difficulty of R&D, 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 (A.9) and that $r = \rho$ holds along the steady state, the R&D equilibrium condition (11) can be written as:

$$\frac{x(t)}{A} = \frac{\frac{\kappa}{1+\kappa}\left[c(t) + \bar{G} + \gamma\Gamma\right]}{\rho + n\left(\frac{1}{\mu} - 1\right)}. \tag{A.10}$$

The resource constraint (12) becomes:

$$1 = \frac{c(t) + \bar{G} - \gamma\kappa\Gamma}{1+\kappa} + \frac{n}{\eta A}x(t). \tag{A.11}$$

Equation (A.10) is an upward sloping line in the (c, x) space while (A.11) 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 (A.10) and (A.11) by applying Cramer's rule uniquely determines the steady-state values of x and c as:

$$x^* = \frac{A\kappa\mu(1 + \gamma\Gamma)}{n(1 + \kappa - \mu) + \mu\rho}, \tag{A.12}$$

$$c^* = \frac{\mu\rho(1 + \kappa + \gamma\kappa\Gamma - \bar{G}) - n[\bar{G}(1 + \kappa - \mu) + (1 + \kappa)(\mu - 1) + \gamma\kappa\mu\Gamma]}{n(1 + \kappa - \mu) + \mu\rho}. \tag{A.13}$$

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):

$$\log u(t) = \int_0^1 \log\left[\frac{c(t)}{\lambda(\omega,t)}\right] d\omega + \int_0^1 j^{\max}(\omega,t) \log\left[\lambda(\omega,t)\right] d\omega, \tag{A.14}$$

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:

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

Following Davidson and Segerstrom (1998), $\int_0^1 j^{\max}(\omega,t)d\omega$ then equals tI. Taking this and (A.9) into account, differentiating (A.14) with respect to time yields the following steady-state growth rate of the per capita utility:[29]

$$\frac{\dot{u}(t)}{u(t)} \equiv g^* = \frac{n}{\mu}\kappa. \tag{A.15}$$

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

[29] Notice that the first integral on the RHS of (A.14) is constant along the balanced-growth path. We further exploit the fact that quality jumps follow a Pareto distribution; thus, using (8), $\int_0^1 \log\left[\lambda(\omega,t)\right] d\omega = \kappa$.

Table A.1: High-tech industries

4-digit NAICS code	Description
3254	Pharmaceutical and medicine manufacturing
3341	Computer and peripheral equipment manufacturing
3342	Communications equipment manufacturing
3344	Semiconductor and other electronic component manufacturing
3345	Navigational, measuring, electro-medical, and control instruments manufacturing
3364	Aerospace product and parts manufacturing
5512	Software publishers
5161	Internet publishing and broadcasting
5179	Other telecommunications
5181	Internet service providers and Web search portals
5182	Data processing, hosting, and related services
5413	Architectural, engineering, and related services
5415	Computer systems design and related services
5417	Scientific research-and-development services

Table A.2: Definition of R&D occupations

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

1990 Census Code	Description	2000 SOC	Description
65	Operations and Systems Researchers and Analysts	17-2051	Civil engineers
68	Mathematical Scientists, n.e.c.	17-2061	Computer hardware engineers
69	Physicists and Astronomers	17-2071	Electrical engineers
73	Chemists, Except Biochemists	17-2072	Electronics engineers, except computer
74	Atmospheric and Space Scientists	17-2081	Environmental engineers
75	Geologists and Geodesists	17-2111	Health and safety engineers, except mining safety engineers and inspectors
76	Physical Scientists, n.e.c.	17-2112	Industrial engineers
77	Agricultural and Food Scientists	17-2121	Marine engineers and naval architects
78	Biological and Life Scientists	17-2131	Materials engineers
79	Forestry and Conservation Scientists	17-2141	Mechanical engineers
83	Medical Scientists	17-2151	Mining and geological engineers, including mining safety engineers
185	Designers	17-2161	Nuclear engineer
213	Electrical and electronic technicians	17-2171	Petroleum engineers
214	Industrial engineering technicians	17-2199	Engineers, all other
215	Mechanical engineering technicians	19-1010	Agricultural and food scientists
216	Engineering technicians, n.e.c.	19-1013	Soil and plant scientists
218	Surveying and mapping technicians	19-1021	Biochemists and biophysicists
223	Biological technicians	19-1022	Microbiologists
224	Chemical technicians	19-1023	Zoologists and wildlife biologists
225	Science technicians, n.e.c.	19-1029	Biological scientists, all other
229	Computer programmers	19-1031	Conservation scientists
233	Tool programmers, numerical control	19-1042	Medical scientists, except epidemiologists
235	Technicians, n.e.c.	19-2012	Astronomers and physicists

1990 Census Code	Description	2000 SOC	Description
		19-2021	Atmospheric and space scientists
		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.5 Summary Statistics and Further Robustness

Table A.3: Descriptive statistics and pairwise correlation of variables

	Descriptive statistics				Pairwise correlation (variables in logs)								
	Mean	**Std. Dev.**	**Min**	**Max**	1)	2)	3)	4)	5)	6)	7)	8)	9)
1) Employment in R&D occupations in the private sector (millions weekly hours)	4.339	5.216	0.115	36.113	1								
2) Employment total in the private sector (millions weekly hours)	75.406	81.269	5.608	456.439	0.966	1							
3) Employment in R&D occupations in the private sector (% in total corporate employment)	5.281	1.703	1.205	10.070	0.612	0.385	1						
4) Hourly earnings in R&D occupations in the private sector (millions $2000)	3.136	4.073	0.577	30.020	0.995	0.952	0.635	1					
5) Federal non-R&D procurement in high-tech industries (billions $2000)	1.500	2.659	0.003	17.708	0.753	0.743	0.411	0.768	1				
6) Federal non-R&D procurement in all other industries (billions $2000)	2.077	2.742	0.033	25.894	0.691	0.744	0.191	0.702	0.784	1			
7) High-tech procurement share (%)	32.957	19.624	1.520	84.563	0.424	0.354	0.426	0.433	0.702	0.117	1		
8) GDP (billions $2000)	207.531	247.729	15.178	1,576.801	0.960	0.986	0.407	0.955	0.768	0.771	0.363	1	
9) Population (millions)	5.793	6.355	0.489	36.962	0.954	0.997	0.357	0.941	0.752	0.764	0.345	0.985	1
10) GDP per capita ($)	34,726	6,639	21,736	59,399	0.203	0.124	0.346	0.252	0.231	0.179	0.169	0.267	0.096

Notes: The number of observations is 650 (50 US states, 1997–2009). *Employment in R&D occupations in the private sector* is the state-level sum of weekly hours worked of part-time and full-time employees in R&D occupations in the private sector. *Employment total in the private sector* is measured as the state-level sum of weekly hours worked in all occupations in the private sector. *Hourly earnings in R&D occupations in the private sector* is the state-level sum of per-hour wages of workers in R&D occupations in the private sector. CPS sampling weights are used when calculating employment and earnings. *High-tech procurement share* is federal non-R&D procurement in high-tech industries as a share of total federal non-R&D procurement in the private sector.

Table A.4: Robustness checks: Using R&D employment share as dependent variable

Dependent Variable: R&D Employment Share (log)	(1) Base- line	(2) State Trend	(3) Industry Structure	(4) With Deob	(5) Original NAICS	(6) Full-Time Only
High-Tech Share (log, t-1)	0.032***	0.022**	0.024**	0.030***	0.010**	0.025***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.004)	(0.008)
Hourly Earnings R&D (log)	0.714***	0.723***	0.741***	0.714***	0.712***	0.764***
	(0.023)	(0.035)	(0.028)	(0.023)	(0.025)	(0.020)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	650	646	650
R-squared (within state)	0.752	0.792	0.793	0.752	0.753	0.801
F-statistic	225.926			227.766	167.389	302.248

Notes: The dependent variable is the share of hours in R&D occupations in total hours in all occupations in the private sector. Column (1) corresponds to Column (1) in Table 1. Columns (2) to (6) correspond to Columns (1) to (5) in Table 2. Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

Table A.5: Robustness checks: Using hours worked in non-R&D occupations as control

Dependent Variable: R&D Employment (log)	(1) Base-line	(2) State Trend	(3) Industry Structure	(4) With Deob	(5) Original NAICS	(6) Full-Time Only
High-Tech Share (log, t-1)	0.026***	0.020*	0.023***	0.025***	0.011***	0.016**
	(0.009)	(0.010)	(0.008)	(0.009)	(0.004)	(0.006)
Hours Worked Non-R&D (log)	0.271***	0.168	0.226*	0.270***	0.259***	0.155***
	(0.077)	(0.123)	(0.122)	(0.077)	(0.071)	(0.050)
Hourly Earnings R&D (log)	0.781***	0.749***	0.768***	0.781***	0.781***	0.850***
	(0.028)	(0.035)	(0.028)	(0.028)	(0.029)	(0.020)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	650	646	650
R-squared (within state)	0.775	0.798	0.797	0.775	0.779	0.853
F-statistic	243.545			243.060	247.980	536.498

Notes: Hours worked in non-R&D related occupations are used instead of total hours worked to control for the labor supply in a state. Column (1) corresponds to Column (1) in Table 1. Columns (2) to (6) correspond to Columns (1) to (5) in Table 2. Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance.

Table A.6: Technological intensity of government demand and private-sector R&D: IV estimates with other lag structure

	(1) One lag First Stage	(2) One lag Second Stage	(3) Three lags First Stage	(4) Three lags Second Stage
Coincidence Gov-Congress (t-2)	0.094*			
	(0.048)			
Coincidence Gov-Congress (t-4)			0.103**	
			(0.039)	
High-Tech Share (log, t-1)		0.032		0.029
		(0.079)		(0.059)
Total Hours Worked (log)	-0.715	0.414***	-0.668	0.412***
	(0.549)	(0.106)	(0.540)	(0.940)
Hourly Earnings R&D (log)	- 0.024	0.761***	-0.048	0.761***
	(0.132)	(0.029)	(0.127)	(0.029)
Robust 95% Confidence Interval		(-0.123, 0.761)		(-0.112, 0.303)
Time Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	650	650	650	650
F-statistic (excluded instrument)	3.820		7.190	
R-squared (within state)	0.044	0.781	0.047	0.782
F-statistic	1.380	276.380	1.610	274.670
Durbin-Wu-Hausman test p-value		0.955		0.974

Notes: Results from 2SLS estimation with the instrument being lagged one period (Columns (1) and (2)) or three periods (Columns (3) and (4)) behind the potentially endogenous regressor. Robust standard errors (clustered by state) are in parentheses. * 10 percent level of significance. ** 5 percent level of significance. *** 1 percent level of significance. If Huber-White robust standard errors are used instead of clustered errors, the excluded instrument is significant at the 1 percent level for both lags and the F-statistic is equal to 9.260 (one lag) and 13.350 (three lags). LIML estimation provides results similar to those presented here.

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