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# Reagan's Innovation Dividend? Technological Impacts of the 1980s US Defense Build-Up

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# Reagan's Innovation Dividend?
## Technological Impacts of the 1980s US Defense Build-Up.

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Abstract

US government spending since World War II has been characterized by large investments in defense related goods, services and R&D. In turn, this means that the Department of Defense (DoD) has had a large role in funding corporate innovation in the US. This paper looks at the impact of military procurement spending on corporate innovation among publicly traded firms for the period 1966-2003. The study utilizes a major database of detailed, historical procurement contracts for all Department of Defense (DoD) prime contracts since 1966. Product-level spending shifts – chiefly centered around the Reagan defense build-up of the 1980s – are used as a source of exogenous variation in firm-level procurement receipts. Estimates indicate that defense procurement has a positive absolute impact on patenting and R&D investment, with an elasticity of approximately 0.07 across both measures of innovation. In terms of magnitudes, the contribution of defense procurement to innovation peaked during the early Reagan build-up, accounting for 11.4% of the total change in patenting intensity and 6.5% for R&D. This compares to a defense sector share in output of around 4%. The later defense cutbacks under Bush Senior and Clinton then curbed the growth in technological intensity by around 2%.

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# I INTRODUCTION

Technological development is central to many debates on economic policy. At the macroeconomic level it underpins economy-wide productivity, so governments invest considerable resources to influence the development of new technologies. Surprisingly, academic research on the determinants of the rate and direction of technical change makes up only a small sub-field of economics. Schmookler's (1966) contribution outlined an agenda for studying technical change that has been followed up heavily in empirical research that has appeared over the last 10-15 years. This work has included research on areas such as medical innovation (Acemoglu and Linn 2004; Finkelstein 2004); the energy sector (Newell, Jaffe and Stavins 1999; Popp 2002); and the impact of low-wage import competition (Bloom, Draca and Van Reenen 2011; Le Large 2010).

However, it is government intervention itself that became a major driver of technical change in the mid-20$^{th}$ century. World War II introduced an era of 'organized innovation' centered on the defense sector (Mowery and Rosenberg 1991). The massive spending in R&D made during WII provided a model for ongoing investment following Vannevar Bush's (1945) policy report, *Science: The Endless Frontier*. As Figure 1 shows, real defense spending has hovered around an average level of around $300 billion per year since WWII with peaks during 'hot war' episodes (Korea, Vietnam, the Gulf Wars) as well as some 'cold war' phases (notably the Reagan-led build-up of the 1980s).

The scale of this spending is significant along a number of dimensions that make it important for the study of innovation. Firstly, defense spending represents a large fraction of government outlays – approximately 15-20% over this period, which is comparable to the budgets for health and social security (OMB 2008). Secondly, this spending has a large role in determining the level of total R&D expenditures. The NSF(2006) estimates that Department of Defense (DoD) funding accounts for around 20% of R&D expenditures in the post-war period, with a peak of around 30% in the late 1950s and early 1960s. Thirdly, the amount of money flowing into high-tech, defense-focused production dwarfs the amount spent on other prominent innovation policy tools. For example, the Federal R&D tax credit costs around $6.5 billion per year while support for basic science through the National Science Foundation figures at $7 billion (NSF 2006). By contrast, around $16 billion per year is spent on military R&D procurement alone along with another $40-50 billion in spending on high-tech products. This makes defense spending – and military procurement in particular – one of the most significant topics for the study of induced innovation in the US economy.

In this paper I assess the impact of military procurement on corporate innovation among listed US firms, who have historically been the main recipients of DoD spending. Specifically, I focus on the impacts of DoD funding on patenting and R&D investment and address two main questions. Firstly, what are the absolute and relative impacts of government defense procurement purchases on corporate patenting and R&D investment? The absolute impact is defined in terms of the elasticity between procurement and the two innovation measures while the relative impact is measured using the benchmark of an equivalent civilian-sector sales shocks. Secondly, given these impacts, what has been the historical magnitude of the defense sector's contribution to corporate innovation through the procurement channel? These questions are important not only because of the size of the procurement budget but also because of debate about the innovative qualities of military spending.

This debate has stressed the special characteristics military spending on a number of counts. On the negative side, it is argued that the effectiveness of defense-oriented production in fostering innovation is likely to be lower than comparable effort directed at the civilian economy. This argument is based on the specialized, mission-focus of defense production. For example, spending on defense R&D has emphasized the "D" component of development rather than "R" element of basic science[2]. Furthermore, defense production is thought to prioritize technical, battlefield performance as a main goal thereby sacrificing efficiency, cost-effectiveness and potential dual-use in the civilian sector. There is also a line of argument regarding the potential 'crowding out' and

[2] Figures from the NSF(2006) indicate that between 1956-2005 work classified as 'Development' accounted for approximately 80% of DoD sponsored R&D while 'Applied' work had a 10-15% share and 'Basic' R&D claimed less than 5%.

displacement effects of federally-funded R&D on private R&D[3]. Finally, defense production is also notorious for its general inefficiency and high costs which have inevitable consequences for productivity.

On the other side of the argument, it is possible that military procurement spending could have a positive impact on innovation. In particular, the high-tech nature of defense procurement sales could push out the 'innovation possibilities frontier' as firms commit their resources to more technically ambitious projects than those demanded by the civilian sector. Cozzi and Impullitti (2010) present a growth model along these lines where the technological composition of government spending matters for innovation. Specifically, they outline a 'demand-pull' channel where a shift towards spending on high-tech goods increases the rewards for innovation and ultimately has an effect on the relative demand for skilled workers[4]. Ruttan (2006) also presents a detailed historical account that tracks the role of military funding in the development of crucial general purpose technologies such as jet passenger aviation, computing, nuclear energy and, most recently, the global positioning system (GPS) network. This historical literature suggests that the contribution of military spending to innovation could be significant but there is limited microeconomic evidence to support this at the level of individual firms.

In this paper I fill this gap and assemble a new firm-level dataset on corporate innovation and defense procurement. This involves the matching of a major historical database of all DoD prime procurement contracts between 1966-2003 to firm-level information on publicly traded firms (from COMPUSTAT) and the NBER US Patent Database. The prime contracts database reports very detailed information including characteristics such as contractor identity, type of product sold, extent of competition, location of work, and

[3] The main crowding out channel here is the input market – federal spending could drive up the price of R&D inputs and lower the real value of spending (Goolsbee 1999). Investment displacement could also occur in cases where (for political or other reasons) the government has funded projects with high rate of private return. Hence the government could be subsidizing projects that private companies would have pursued with their own funds (David, Hall and Toole 2000)

[4] Their calibrated model posits that this government policy channel has an impact on innovation which then explains between 12-15% of observed changes in wage inequality between 1976-2001. This is consistent with earlier evidence by Berman, Bound and Griliches (1994) which found that changes in defense shipments accounted for just over 15% of the increase in non-production worker employment shares in the 1979-87 period.

dates of action among other features. This level of detail greatly facilitates the analysis in terms of both the heterogeneity of spending and the scope for identifying exogenous shifts in firm procurement receipts.

Empirically, the potentially endogenous allocation of funding makes it important to identify such exogenous shifts in the amount of procurement contracts received by companies. The fact that changes in defense spending have historically been driven by strategic considerations assists in tracing out these spending shocks. In general, the procurement receipts of individual firms have been at the mercy of major turning points in defense spending such as the Korean war, Vietnam, the 'Reagan build-up' after the invasion of Afghanistan, the fall of the Berlin Wall, and latterly 9/11[5]. Historically, this means that some firms have been exposed to very sharp increases and decreases in DoD spending. In this paper, I identify exogenous shocks to firm procurement receipts by using the lagged product specialization of firms interacted with the current level of DoD spending in the firm's hypothesized defense 'product market'.

Practically, this approach measures how the DoD's aggregate and product-level spending decisions affect the procurement receipts of individual firms. The central assumption here is that no individual firm can influence the level of DoD demand for goods and services at the product (or indeed aggregate) level. Since my sample covers the period 1966-2003[6] the major 'turning point' in aggregate spending is the 1980s Reagan build-up and subsequent cutbacks in the 1988-2000 period under Bush and Clinton. My analysis therefore pays special attention to the structure of the build-up and the impact of this overall spending policy.

The main results analyze the impact of defense-based sales relative all other non-defense or 'civilian' sales. The OLS estimates indicate the elasticity between defense procurement and both measures of innovation is around 0.07. This implies that a 10%

[5] Changes in military strategy have also shifted the composition of spending. Markusen et al (1990) document how the rise of the 'air power' doctrine shifted the structure of spending circa WWII. This was followed by further changes as ballistic missile technology became strategically important in the 1950s.
[6] Changes in the procurement reporting system after 2003 make it difficult to link up the data from 2004 onwards. See the data section for further notes.

increase in procurement contracts is associated with a 0.7% increase in patenting and company-sponsored R&D. Benchmarking this elasticity against non-defense or 'civilian' sales I find that the estimated effect for patents is twice as high as its civilian benchmark, supporting the idea that defense procurement is a source of demand for high-tech production. Furthermore, this effect also holds for cite-weighted patents indicating that the additional patents are not secured through a quality trade-off. The effects for company-sponsored R&D are broadly in line with the civilian sales benchmark but are much higher when total R&D (including external, defense-funded R&D) is considered. The proposed IV (firm-specific product market shocks) strongly predicts defense procurement and suggests elasticities higher than the OLS estimates for both patents and R&D. The effectiveness of the IV strategy is supported by an analysis of the DoD's product level spending patterns. Specifically, following the main identification assumption outlined above, there is no evidence that firms in concentrated industries are able to tilt DoD spending in their own favor.

Finally, in terms of historical magnitudes, the contribution of defense procurement to innovation peaked during the early Reagan build-up when the defense sector accounted for 11.4% of the total increasing in patenting and 6.5% of the change in R&D. This is a large effect given that the defense share of sales is around 4% for the full corporate sample. These magnitudes are calculated using an industry-level decomposition and it is notable that the majority of the patenting effect is due to within industry changes. This is consistent with the firm-level estimates which indicate that defense procurement spending strongly stimulates patenting. The later cutbacks under Bush Senior and Clinton then served to moderate the growth in technological intensity with the between industry shifts in defense output curbing the total trend increase by 2%.

The remainder of the paper is as follows. The next section offers more background and a discussion of data. The modeling approach is then outlined, followed by the discussion of results and conclusions.

## II BACKGROUND

*Defense Procurement Policy in the US*

In this section I discuss three main features of US defense procurement policy relevant to this study. The first important feature is the scale of procurement spending in this area. Figure 2a plots the total amount of procurement spending by fiscal year from 1966 (expressed in 2003 prices). This data is derived from the historical files used for the empirical work in this paper. Spending peaks at over $220 billion in 1985 and records its lowest levels after Vietnam and in the mid-1990s prior to end of the Clinton administration. This total includes goods and services purchased from all types of contractors, including listed firms, non-listed firms and universities or other research institutes. Based on the calculations from my matched dataset the COMPUSTAT-listed firms are the biggest group of contractors in weighted dollar terms, accounting for 60-70% of all spending per fiscal year.

The second important feature of procurement policy relates to the structure of spending. Contracts in the DoD procurement database are classified according to a 4-digit product code. While there are over 1500 4-digit products across 155 2-digit groups, spending is still heavily concentrated amongst a subset of products. Figure 2b shows the procurement spending shares of the 'Top 10' products at the 2-digit level. The DoD's purchases are massively capital and research intensive with R&D, electronics, ships, and missiles making up a large fraction of spending alongside regular armed forces supplies such as subsistence and fuel. This large share for the Top 10 products is a consistent feature and in later analysis I explore how product shares changed over time.

The final important background feature to DoD policy is the way that procurement spending decisions are taken. Specifically, the DoD purchases its major goods and services on both a competitive and non-competitive basis following a 'life-cycle' model. For example, when the DoD commissions a new weapons system it establishes a 'technical design competition' and solicits detailed, scientific proposals from potential contractors. Firms contest this stage vigorously because winning a design contest assures them of receiving non-competitive follow-on contracts. These follow-on contracts relate to supply and maintenance – since the firm designed the weapon system it has monopoly power over its ongoing provision. The DoD's power in this situation depends on its ability to substitute across weapons system which according to a study by Lichtenberg (1990) is limited[7]. The uncertainty inherent in high-tech defense projects (Peck and Scherer 1962) also means that costs for the DoD often increase after the competitive stage, enhancing the financial position of the locked-in contractor.

Practically, the DoD supports the design competition process by providing on ongoing R&D subsidy for firms so that they are primed to submit detailed technical bids. The effects of the DoD's overall policies are therefore felt by firms both on the demand-side (through procurement policy) and the supply-side (via the R&D subsidy).

*Analytical Framework*

The demand and supply-side effects of DoD policy on firm-level innovation can be understood using the general framework established by Hall, David and Toole (2000) who in turn built on the work of Howe and McFetridge (1976). This framework is illustrated in Figure 3 and contains some obvious components. Over each planning period, firms rank potential innovation projects according to their anticipated yield thereby forming a marginal rate of return (MRR) schedule. The volume of innovation investment here is denoted as R&D. The marginal cost of capital for funding these potential innovation projects is then traced out by the upward sloping MCC schedule. The upward slope of the MCC reflects the increasing cost of funds as the volume of R&D increases. The use of internal firm funds is represented by the flatter area of the MCC with external financing accounting for the upward slope. This very simple framework can be set up as:

$$MRR = f(R, Z_1) \qquad (1)$$

$$MCC = g(R, Z_2) \qquad (2)$$

[7] Lichtenberg (1990) studies data on cost and quantity revisions at the weapon systems level and finds an elasticity of demand of 0.55.

with $R$ standing for R&D expenditures while the $Z_1$ and $Z_2$ vectors capture 'shift variables' that respectively affect the range of project rates of return and the marginal costs of capital. Of course, the optimal R&D occurs where the MRR and MCC are equalized, such that $R^* = h(X, Z)$.

The impact of federal procurement funds can then be nested according to potential shift factors. Hall et al (2000) summarize the $Z_1$ vector for the MRR according to three types of variables: those that affect technological opportunities; those influencing the state of demand for a firm over its lines of business; and finally, institutional factors that affect the appropriation of innovation outputs. By analogy the MCC shifters can be categorized as: firstly technology policy measures that directly target the cost of capital; then macroeconomic conditions that affect internal funds; bond market conditions underpinning the cost of external finance; and finally institutions affecting the availability of finance (i.e. venture capital).

Procurement contracts such as those offered by the DoD are therefore best framed as demand shifters affecting the MRR. As discussed, contracts for R&D services are frequently coupled with valuable, non-competitive follow-on contracts for the final goods designed as part of the research process. The large demand component therefore has the effect of moving the firm MRR schedule outwards. Furthermore, this is not a secular increase in demand but rather one that applies for military-related innovation investments. Following the introductory discussion, the increased emphasis on military-related investments could then have a positive or negative effect on the subsequent innovation outputs of firms (chiefly measured in this paper by patents).

This type of shift in the MRR contrasts with the effects of a direct R&D grant or subsidy. Such policies increase the effective level of internal funds and shift the MCC schedule to the right. It should be noted that there is a clear distinction in DoD policy between procurement and subsidy-based R&D funds. The DoD administers a subsidy policy known as the Independent Research and Development (IR&D) program. This program reimburses firms for the overhead costs incurred as part of non-contract work that is related to military R&D priorities broadly defined. The work is independent in the sense that the research projects involved are selected and initiated by the private company itself. The main objective of the program is to underwrite the efforts of firms in participating in technical design competitions for new projects as outlined in the previous section. The role of the IR&D program was studied in detail by Lichtenberg (1989, 1990).

Given this overall background, this paper mainly treats procurement spending as working through the demand–side of the firm innovation investment decision. While some shifts in the MCC could still be induced by changes in procurement spending policy[8] the majority of procurement effects are likely to fall on the demand-side. However, the presence of the IR&D program complicates the analysis. This program operates in parallel to procurement spending and will have the effect of pushing the MCC outwards.

Systematic data on the IR&D subsidy is not as readily available as the information on procurement but some conclusions about its influence can be drawn. Firstly, the level of the IR&D subsidy is determined by a formula that depends in part on lagged level of procurement spending. As such, the IR&D subsidy will be correlated with firm procurement receipts, albeit with a delay[9]. Secondly, while the IR&D subsidy is valuable to firms it is still small compared to the total value of procurement. For example, Lichtenberg (1990) calculates that allowable costs under the IR&D policy were worth \$3.5billion in 1986 for all contractors which represents only 2.5% of the total procurement budget. The ultimate implication of this correlation between the two policies (that is, the IR&D subsidy and procurement spending) is that the reduced form estimates I

[8] For example, this could occur in cases where the signal of demand from the DoD makes firms more attractive to external sources of finance and in situations where procurement has a 'pump priming' effect that lowers the fixed costs of research.

[9] Lichtenberg (1989,1990) explains that the IR&D subsidy is calculated as the firm's defense sales-to-total sales ratio multiplied by a ceiling amount for allowable R&D costs. This ceiling is determined by lagged R&D expenditures claimed under the program. In turn, this means that firms are able to claw back expenditures that exceed the ceiling in the current period because the overspend has the effect of ratcheting up the ceiling in future periods.

present below will be picking up some degree of shift in the MCC along with the bigger effects of procurement on the MRR.

## III DATA

Three main datasets are used to build the long-run firm panel used in this paper: historical military procurement data from the National Archives and Records Administration (NARA); US Patent and Trademark Office (USPTO) information on patents (as compiled by Hall, Jaffe and Trajtenberg (2002) as part of their NBER project); and company accounts information from COMPUSTAT. The details of each dataset are discussed in turn.

*DoD Procurement Contracts*

The NARA historical files on military procurement contain all prime military contracts awarded by the Department of Defense (DoD) since the 1966 Fiscal Year (FY) and until FY 2003. After 2003, the DoD changed its procurement reporting format. It began to report its procurement information as part of the highly complicated Federal Procurement Data System (FPDS). I plan to include post-2003 data from the FPDS in future iterations of the paper.

The file for each FY contains records on approximately 250,000 different contracts awarded by all DoD sub-agencies for the purchase of goods and services. The records are drawn from a standardized departmental form known as the DD 350 or more eloquently as the “Individual Contracting Action Report”. The minimum reporting threshold for purchases is $10,000 for FY1966 – FY1983 and $25,000 for FY1984 onwards.

The data are exhaustive and summarize many details of each contract, such as: the names and unique identifiers of the awardees; contracting office within the DoD; types of contracts (e.g. competitive versus non-competitive); dates of action; estimated completion date; geographic location of the contractor (city, county and state); weapon system code; and importantly a 4-digit product code (known as the Federal Supply Code (FSC)). While there is some addition and deletion of products the FSC classification is consistently defined from 1966, making it feasible to define a 155 product panel across the 1966-2003 period. The NARA data are probably the most detailed historical data on government procurement available anywhere and were only released in this form in the late 2000s. As a result, research using these military procurement files is still very limited. Some examples of work that uses defense procurement data of this type includes Hines and Guthrie (2011) and Nakamura and Steinsson (2011), along with the Frank Lichtenberg's program of work in the 1980s and early 1990s (summarized in Lichtenberg 1995).

*COMPUSTAT Accounts data*

The COMPUSTAT database provides accounts information on stock-market listed firms, with annual information available from 1950 onwards. I extracted the raw data for all firms from 1966 onwards. In cleaning the sample, all accounting and procurement variables were winsorized at the 1st and 99th percentiles. The final sample reported in the regressions from Table 2 onwards drops all firms with fewer than four years of consecutive data. Furthermore, note that the sample used from Table 2 also conditions on the existence of a 10-year lag for procurement receipts and therefore begins in 1976. This is because the proposed exogenous shocks term is based on 10-year lagged product shares.

In terms of variable definitions, sales (mnemonic SALE) is used as the output measure; the net stock of property, plant and equipment (PPENT) is used for the book value of capital, and the labour input is represented by employees (EMP). The R&D capital stock is defined following the perpetual inventory method (PIM) using a 15% depreciation rate as $G_t = R_t + (1-\delta)G_{t-1}$ where $R_t$ represents the flow of company-sponsored R&D expenditures (mnemonic XRD). Note that this is also the approach taken for the calculation of patent stocks using the USPTO data. The return on assets is define as Net Income (NI) over Current Assets (ACT). The return on sales from data on Sales, Cost of Goods Sold (COGS) and Selling and Administrative Costs (XSGA).

*Measuring R&D*

The measurement of R&D deserves special attention in the context of defense procurement spending. The flow of R&D expenditures reported in COMPUSTAT represents the sum of company-sponsored R&D. This follows the Securities Exchange Commission (SEC) definition of R&D as all costs incurred for research and development into new products, processes or services. Importantly, this SEC definition excludes customer and government sponsored R&D, including the R&D awarded to firms as part of defense procurement contracts[10]. Practically, this means that the COMPUSTAT measure of R&D is not picking up the total amount of R&D activities conducted at a firm. In contrast, the Science Research Statistics (SRS) branch of the NSF conducts a Survey of Industrial Research and Development (SIR&D) which surveys R&D spending according to all types of funds. This survey indicates that the company-sponsored R&D measured in COMPUSTAT represents around 80% of total R&D expenditures, with the remainder made up mainly of government sponsored R&D.

This measurement issue impinges on some of the econometric models estimated in this paper. For example, it means that the implied elasticity between R&D and patenting will be biased upwards for firms that receive large sums of defense procurement business. This is simply because the full sum of the firm's expenditure on R&D inputs is not factored into the company-sponsored measure that is given by COMPUSTAT.

The extent of this bias can be evaluated by comparing the COMPUSTAT measure to other measures of R&D (such as that reported in the SIR&D) that *do include* government-sponsored portion of expenditures. However, in lieu of access to the SIR&D survey I construct a measure of 'Company Plus' R&D that is based on the company-sponsored R&D reported in COMPUSTAT plus the value of the procurement contracts reported in the NARA files that are product coded as R&D. Results using this 'Company

[10] Other items excluded from the COMPUSTAT measure of R&D include: software-related expenses, the cost of extractive activities (ie: prospecting, drilling); routine engineering activities directed at product and process improvements; inventory royalties; and market research or testing (NSF 2006).

Plus' measure of R&D are reported alongside results for the company-sponsored only measure[11].

*Patents Data - General*

The final key dataset for the project is the NBER US Patents Database (Hall et al. 2002). These data were produced as part of an ongoing NBER project that processes raw USPTO patent data and matches patent assignees against the full historical set of stock-market listed firms. The data were first produced in 1999 with an update in 2006 and ongoing work to deepen the dataset.

The NBER Patents data provides the frame for the name matching exercise that I conduct across the three datasets. That is, I used the list of the assignees from the NBER database as the main source of names to be matched to the NARA procurement database. The string-based name-matching is implemented using the usual procedures outlined in work such as Hall et al (2002) and Bloom, Draca and Van Reenen (2010). The presence of Dun and Bradstreet (DNB) business numbers allows me to consolidate establishments in the procurement data to the HQ level before matching. For completeness, I match COMPUSTAT company names directly to the procurement database to capture cases where firms receive defense contracts but do not necessarily patent. Finally, I also manually match assignees and contractors in cases where high-value contracts cannot be matched using the automatic method. Final match rates are high in weighted dollar value terms. Approximately 78% of contracts by weighted value are matched to either the NBER Patents Database or COMPUSTAT. This rises to around 94% for contracts classed under R&D product codes.

*Patents Data – Defining Military Patents*

Given the focus of this paper, it is interesting to ask whether defense procurement has induced more innovation directed at defense-based technologies. To look at this I define a

[11] While defense-sponsored R&D represents a large fraction of all government-sponsored R&D (approximately 50% for the main sample considered in this paper), other federal departments will also contribute funds. Future iterations of this paper will match in data on non-defense Federal procurement contracts in order to complete this picture of total firm R&D expenditures.

measure of ‘military-intensive’ patent classes. This measure is meant to represent patents produced under conditions where clear DoD interests can be inferred. The logic here is that patents falling in these technology classes are more likely to represent specialized military technologies.

These military technology classes are defined following two criteria. Firstly, I filter out all private company patents where the DoD holds some shared property rights. This is derived using the Government Support field within the *USPTO Patent Grant Full Text* files[12]. This field notes cases where a patent was ‘made with Government Support’ such that public agencies can claim some legal rights to the invention. Typically, the Government Support section of the full text files gives the name of the agency concerned (for example, the US Navy) and the procurement contract number. An example of a ‘Government Interest’ declaration in a 1987 Navy-sponsored missile patent by the Hughes Aircraft Company is given in Appendix A.2. As part of this work, I extract all cases of government-supported patents involving DoD agencies.

Secondly, these DoD Government Interest patents are then pooled with the DOD patents created in-house by the Army, Navy and Air Force in order to create a group of military specialized patents. The patents in this pool are then allocated according to their technology class, with these classes ranked according to the proportion of military patents falling within them. The distribution of military patents is highly concentrated with over 45% of patents falling into the top 10% of technology classes by rank. I then classify all patents falling within this top 10% of technology classes as the group of ‘military specialized patents’. As discussed, the rationale for this is based on the fact that these are the technology classes most commonly associated with direct DOD involvement and therefore represent the classes that are closest to the production of pure, military specialized goods.  Finally, patents falling in technology classes outside of this top 10% are then classified as non-military or civilian patents.

[12] The specific version of the files used is that available from the Google Patents bulk download facility located at: http://www.google.com/googlebooks/uspto-patents-grants-text.html.

## IV MODELLING APPROACH

*Basic Econometric Approach*

This paper considers two main technological outcomes of interest: patenting and R&D spending. Theoretically, these two equations can be motivated using a simple framework. First, consider a factor demand for R&D inputs derived from a simple production function $Q = AG^{\delta}K^{1-\lambda}L^{\lambda}$ where Q is firm output, *G* is knowledge capital (measured by R&D) and *K* and *L* are the labor and capital inputs:

$$\ln G = \mu \ln Q - \sigma \ln[p^g / p^x] \qquad (3)$$

where $(p^g / p^x)$ is the relative price ratio between R&D and other types of input. Since patents are then produced by the firm mainly using these R&D inputs we can think of a firm-level patents production function defined as $PAT = BG^{\gamma}$ where *B* is an efficiency parameter. Taking logarithms and substituting in our expression for *G* above, we have:

$$\ln PAT = \ln B + \gamma \left[ \mu \ln Q - \sigma \ln[p^g / p^x] \right] \qquad (4)$$

Empirically, note that the price ratio terms in (3) and (4) are constant across firms and absorbed by time effects. The most important term for the models estimated in this paper is output *Q* (measured by reported firm sales) which enters directly into (3) and indirectly with a coefficient of $\gamma\mu$ into the patents equation defined by (4).

This term is important because the value of defense contracts received by a firm in a given period can be interpreted as a sales term subject to caveats regarding measurement error. This sales-based interpretation of defense contracts provides the basis for the two main reduced form technology equations I estimate in this paper. Firstly, consider a generic firm-level outcome equation as follows:

$$\ln TECH_{ijt} = \alpha_i + \beta_1 \ln D_{ij(t-1)} + \delta' X_{ijt} + sic_j * t + u_{ijt} \qquad (5)$$

where $TECH_{ijt}$ is a measure of innovation (either R&D or patents) observed at the level of firm *i* in industry *j* at time *t*; $\alpha_i$ is the firm fixed effect; $X_{ijt}$ is a vector of explanatory variables; $sic_j*t$ stands for industry-level time trends and $u_{it}$ is the disturbance term. The key variable of interest is $D_{ij(t-1)}$, the amount of defense procurement dollars received by firm *i*, lagged by one-period here to avoid immediate feedback effects.

The most general issue for this type of reduced form is the potential bias on $\beta_1$. The DoD is likely to award contracts to the most innovative and competitive firms in the market for defense-related goods, contributing to an upward bias on $\beta_1$. Furthermore, the DoD also has an interest in acquiring and developing the latest technologies which means it could allocate its $D_{ijt}$ funds according to areas of growing technological opportunity. That is, the DoD's spending could be targeting fields and product classes where *TECH* is already growing for exogenous scientific reasons, again contributing to an upward bias on $\beta_1$. The inclusion of firm fixed effects $\alpha_i$ and industry trends $sic_j*t$ terms are two steps that can be taken to deal with these issues and I discuss this more in the next sub-section.

A second important issue is the interpretation of $\beta_1$, the coefficient on the value of defense procurement contracts. Extending the interpretation of this variable as a form of 'defense sales' we can add a further term to this reduced form as follows:

$$\ln TECH_{ijt} = \alpha_i + \beta_1 \ln D_{ij(t-1)} + \beta_1 \ln C_{ij(t-1)} + \delta' X_{ijt} + sic_j * t + u_{ijt} \qquad (6)$$

where $C_{ijt}$ is the amount of all non-defense or 'civilian' customer sales. Practically, the civilian sales are calculated by subtracting the value of defense procurement contracts reported in the NARA data from total reported sales given by firms in COMPUSTAT. Including civilian sales in this way helps interpretation by giving us a benchmark to judge the value of $\beta_1$. It can be expected that $\beta_2 > \beta_1$ simply due to the size of civilian sales relative to defense sales. That is, a 10% change in civilian sales is necessarily larger than a 10% change in defense sales. However, the comparison we are interested in is the effect of given changes in defense or civilian sales that are of equal size. This is simply a matter of normalizing the elasticities by the defense-civilian sales ratio which allows us to test whether the implied coefficient for $\beta_1$ (calculated as $(D/C)*\hat{\beta}_2$) is different to the estimated $\hat{\beta}_1$[13]. The implied coefficient here gives us the impact that a dollar of defense procurement sales would have on *TECH* if that dollar affected the firm in exactly the same way as any other dollar of civilian sales.

[13] To see this note that we are interested in $\partial \ln TECH / \partial D > \partial \ln TECH / \partial C$. Re-arranging this with respect to the elasticities gives us $\partial \ln TECH / \partial \ln D > (D/C)*[\partial \ln TECH / \partial \ln C]$.

The main difficulty with this approach to interpreting the effects of defense procurement is the measurement error involved in treating procurement as a form of sales. At face-value, the procurement contracts reported in the NARA are indeed the administratively recorded 'sales' of defense goods and services made by a firm to the government. However, the translation of the procurement dollars reported in the NARA data to the language of company accounts is distorted at two points. Firstly, the procurement dollars reported in the contracts data are aggregated according to start-date such that many multi-year projects are recorded up-front[14]. Secondly, the accounting treatment of procurement receipts as they enter into company accounts is very complicated (Lichtenberg 1992; Rogerson 1992, Thomas and Tung 1992).

One key matter identified by Rogerson (1992) is the cost-shifting of overheads. Under certain contract structures firms can shift their overheads on non-defense projects onto the overhead claims made for defense projects. Other accounting issues also include: the treatment of procurement receipts as 'income' rather than revenue[15] ; interactions with non-defense policies such as the R&D tax credit; and accounting for sub-contracts within the NARA prime contracts. However, the main empirical implication here is that we can expect the measurement error to affect account-based variables such as R&D more severely than non-accounting variables such as patents. I return to this issue of measurement error in the discussion of results.

*Analysis of Patents*

Patenting is measured in terms of integer 'counts' of the number of applications made in a given year. This introduces a non-negligible number of zero observations. I deal with this firstly by applying the log '1 plus patents' normalization that is commonly adopted. However, this is an arbitrary truncation. In the interests of robustness a more formal count data model is necessary. This can be specified as:

[14] The NARA data does contain information on the both the start date and end date of contracts. Hence it is possible to allocate the sales from multi-year contracts according to these dates. Future iterations of this paper will conduct this exercise.

[15] For example, a firm can record the initial receipts for (say) a helicopter supply contract at first in income and then only as revenue when the final units are individually priced and delivered to the DoD.

$$P_{ijt} = \exp\left(\alpha_i^P + \beta_1^P \ln D_{ij(t-1)} + \beta_1^P \ln C_{ij(t-1)} + \delta^P X_{ijt} + sic_j^P * t + u_{ijt}^P\right) \qquad (7)$$

where $P_{ijt}$ is the count of the firm *i* at time *t*, with the *P* superscripts denoting this as the patenting version of the general technology equation outlined previously in (6). Since the usual Poisson assumption that the variance and mean are equal is not valid in this context (the 'overdispersion' problem), I adopt a negative binomial specification. This is estimated following the conditional maximum likelihood approach of Hausman, Hall and Griliches (1984).

*Exogenous Shifts in Firm Procurement Receipts*

As discussed, the allocation of procurement funds is likely to follow some endogenous patterns. It is logical that the DoD will award contracts to firms that are already highly innovative – indeed the competitive structure of the procurement process is designed to do this (subject to price considerations). It is also plausible that the DoD may target areas of growing technological opportunity as part of its objective to build the best military equipment possible. To address these endogeniety issues I will take three steps: (i) control for firm-level unobservables with fixed effects; (ii) include a full set of 4-digit industry trends; and (iii) adopt an IV strategy based on exogenous shocks to firm procurement receipts. This section outlines the construction of the exogenous shocks variable.

The detailed product-level information reported in the DoD prime contracts data provides a rich setting for defining identification strategies using a 'shift-share' approach. This approach is based on taking the lagged product specialization of a firm or location and then calculating the current demand based on DoD procurement spending. Intuitively, the premise is that firms have a pre-existing specialization in types of goods purchased by the DoD. As the DoD varies its spending year by year then the size of the potential defense market for the firm changes. If the firm's shares across product groups are defined with a sufficient lag we can limit the influence of situations where firms endogenously enter into new product categories where the DoD is increasing spending. The lagged pattern of specialization is therefore designed to capture the firm's core products for sale to the DoD.

We can express this by first defining the historical product shares (here using a 10-year lag) for a firm:

$$\Phi_{il,(t-10)} = \frac{d_{il,(t-10)}}{\sum d_{il,(t-10)}} \tag{8}$$

where $d_{il,(t-10)}$ represents the amount of procurement dollars received by firm *i* in product category *l* at lagged time period *(t-10)*. This measures the firm or location's degree of specialization across a basket of products. The level of total product demand for firm *i* in the current period can then be calculated as follows:

$$d_{it}^{L} = \sum \Phi_{il,(t-10)} D_{ilt} \tag{9}$$

where $D_{ilt}$ is the sum of all procurement spending by the defense department in product category *l* during current period *t*. The expression in (9) therefore measures how the department's spending patterns affect firm or location *i* based on a predetermined, historical specialization. A key assumption here is that no individual firm can affect the level of demand in product group *l* (e.g. through political lobbying). The efficacy of this assumption can be tested by studying the pattern of spending at the product group level and relating it to group characteristics such as concentration ratios, market power or political clout.

*Calculating Magnitudes*

The modeling approach presented up until now has focused on estimating the firm-level relationship between procurement and innovation outcomes. Aggregate magnitudes can be calculated using these firm-level parameters and nesting them alongside a decomposition of changes in technology. Defense procurement spending will have effects on both the 'between' firm or industry distribution of technology as well as the level of technology 'within' an industry or continuing firm. Berman, Bound and Griliches (1994) put forward an industry-level decomposition of skilled labor that incorporated the effects of defense-induced demand. Adapting this approach, a basic industry decomposition for changes in technology can be defined as follows:

$$\Delta Tech_t = \sum_j \Delta q_j \overline{Tech_j} + \sum_j \Delta Tech_j \overline{q}_j \qquad (10)$$

where $q_j = \left( Q_j \middle/ \sum Q_j \right)$ is the share of industry *j* output in total output across industries and $Tech_j = \left( TECH_j / Q_j \right)$ is a measure of technological intensity per industry (ie: patents or R&D per dollar of sales). The $\Delta Tech_t$ term represents the aggregate change in technological intensity summed across all industries. The first term on the right-hand side of (9) then represents the change in overall technology that is explained by between industry shifts in output shares with industry-level technological intensity held constant. The second term measures the within industry shift in technological intensity while holding output shares fixed. Berman et al (1994) modify this basic decomposition to account for three sectors operating within industries: domestic civilian production, defense-related production, and production for import and export. For current purposes I will focus only on the split between the civilian and defense production sectors. Assuming that technological outputs by sector are proportional to the sectoral share of industry output we can re-write the between component as:

$$\sum_j \Delta q_j \overline{Tech_j} = \sum_j \Delta q_j^D \overline{Tech_j} + \sum_j \Delta q_j^C \overline{Tech_j} \qquad (11)$$

where the *D* and *C* superscripts represent the defense and civilian production sectors within an industry. The within component can then be written in a similar fashion as:

$$\sum_j \Delta Tech_j \overline{q}_j = \sum_j \Delta Tech_j \overline{q}_j^D + \sum_j \Delta Tech_j \overline{q}_j^C \qquad (12)$$

with the same convention on the *D* and *C* superscripts. Note that the assumption that technological outputs are proportional to sectoral industry shares links back to the firm-level technology model outlined in equation (6). This earlier model tests whether the within-firm production of technology is more responsive to defense procurement sales compared to non-defense or civilian sales. If technology is indeed more responsive to defense procurement sales then this means the defense sector contribution measured in equation (11) is actually a lower-bound. In such a case, the defense sector contribution to industry-level technology will be larger than its proportional share in industry output.

## IV RESULTS

*Basic Patenting and R&D Results*

Table 1 summarizes the sample constructed from the matching of the NARA, COMPUSTAT and NBER Patents data. For this table, the data is divided into three types of firms: those who never receive any defense procurement funding; the firms who receive funding in some of the years that they are observed but not all; and the firms that receive funding in all of the years that they are observed. In this paper my primary focus is on the latter section of the sample whose characteristics are reported in column (3). This is to done to capture the effects of intensive margin changes and avoid the problems of censoring that occur at zero values of defense sales. The main sample based on column (3) is therefore a selected sample, albeit representative of the majority of defense expenditures in weighted dollar terms. Of course, it is possible to estimate selection models and estimate bounds to evaluate the influence of this sampling choice.

The data in Table 1 indicates that the firms selling goods and services to the DoD in all observed years are very research intensive, with more than three times as many patents as the firms in column (2), although mean R&D expenditures are comparable if we take account of the difference in sales. On average, defense procurement is equal to 4.9% of total firm sales for column (3) sample and this group of firms is responsible for 84% of all DOD procurement purchases from listed firms. Clearly then, the fact that the 'All Years' sample represents such a large share of DoD purchases mitigates the sampling choice since most of the government procurement spending is encompassed by this definition.

Table 2 then presents the basic results on patenting for variations of equations (3) and (4). Column (1) provides a basic specification with SIC4 fixed effects, resulting in a high coefficients of 0.320 and 0.409 for patenting and company-sponsored R&D respectively. This is unsurprising insofar that we expect DoD purchases to be associated with the largest and most innovative firms *ex ante*. The second column in Panels (A) and (B) includes firm fixed effects to account for the unobservable characteristics of firms. This reduces the coefficient on defense procurement by 75% compared to the initial specification. The third column then includes SIC4*year industry trends as an additional control since both patenting and R&D have experienced strong upward trends in recent decades, with some industries increasing at higher rates than others[16]. This results in a coefficient of around 0.07 for both outcomes. Applying this as an elasticity suggests that a 10% increase in procurement contracts is associated with a 0.7% increase in patenting and company-sponsored R&D. This is suggestive of a very high elasticity of around 1 between the defense-induced increase in R&D and the similar induced increase in patenting. To this end, column(4) of Panel B reports the result of a regression using the 'company-plus' measure of R&D outlined in section III. This measure directly includes defense-funded R&D in addition to company-sponsored R&D and the result in column (4) indicates an elasticity of around 0.70. This is closer in line with the observed elasticity between patents and R&D for this sample, which is approximately 0.67 (0.023).

Finally, note here also that the negative binomial model for patents (column (4)) yields a similar estimate to the OLS model which adopts the log '1 plus patents' normalization. Only around 15% of observations in this sample record a zero count for patents. As in Hausman, Hall and Griliches' (1984) study of patents, R&D and count data methods it is therefore not surprising that the two estimates are similar.

Table 3 tackles the question of whether this elasticity is large in terms of its economic context. This table estimates different versions of equation (6) which includes civilian sales as an additional term alongside defense procurement. As expected, the coefficient on civilian sales is much higher than that for defense sales. For example, the civilian sales coefficient for patenting is 0.45 in the basic column (2) specification compared to 0.060 for defense procurement. Following the discussion in section IV, this is down to the fact that a 10% change in civilian sales is necessarily larger than a 10% increase in defense

[16] See Hall, Jaffee and Trajtenberg (2001) for full details. For example, Computer and Communication related patents increase from around a 5% share in 1975 to over 15% by the mid-1990s. The share for the Mechanical category fell from over 25% to around 17-18% in the same time period.

procurement. The implied $\beta_1$ reported in this table therefore normalizes the civilian coefficient by the ratio of defense procurement to civilian sales. This provides a benchmark for the effect that defense procurement would have if it were just another increment of sales.

The results indicate that the estimated $\beta_1$ is significantly higher than the benchmark for patenting but not for company-sponsored R&D. Specifically, the estimated $\beta_1$ for patenting is twice as high as the implied benchmark and the point estimate for company-sponsored R&D in panel (B), column(3) is over 15% higher than its relevant benchmark, although not significant. In contrast, the elasticity is much higher than the benchmark when the 'company-plus' measure of R&D is used (panel(B), column (4)). Importantly, this difference in results across the R&D measures gives us some indication of how defense procurement is impacting overall company R&D. Specifically, the results show that the *additional* effect of defense procurement comes into play once defense-funded R&D is measured. However, the fact that defense procurement and civilian sales have similar effects on the private, company-sponsored portion of R&D (panel (B), column (3)) counts as evidence against any 'crowding out' of private R&D expenditures by defense R&D. Finally, as in Table 2, the implied elasticity between 'company-plus' R&D and patenting is approximately 0.54, which is in range of the baseline estimate for this sample of 0.65.

To summarise, the results in Table 3 do strongly suggest that defense procurement sales are a source of demand for high-tech goods. The magnitude of this relationship for patenting indicates that this could be a very strong effect, with twice as many patents produced for a given dollar of defense sales compared to the same dollar of civilian sales. The effect on R&D is also twice as high as the civilian benchmark, although only when considering the expanded 'company-plus' measure of R&D. However, it is notable that (contrary to the 'crowding out' hypothesis) a dollar of defense sales is associated with at least as much company-sponsored R&D as a dollar of civilian sales.

*Type and Quality of Patents*

Table 4 takes the analysis of patents further by studying the quality and type of patents. Following the discussion in section III, the total number of patents produced by firm *i* in year *t* is divided into two groups: military specialized or 'defense' patents (ie: those patents belonging to technology classes that are the main focus of direct DoD invention); and non-military or 'civilian' patents (in practice, all patents belonging to technology classes outside of the military specialized set). Panel (A) of Table 4 provides evidence on the effect of sales on different types of patents, with the first column repeating the result for total patents initially reported in Table 3. There are two points to note about panel (A). Firstly, there is some suggestive evidence that military patents are more affected by defense sales than civilian sales. The civilian sales coefficient is lower in column (2) relative to column (3) and the defense sales coefficient in column(2) is further away from its implied benchmark value as a result. Secondly, it is clear that defense sales are strongly associated with both types of patents. This indicates that defense procurement has an effect on innovation outside of a limited set of military patent classes. Specifically, this means that increases in defense sales do not strongly favor military technologies over civilian technologies but rather there is a general effect on innovation across technology classes.

Table 4 also addresses the issue of patent quality by examining backward citations. This represents a measure of scientific importance based on the number of citations made to a patent subsequent to its granting. The issue of quality is important insofar that the higher patenting due to defense sales could be a function of firms moving down their investment curves for innovation, that is, producing a higher quantity but lower quality of innovations in terms of scientific importance. Table 4 tests this first by using a count of citations as the dependent variable in columns (4). This leads to a coefficient of 0.067 for the specification with industry trends which is comparable to the coefficient of 0.059 for patenting in Table 3. This estimate for citations is still well above the implied benchmark of 0.032 but there is less precision compared to the Table 2 result. The next two columns then distinguish between cite-weighted military and civilian patents. Again, the effect of defense sales is well above the implied benchmark for both measures, although the effect is stronger for military patents. The overall conclusion from Table 4 then is that defense procurement stimulates patenting significantly above the civilian benchmark with a minimal trade-off in terms of cite-weighted quality.

*Impact of Exogenous Shocks*

The results presented so far have dealt with endogeniety issues firstly by including firm fixed effects (to deal with unobservables) and then by including a full set of 4-digit industry time trends (to capture trends in patenting). Both of these measures reduced the coefficient on defense sales across specifications. Table 5 reports further evidence based on the exogenous shocks variable outlined in section III. Panels (A) and (B) cover patents and the 'company-plus' measure of R&D respectively, with columns (1) and (4) repeating the analogous OLS models from earlier tables.

Column (2) reports the first stage reduced form equation for patents. This indicates that the product market shocks variable is a positive and highly significant predictor of firm procurement receipts. This carries through to the reduced form regression of product market shocks directly on patents reported in column (2). These results are consolidated in the IV estimate reported in column (3). Interestingly, the estimates here are higher than those for the equivalent OLS, within-groups specification (column(1)). A similar pattern of results holds for R&D in panel (B). Given the probable influence of the measurement error in defense sales (exacerbated by within groups estimation) the fact that the IV is estimate is higher than the OLS can be expected to some extent. Furthermore, the IV estimates in column (4) and (8) are still lower than the basic OLS estimates without fixed effects presented in Table 2. Finally, the IV estimates could conceivably be picking up the effects of spillovers from defense-induced increases in R&D and knowledge capital stocks that are external to the firm. I discuss this in more detail at the end of the next section.

*Validity of IV Strategy*

The validity of the overall IV result depends on the robustness of the identification strategy. One of the key assumptions of this strategy is that individual firms (or indeed groups of firms operating in the same product area) are unable to affect the level of spending chosen by the DoD. Specifically, it would be problematic if large, highly innovative firms were able to influence the pattern of the DoD's spending towards their own industries and product groups. Two pieces of evidence on DoD spending patterns are useful here. Firstly, Figure 4 shows how the share of spending for the Top 10 product groups has changed over time. As discussed, spending is very concentrated on this group of 10 products which unsurprisingly contain the major categories for the production of aircraft, ships, engines and electronics. The share of spending for the top 10 only begins to trend downwards after the end of the Reagan build-up in the late 1980s. Hence, stability in product shares up until this time was followed by a period where spending began to shift *away* from the technologically intensive Top 10 group. This is of course opposite to the expectation that firms in these industries could be influencing DoD spending policy in their own favor.

Table 6 provides a second piece of evidence that reinforces the message from Figure 4. This table is based on a collapsed 2-digit product panel of all DoD procurement spending. The objective here is to test whether spending changes are correlated with the level of market concentration in each product group. The independent variable used is a Herfindahl index, defined as:

$$H_{lt} = \sum_{i=1}^{N} h_{ilt}^2$$

Where $h_{ilt}$ is the market share of a contractor selling goods to the DoD in product group *l*. These shares are calculated for the top 50 contractors in each 2-digit product group. Higher values of the index are associated with more concentrated product groups. The results indicate a negative associated between the Herfindahl index and changes in spending at the 2-digit level. This is consistent with the trend evident in Figure 4, namely that DoD spending has been trending strongly away from the concentrated, technologically-intensive product groups. This supports the assumption that firms in these industries  are unable to affect the level of spending chosen by the DoD in their own favor[17].

Finally, another issue for the identification strategy is the potential role of spillovers. As outlined in Appendix A, the product market shocks variable could affecting firms indirectly via spillover channels as well as directly through increased firm procurement receipts. Put simply, any DoD demand shocks that impact a given firm *i* will affect other firms working in the same technology space as *i*. If these other firms then increase their R&D and patenting firm *i* could benefit following the standard spillovers argument. Hence the spillover provides an extra effect of defense procurement in addition to direct effect of firm receipts.  The fact that the IV estimates are higher than the OLS bears this out. Hence, future iterations of this paper will test for these spillover effects following the approach outlined in Appendix A.1.

*Historical Magnitudes*

The results up until this point have focused on the firm-level relationship between technology and defense procurement sales.  These results can be nested alongside an industry decomposition to understand the historical magnitude of the defense sector's contribution to innovation over different policy phases. Table 7 reports the results of a SIC3 industry decomposition of patenting and R&D intensity for each 4-year Presidential administration. As discussed, this decomposition follows the approach of Berman et al (1994) who studied the impact of trade, the defense build-up and biased technical change on the demand for skilled labor in US manufacturing.  Note that the results in Table 7 are calculated using the full, collapsed COMPUSTAT database rather than just the sub-sample of firms who receive funding from defense contracts at some point. This is in line with the goal of estimating the defense sector's contribution with respect to the whole population of listed, corporate innovators.

[17] As discussed, another issue for this identification strategy is the potential role of spillovers that are correlated with firm-level spending shocks. This issue was outlined in detail in earlier sections and will implemented in future iterations of the paper.

Technological intensity grew strongly over the period being considered. The aggregate R&D share of sales grew from 0.014 in the 1977 to 0.024 in 1988 and 0.036 by 2000. Similarly, the number of patents per dollar of sales grew from approximately 0.036 per ten million dollars of industry sales in 1977 to 0.043 in 1988 and 0.075 in 2000. The first point to note from Table 7 is the overall breakdown of the within and between components behind this growth in R&D and patenting intensity. The first column indicates that between industry shifts account for around 35-45% which is comparable to other studies of this type[18]. Columns (2) and (3) then report the share of the between and within components that is accounted for by the defense sector. For example, 5.5% of the total between share of 43.1% in 1981-1984 is due shifts in the defense sector. In turn, this yields the total defense contribution of 2.4% (column 4). In plain english, this says that the between industry shifts induced by the defense sector accounted for 2.4% of the total rise in patenting intensity in the 1981-1984 period.

The main qualitative message from Table 7 is the big role that the defense sector had in the first half of the Reagan build-up. The defense contribution peaked in the 1981-84 period, accounting for 11.4% of the change in the aggregate patenting intensity and 6.5% for R&D intensity. In the case of patenting, most of the effect (9%) is due to the within component. This is consistent with the findings of the firm-level models which showed that defense procurement stimulated within-firm patenting by more than would be expected from a conventional sales shock. The within industry component for R&D intensity (3.3%) is lower than the analogous figure for patenting and again this is consistent with the firm-level evidence of more limited R&D effects.

The figures for the later post-Cold War periods show the predicted impact of reductions in defense procurement on patenting and R&D intensity. Specifically, since we are dealing with changes over time, these figures show how the reduction in defense spending slowed down the growth in technological intensity. This effect is strongest for the period immediately after the Reagan build-up (1989-1992) where the between

[18] For example, the Berman et al (1994) study of skilled labor shares estimates a total between component of 37% for the 1973-79 period and 30% for 1979-1987.

industry shift away from defense production had a negative contribution of around -2% across both measures of technology. Interestingly, these is a persistent, positive within-industry defense contribution for patenting in the 1989-1996 period. Finally, note that while the cuts to defense procurement slowed down the growth of technology this was offset at the aggregate level by surges of patenting and R&D investment in other parts of the economy[19].

## V CONCLUSION

In this paper I have examined the impact of defense procurement spending on innovation and other related outcomes in a long-run sample of US listed firms. The motivation is straightforward: defense procurement spending is one of the major, direct policy channels through which the government can affect firms. This has been the case since WWII and the sharp increase in defense spending that occurred after 9/11 makes it of continued relevance. The high-tech composition of procurement spending also makes it a significant *de facto* innovation policy, alongside more explicit policies such as R&D tax credits and government support for basic science.

The paper has put forward evidence on two main questions. First is the relative impact of defense procurement sales on firm patenting and R&D expenditure, using civilian sales as the benchmark. The results indicate that the elasticity between defense procurement and both measures of innovation is approximately 0.07. This elasticity is in line with the civilian benchmark for R&D but well above the same benchmark for patenting. Furthermore, the patents stimulated by defense procurement maintain their level of quality measured in terms of citations. Direct evidence on this question has not been available before. It has been often speculated that the narrow, mission-focus of defense spending may limit its potential impact on innovation. On the other hand, the high-tech composition of defense procurement sales was always likely to skew the innovative impact of this spending upwards. The results in this paper strongly support this second view of procurement as a source of demand for high-tech products.

[19] See Kortum and Lerner (1998) and the Congressional Budget Office (2005) for discussions of these trends for patenting and R&D investment respectively.

However, it must be noted that the results currently compare average defense sales against average civilian sales, with no allowance for the composition of civilian spending. The availability of data on non-defense Federal contracts allows me to look at this issue in more detail[20]. Future iterations of this paper will therefore test the efficacy of defense sales against the sales of comparable goods purchased by other Federal departments. This will allow me test whether there is a distinctive effects of defense procurement after controlling for product composition.

The second major question discussed has been the magnitude of the impacts from defense procurement. The basic magnitudes calculated here indicate that defense procurement accounted for 6-11% of the growth in patenting and R&D during the early Reagan-build-up. Cutbacks in spending during the Bush and Clinton administrations then acted as moderating influence, slowing innovation by up to 2%. Finally, it must be noted that this finding on magnitudes should not be considered an endorsement of defense procurement as a primary innovation policy tool. The final ledger entry on procurement impacts needs to take account of cost-effectiveness and directly compare dollar-for-dollar impacts from procurement against policy tools such as R&D tax credits.

[20] The National Archive holds also records for all non-defense Federal procurement contracts from 1979-97. After 1997 these contract records are kept as part of the Federal Procurement Data System (FPDS).

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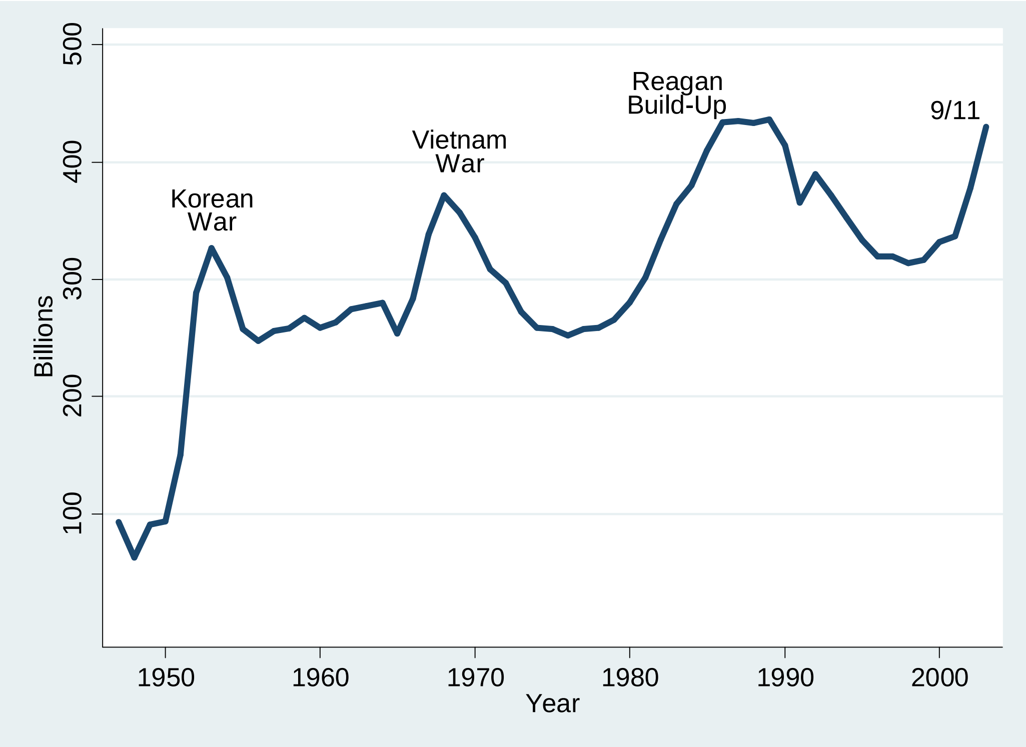
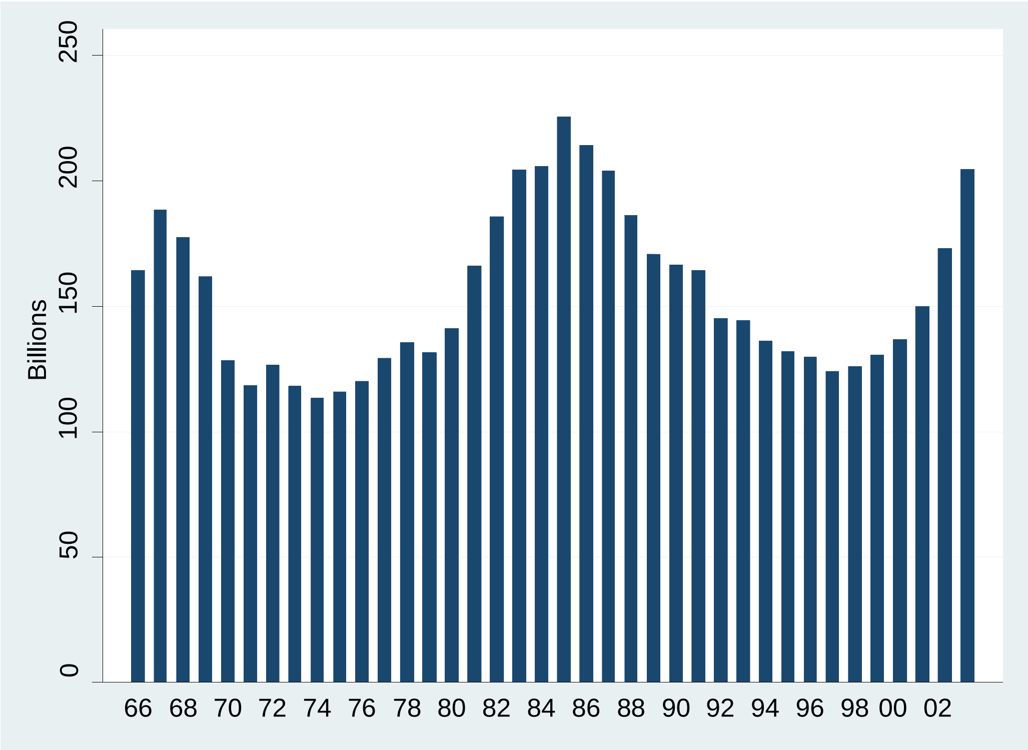
**Figure 1a: Real Defense Spending, 1946-2003.**



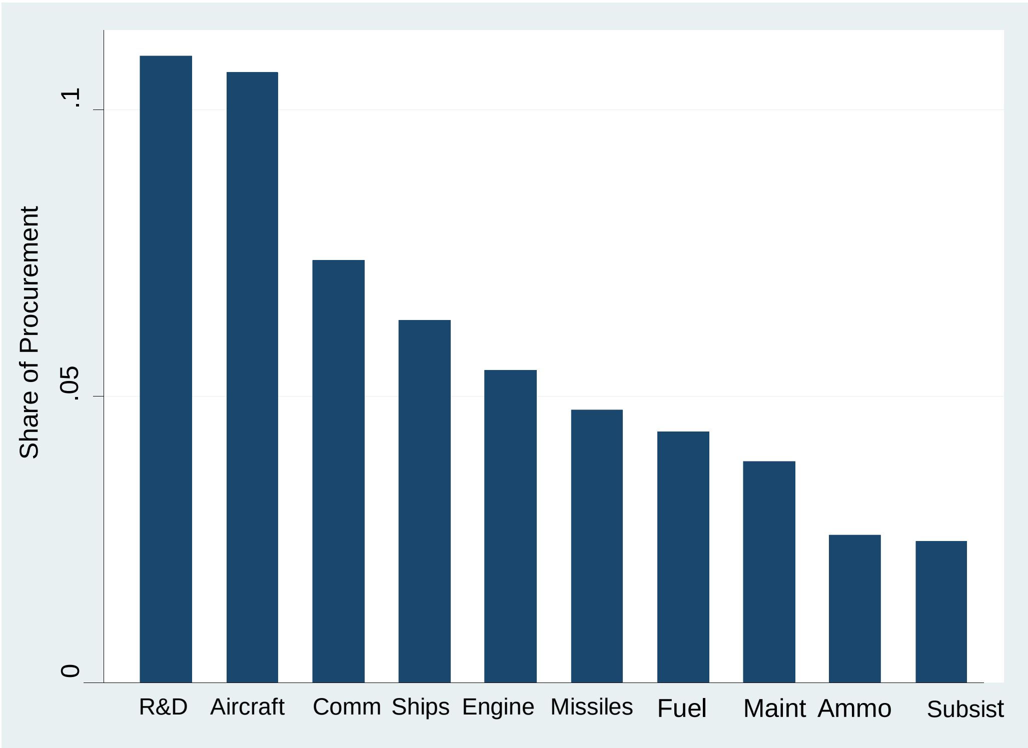

Notes: Source is Table 6 (Composition of Outlays) in *Historical Tables, Budget of the US Government, Fiscal Year 2005*. Deflated by the GNP deflator (base year 2003).

**Figure 2a: Total Defense Procurement Expenditure, FY1966 – FY2003.**



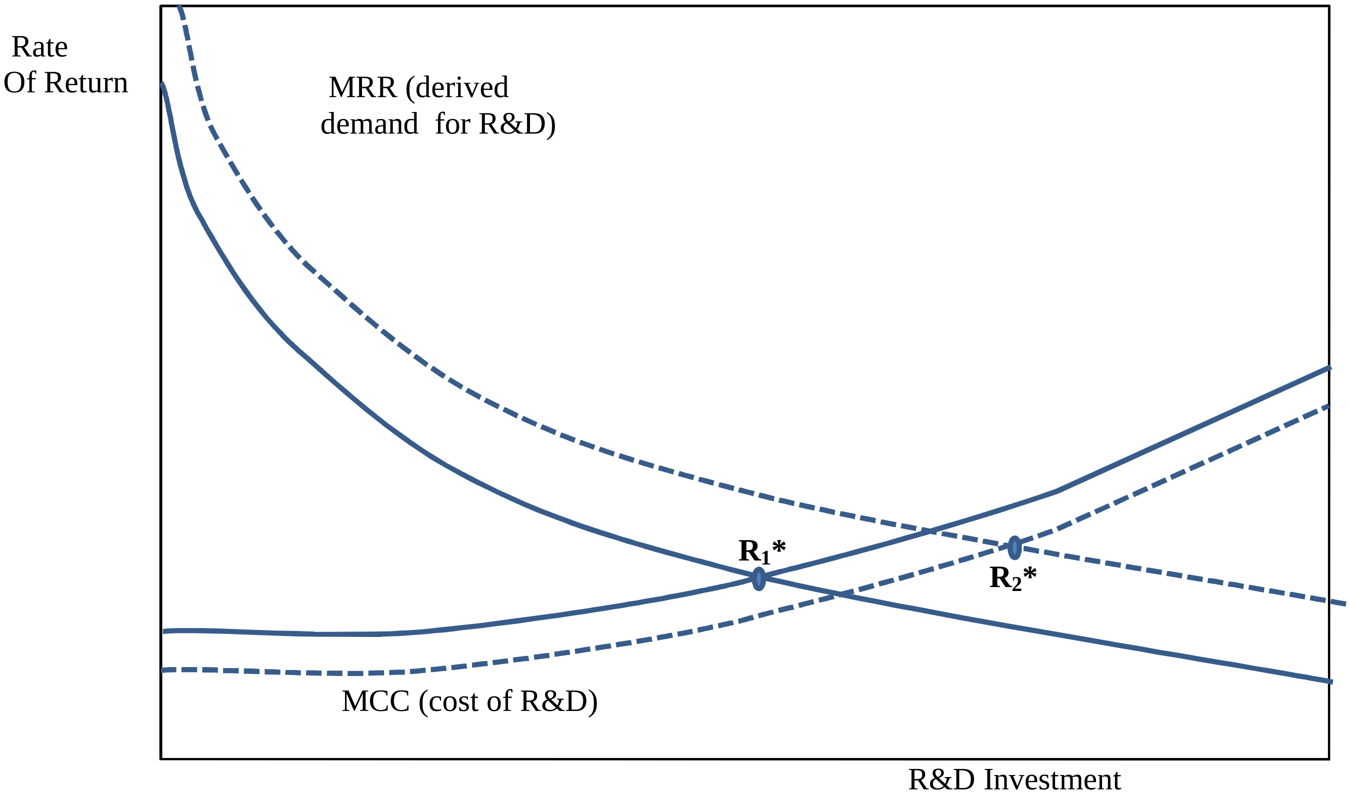

*Source:* National Archives and Records Administration (NARA) Historical Files on military procurement. Deflated by the GNP deflator (base year 2003).

**Figure 2b: Procurement Spending Shares, Top 10 2-digit Products**



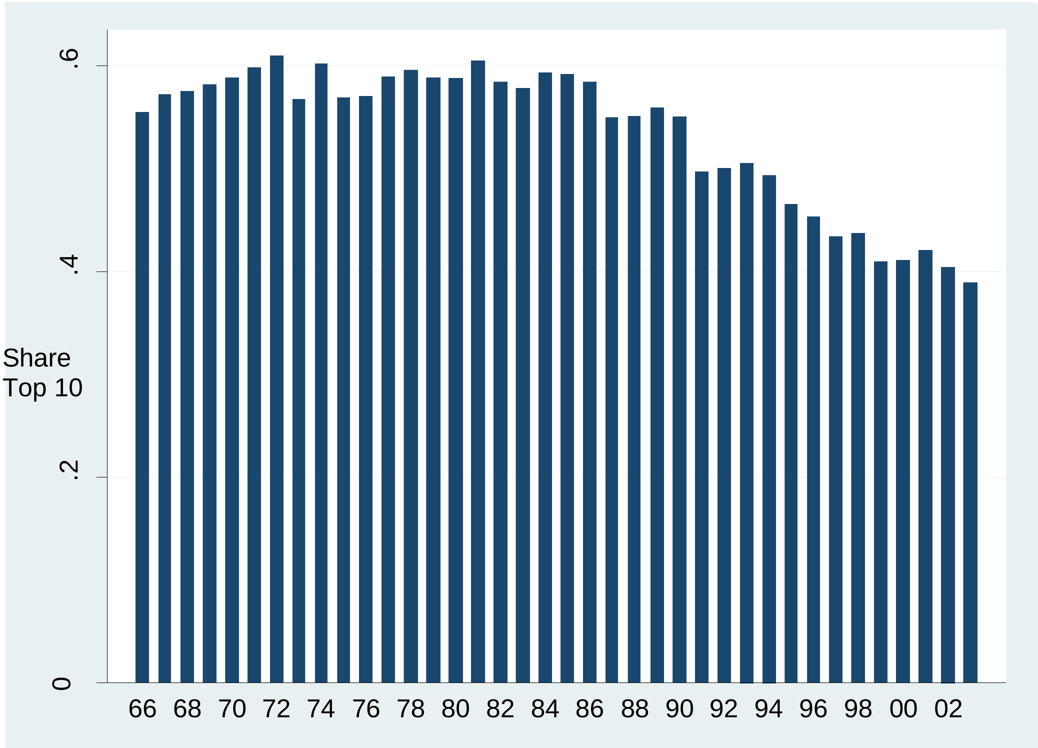

Notes: These top 10 products are: R&D (for Equipment); Aircraft & Airframe Structural Components; Communications, Detection and Coherent Radiation equipment; Ships and Small Craft; Engines, Turbines and Components; Guided Missiles; Fuel and Lubricants; Ammunition & Explosives; Maintenance and Repair; and Subsistence. Note that the R&D (for Equipment) category includes R&D on Aircraft, Missiles, Ships, Tanks, Weapons and Electronics. Source is National Archives and Records Administration (NARA) Historical Files on military procurement.

**Figure 3: Determinants of Private R&D Investment**




Notes: This figure illustrates the discussion in Section II (Background). Defense contractors receive a subsidy as part of the Independent Research and Development (IR&D) program to assist them in participating technical bids for DoD design competitions. This subsidy lowers the cost of capital shifts the MCC schedule down. Procurement contracts (often occurring as non-competitive follow-ons from design competitions) shift the MRR schedule outwards and are quantitatively more valuable than the IR&D subsidy.

**Figure 4: Share of Top 10 Products in Defense Procurement, FY1966 – FY2003.**




Notes: This figure shows the share of the 'Top 10' 2-digit products by dollar value in total procurement spending. These top 10 products are: Aircraft & Airframe Structural Components; Ships and Small Craft; Engines, Turbines and Components; Communications, Detection and Coherent Radiation; Aircraft R&D; Ammunition & Explosives; Guided Missiles; Subsistence; Fuel and Lubricants; and Maintenance and Repair. Source is National Archives and Records Administration (NARA) Historical Files on military procurement.

**Table 1: Descriptive Statistics, Matched Sample, 1966-2003 (Manufacturing).**

| | (1) No Defense Procurement | (2) Receive Defense Procurement (Some Years) | (3) Receive Defense Procurement (All Years) |
|---|---|---|---|
| Patent Count | 1.9 | 10.4 | 24.0 |
| | (21.4) | (80.0) | (87.6) |
| Citation Count | 11.4 | 82.9 | 216.5 |
| | (121.8) | (656.2) | (828.6) |
| ‘Military’ Patent Count | 0.7 | 4.0 | 7.2 |
| | (11.5) | (33.0) | (24.8) |
| Employment (in 1000s) | 2.9 | 5.1 | 11.3 |
| | (8.2) | (12.2) | (18.1) |
| Employment (median) | 0.51 | 1.1 | 3.1 |
| Sales | 648.4 | 1073.3 | 2272.0 |
| | (2133.0) | (2953.8) | (4115.8) |
| Sales (median) | 93.9 | 181.2 | 439.4 |
| Company-sponsored R&D | 18.2 | 39.1 | 73.1 |
| | (79.3) | (111.3) | (170.9) |
| Defense R&D | na | 2.6 | 12.0 |
| | | (28.8) | (55.3) |
| (R&D/Sales) | 0.045 | 0.040 | 0.040 |
| | (0.123) | (0.095) | (0.060) |
| (Defense Sales / Sales) | na | 0.014 | 0.049 |
| | | (0.071) | (0.116) |
| Defense Sales (DS) | na | 7.0 | 52.4 |
| | | (106.5) | (238.3) |
| SIC35 Share | 0.108 | 0.159 | 0.188 |
| SIC36 Share | 0.128 | 0.156 | 0.217 |
| SIC37 Share | 0.043 | 0.054 | 0.080 |
| SIC38 Share | 0.088 | 0.125 | 0.174 |
| Number of Firms | 5,976 | 2,207 | 664 |
| Number of Observations | 56,394 | 36,270 | 19,579 |

Column (1) reports statistics for firms who never receive any defense procurement contracts, Column (2) reports for firms who receive contracts in some but not all years. Column(3) reports for the sample of firms who receive contracts in all observed years. Sales, R&D, Defense Sales in million dollar units.

**Table 2: Patenting, R&D and Defense Procurement, 1976-2003.**

| (A) Patenting | (1) ln(1+PAT) | (2) ln(1+PAT) | (3) ln(1+PAT) | (4) (PAT) |
|---|---|---|---|---|
| ln(Defense)$_{t-1}$ | 0.320***<br>(0.029) | 0.079***<br>(0.016) | 0.071***<br>(0.014) | 0.080***<br>(0.008) |
| Firm Fixed Effects | No | Yes | Yes | Yes |
| SIC4*Year Trends | No | No | Yes | Yes |
| Number of Firms | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 |

| (B) R&D | (1) ln(CR&D) | (2) ln(CR&D) | (3) ln(CR&D) | (4) ln(GR&D) |
|---|---|---|---|---|
| ln(Defense)$_{t-1}$ | 0.409***<br>(0.029) | 0.071***<br>(0.016) | 0.065***<br>(0.012) | 0.095**<br>(0.014) |
| Firm Fixed Effects | No | Yes | Yes | Yes |
| SIC4*Year Trends | No | No | Yes | Yes |
| Number of Firms | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 |

**Notes:** Standard errors clustered by firm in parentheses. Column (1) includes SIC4 fixed effects. The dependent variable ln(1+PAT) is the log of 1 plus the patent count (patents applied for by firm *i* in year *t*). The variable ln(CR&D) is the log of company-sponsored R&D expenditures by firm *i* in year *t*, as reported in COMPUSTAT. The variable GR&D represents the sum of company-sponsored R&D reported in COMPUSTAT plus the sum of Department of Defense procurement-funded R&D reported in the NARA files for firm *i* in year *t*. ln(Defense Sales)$_{t-1}$ is the log of the total value of procurement contracts received by the firm *i* in year *t-1*. Column (4) is uses the count of patents as the dependent variable with the model estimated using a negative binomial conditional MLE.

**Table 3: Benchmarking Against Civilian Sales, 1976-2003.**

| (A) Patenting | (1) ln(1+PAT) | (2) ln(1+PAT) | (3) ln(1+PAT) | (4) (PAT) |
|---|---|---|---|---|
| $\ln(\text{Defense})_{t-1}$ | 0.069*** | 0.060*** | 0.059*** | 0.041*** |
| | (0.019) | (0.015) | (0.012) | (0.007) |
| $\ln(\text{Civilian})_{t-1}$ | 0.638*** | 0.446*** | 0.396*** | 0.303*** |
| | (0.026) | (0.051) | (0.044) | (0.014) |
| Implied $\beta_1$ | 0.038 | 0.027 | 0.024 | 0.018 |
| Test $\beta_1$ (p-value) | 0.10 | 0.028 | 0.003 | 0.606 |
| Firm Fixed Effects | No | Yes | Yes | Yes |
| SIC4*Year Trends | No | No | Yes | No |
| Number of Firms | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 |

| (B) R&D | (1) ln(CR&D) | (2) ln(CR&D) | (3) ln(CR&D) | (4) ln(GR&D) |
|---|---|---|---|---|
| $\ln(\text{Defense})_{t-1}$ | 0.040*** | 0.039*** | 0.045*** | 0.077*** |
| | (0.013) | (0.011) | (0.009) | (0.012) |
| $\ln(\text{Civilian})_{t-1}$ | 0.941*** | 0.751*** | 0.646*** | 0.600*** |
| | (0.018) | (0.043) | (0.039) | (0.040) |
| Implied $\beta_1$ | 0.056 | 0.045 | 0.038 | 0.036 |
| Test $\beta_1$ (p-value) | 0.215 | 0.59 | 0.499 | 0.005 |
| Firm Fixed Effects | No | Yes | Yes | Yes |
| SIC4*Year Trends | No | No | Yes | Yes |
| Number of Firms | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 |

**Notes:** Standard errors clustered by firm in parentheses. Column (1) includes SIC4 fixed effects. The dependent variable ln(1+PAT) is the log of 1 plus the patent count (patents applied for by firm *i* in year *t*). The variable (PAT) is the count of patents applied for by firm *i* in year *t*. The variable ln(CR&D) is the log of company sponsored R&D expenditures by firm *i* in year *t*, as reported in COMPUSTAT. The variable GR&D represents the sum of company-sponsored R&D reported in COMPUSTAT plus the sum of Department of Defense procurement-funded R&D reported in the NARA files for firm *i* in year *t*. $\ln(\text{Defense Sales})_{t-1}$ is the log of the total value of procurement contracts received by the firm *i* in year *t-1*. ln(Civilian Sales) is the log of 'Civilian' non-defense sales calculated as total reported accounting sales (from COMPUSTAT) minus the total value of procurement contracts given in the NARA files (ie: Defense Sales). The implied $\beta_1$ is calculated as $\beta_2 * (D / C)$, the coefficient on Civilian sales multiplied by the ratio of defense to civilian sales. The (D/C) ratio for this sample is 0.060.

**Table 4: Types of Patents and Citations, 1976-2003.**

| | (A) Patents | | | (B) Citations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | ln(1+PAT) | 1n(1+MPAT) | 1n(1+CPAT) | ln(1+CITE) | ln(1+MCITE) | ln(1+CCITE) |
| ln(Defense)$_{t-1}$ | 0.059*** | 0.048*** | 0.050*** | 0.067*** | 0.085*** | 0.063*** |
| | (0.012) | (0.010) | (0.012) | (0.021) | (0.022) | (0.020) |
| ln(Civilian)$_{t-1}$ | 0.396*** | 0.268*** | 0.352*** | 0.532*** | 0.435*** | 0.496*** |
| | (0.044) | (0.036) | (0.042) | (0.065) | (0.061) | (0.065) |
| Implied $\beta_1$ | 0.024 | 0.016 | 0.021 | 0.032 | 0.026 | 0.030 |
| Test $\beta_1$ (p-value) | 0.004 | 0.003 | 0.011 | 0.080 | 0.007 | 0.097 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| SIC4*Year Trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Firms | 664 | 664 | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 |

Notes: Standard errors clustered by firm in parentheses. The dependent variable ln(1+PAT) is the log of 1 plus the patent count (patents applied for by firm *i* in year *t*). The variable ln(1+MPAT) is the log of 1 plus the count of patents belonging to military patent classes following the discussion in section III ("Patents Data – Defining Military Patents"). The variable ln(1+CPAT) represents the count of patents in all the remaining non-military or 'civilian' patent classes. The variable ln(1+CITE) is the log of 1 plus the count of citations (ie: forward citations for the patents applied for by firm *i* in year *t*). The variables ln(1+DCITE) and ln(1+CCITE) are then the defense and civilian analogues of the total citations variable.

**Table 5: Impact of Defense Product Market Shocks – Reduced Form and IV Estimates, 1976-2003.**

| | (A) Patenting | | | | (B) R&D | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | OLS | Reduced Form | First Stage | IV | OLS | Reduced Form | First Stage | IV |
| | ln(1+PAT) | ln(1+PAT) | $\ln(\text{Defense})_{t-1}$ | ln(1+PAT) | ln(R&D) | ln(1+PAT) | $\ln(\text{Defense})_{t-1}$ | ln(R&D) |
| $\ln(\text{Defense})_{t-1}$ | 0.071*** | | | 0.173** | 0.095*** | | | 0.265** |
| | (0.014) | | | (0.077) | (0.014) | | | (0.077) |
| $\ln(\sum \Phi_{ij,(t-10)} D_t^L)$ | | 0.022** | 0.130*** | | | 0.034** | 0.130*** | |
| | | (0.011) | (0.020) | | | (0.010) | (0.020) | |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SIC4*Year Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Firms | 664 | 664 | 664 | 664 | 664 | 664 | 664 | 664 |
| Number of Observations | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 | 7,116 |

**Notes:** Standard errors clustered by firm in parentheses. Estimated for the period 1976-2003 (Fiscal Years) where a 10-year lag of the firm-specific defense shift-share variable is defined. The dependent variable ln(1+PAT) is the log of 1 plus the patent count (patents applied for by firm *i* in year *t*) . $\ln(\text{Defense Sales})_{t-1}$ is the log of the total value of procurement contracts received by the firm *i* in year *t-1* . The variable $\ln(\sum \Phi_{ij,(t-10)} D_t^L)$ is the log of the firm-specific Department of Defense (DoD) product market. This is defined as the firm's share of own sales to the DoD in each 2-digit Federal Supply Code (FSC) 10 years ago multiplied by the current, period (t-1) value of DoD spending in each 2-digit category.

**Table 6: Changes in DoD Spending and Product Market Concentration, 1976-2003**

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent Variable | $\Delta\ln(D^L)_{lt}$ | $\Delta\ln(D^L)_{lt}$ | $\Delta\ln(D^L)_{lt}$ |
| $(\text{Herfindahl})_{t-2}$ | -0.087 | | |
| | (0.092) | | |
| $(\text{Herfindahl})_{t-5}$ | | -0.061 | |
| | | (0.059) | |
| $(\text{Herfindahl})_{t-10}$ | | | -0.024 |
| | | | (0.066) |
| 1-Digit Trends | Yes | Yes | Yes |
| Number of Product Groups | 154 | 154 | 154 |
| Number of Observations | 3353 | 3353 | 3353 |

Notes: Standard errors clustered by 2-digit product category in parentheses. The data is a 2-digit product level panel of NARA procurement data. The dependent variable is the log 1-year change in the total amount of procurement spending at the 2-digit level. The Herfindahl index is calculated as the sum of the squared market shares for the top 50 contractors in each 2-digit product group. There are 34 1-digit groups with a trend term included for each group.

**Table 7: Industry Sector Decomposition, 1977-2000.**

**Panel (A) Patents/Sales**

| Period | (1) Total Share Of Between | (2) Defense Share Of Between | (3) Defense Share Of Within | (4) Defense Contribution Between | (5) Defense Contribution Within | (6) Defense Contribution Total |
|---|---|---|---|---|---|---|
| **Pre Build-Up** | | | | | | |
| 1977-1980 | 0.353 | 0.041 | 0.029 | 0.014 | 0.019 | 0.033 |
| **Reagan Build-Up** | | | | | | |
| 1981-1984 | 0.431 | 0.055 | 0.159 | 0.024 | 0.090 | 0.114 |
| 1985-1988 | 0.381 | 0.026 | -0.001 | 0.010 | -0.001 | 0.009 |
| **Post Cold War** | | | | | | |
| 1989-1992 | 0.378 | -0.044 | 0.022 | -0.017 | 0.014 | -0.003 |
| 1993-1996 | 0.370 | -0.019 | 0.014 | -0.010 | 0.009 | 0.002 |
| 1997-2000 | 0.344 | -0.007 | 0.004 | -0.002 | 0.003 | 0.001 |

**Panel (B) R&D/Sales**

| Period | (1) Total Share Of Between | (2) Defense Share Of Between | (3) Defense Share Of Within | (4) Defense Contribution Between | (5) Defense Contribution Within | (6) Defense Contribution Total |
|---|---|---|---|---|---|---|
| **Pre Build-Up** | | | | | | |
| 1977-1980 | 0.43 | 0.031 | 0.030 | 0.013 | 0.017 | 0.030 |
| **Reagan Build-Up** | | | | | | |
| 1981-1984 | 0.348 | 0.093 | 0.050 | 0.032 | 0.033 | 0.065 |
| 1985-1988 | 0.391 | 0.028 | 0.032 | 0.011 | 0.019 | 0.030 |
| **Post Cold War** | | | | | | |
| 1989-1992 | 0.517 | -0.040 | -0.021 | -0.021 | -0.010 | -0.031 |
| 1993-1996 | 0.456 | -0.020 | -0.007 | -0.009 | -0.004 | -0.013 |
| 1997-2000 | 0.450 | -0.005 | 0.006 | -0.002 | 0.003 | 0.001 |

Notes: This table reports the result of a SIC3 level decomposition of the growth in aggregate patenting and R&D expenditure. The full COMPUSTAT database is used with sales, patents and R&D collapsed to the SIC3 level, as defined by the main SIC code for each listed firm. The technology measures (patents and R&D) are normalized by industry sales to construct measures of technological intensity. Column (1) reports what share of the total change in intensity is due to between effects with column (2) then reporting what share of this between component is accounted for by the defense sub-sector. Column (4) then calculates the total contribution of the defense sector to the aggregate change in technological intensity. For example, in 1981-1984 2.4% of total change in patenting intensity is due to between industry shifts associated with the defense sub-sector. See section IV ('Calculating Magnitudes') for a full description of the decomposition.

## APPENDIX A.1

*Spillovers in the Defense Product Market*

The above shift-share approach to identifying exogenous shocks to procurement spending is complicated by the potential role of knowledge spillovers at the levels of industry, product or technological class. Empirically, spillovers are best described as a type of 'outside' capital that benefits the firm (Griliches 1992). The typical approach is to add up the stock of knowledge capital (measured most commonly by R&D) according to an external criteria. This basic scheme can be formulated as:

$$SPILL = \sum_{-i} v_{(i,-i)} G_{-i} \tag{9}$$

where $v_{(i,-i)}$ represents the 'distance' between firm *i* and all other firms –*i* and $G_{-i}$ is the value of the knowledge capital for firm –*i*. In this paper's setting distance is a weight on the –*i* firms that can be measured in terms of industry (*j*), patent technological class (*k*) or DoD product code (*l*). If a –*i* firm is in the same industry, technological or product market space as firm *i* then it has a non-zero weight. Following the approach of Jaffe(1986) and latterly Bloom, Schankerman and Van Reenen (2011) we can define a measure of closeness in the defense product code space as:

$$PROD_{i,-i} = \frac{\left(D_i D'_{-i}\right)}{\left(D_i D'_i\right)\left(D_{-i} D'_{-i}\right)} \tag{10}$$

where $D_i = \left(d_{i1}, d_{i2}, \ldots d_{i120}\right)$ is the vector of firm *i*'s share of product *l* in its total defense sales across the 155 2-digit product codes. The term in (8) is therefore the uncentred correlation between pairings of firm *i* and all other -*i*. The spillover pool is then constructed by applying these weights and summing over the relevant firms:

$$SPILLPROD_{it} = \sum_{-i} PROD_{(i,-i)} G_{(-i)t} \tag{11}$$

The main issue here is that both the spillover weights and the share vector for our exogenous shocks term in (6) are defined in the defense product space. Consider the simple case of a firm *i* that specializes in one defense product *l* over time. Then any DoD spending shock in category *l* affects both the direct procurement receipts of firm *i* as well as the receipts of all firms also selling product *l*. If all of these firms invest in R&D as a consequence of the shock this will increase the accumulated R&D stock in product space *l*. It is then possible that this additional induced R&D at the product space level will go on to affect firm *i* through a knowledge spillover mechanism. In principle, this could lead to upward bias on the proposed IV estimate since it could pick up the indirect spillover effects along with the direct effects of procurement that are the main focus of the paper. Practically, this problem can be mitigated by conditioning on extra spillover terms when estimating the main models.

**APPENDIX A.2**

**EXAMPLE OF FULL TEXT PATENT SUBJECT TO GOVERNMENT SUPPORT**

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## Method and apparatus for a reprogrammable program missile memory

**Abstract**A method and apparatus are disclosed for a reprogrammable program missile memory module 26 which is placed within a missile 14 in substantially the same manner as the currently used programmable read only memory. The reprogrammable program memory module 26 provides for remote writing of tactical program data thereto while allowing the missile 14 to remain in a substantially operational state.

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Inventors: **Siering; Erik R.** (Woodland Hills, CA)
Assignee: **Hughes Aircraft Company** (Los Angeles, CA)
Appl. No.: **07/437,044**
Filed: **November 15, 1989**

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| | |
|---|---|
| **Current U.S. Class:** | **244/3.15** ; 711/103 |
| **Current International Class:** | F41G 7/00 (20060101); G06F 001/00 () |
| **Field of Search:** | 364/900 244/3.15,3.11 |

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|---|---|---|
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| 4660170 | April 1987 | Hui et al. |
| 4935881 | June 1990 | Lowenson et al. |

*Primary Examiner:* Hellner; Mark
*Attorney, Agent or Firm:* Brown; C. D. Heald; R. M. Denson-Low; W. K.

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***Government Interests***

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This invention was made with Government support under Contract No. N00019-85-G-0171 awarded by the Department of the ***Navy***. The Government has certain rights in this invention.