The Technological Legacy of the Cold War: Military Procurement and US Innovation

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Abstract

This paper estimates the causal impact of US military procurement during the Cold War on the development of regional innovation clusters. I use a shift-share instrument that leverages exogenous variation in spending across different technological categories. The findings show that procurement spending significantly increased patenting activity and the results are robust to various specifications. The effects are stronger in counties with higher levels of local competition, consistent with the presence of local knowledge spillovers. An event study of Reagan's military build-up confirms that the results are not driven by differential pre-trends across counties. These findings highlight the long-run effects of public spending and suggest that to foster innovation governments should harness pre-existing ecosystems of innovative firms.

Acknowledgements

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Dedicated to my father, Vincenzo Cerundolo, who would be proud to see me graduate.

Contents

1 Introduction

Private investment in R&D creates large positive spillovers which are not fully internalised by innovating firms ([13], [5], [19]). This justifies government expenditure to increase R&D to the socially optimal level. Whilst there has been much investigation of how public R&D investment stimulates firm innovation and firm-to-firm knowledge spillovers, there has been less focus on the role of geographic proximity in this process. I provide some preliminary evidence on this question by studying the long-run effects of public R&D programmes on the formation of regional innovation clusters. I study this question by focusing on defence procurement in the US during the Cold War and the surge in spending under Reagan.

I use data on all the procurement purchases made by the US Department of Defence (DoD) between 1966 and 2003 to evaluate the effect of procurement spending on patenting in a given county. When Reagan began his first term as president in 1981, defence became a far greater priority and the DoD's budget increased enormously, as shown in Figure 1. Counties were differentially exposed to this spending surge, allowing us to to evaluate the effect of spending on innovation.

To motivate the analysis, I first run a Difference-in-Differences to evaluate the effect of being amongst the counties which received the largest surge in defence spending under Reagan. The analysis confirms that counties differentially exposed to spending under Reagan were not following different trends in patenting prior to his election. In addition, the results highlight the long-run impact of procurement spending on county

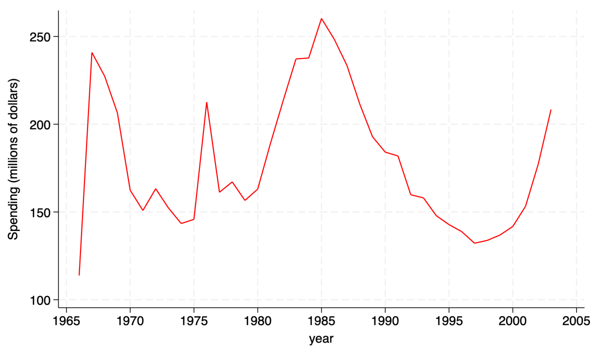

Figure 1: Yearly Procurement Spending by the US Department of Defence

innovation.

In the main-analysis, I construct a shift-share instrument to isolate exogenous variation in procurement spending. This is done by exploiting the 176 different product categories of the procurement purchases made by the DoD. National-level spending across product categories depends exogenously on external geopolitical considerations, and given that counties have different specialisations across product categories they are differentially exposed to the common exogenous shocks. The main analysis finds that a 1% increase in procurement spending causes a 0.039% increase in citation weighted patents. When the analysis is restricted to those counties which regularly patent and receive procurement contracts, the effect increases to 0.11%.

In the short-run, procurement contracts are likely to boost innovation within a county by increasing the R&D of the recipient firms. However, in the long-run, it is unclear to what extent the observed effect is driven solely by the recipient firms becoming more innovative or there being shared benefits to other firms in the county. To provide suggestive evidence on this question, I test for heterogeneous treatment effects across counties with differing levels of competition. The analysis finds that the effect is largest in those counties with the highest levels of competition. This could suggest that the innovation induced from procurement spending creates local knowledge spillovers which local competitors can benefit from. These knowledge spillovers can be transmitted both through the contents of patents and through the movement of inventors between firms. In the Conclusion I discuss how this mechanism could be more formally tested in future work.

The results are of broad interest to policymakers. As Western governments increasingly engage in industrial policy, there are competing questions of how best to promote innovation and how best to promote regional development. With rapidly increasing defence budgets across many countries, the answers to these questions are especially important within the context of defence procurement. The results suggest that, to maximise innovation, public funding should be targeted not simply to the most innovative firms, but to those innovative firms which are located in locally competitive environments. In this way, funding not only benefits the recipient firms but also the neighbouring competitors. This will of course, however, only increase the geographic concentration of innovative activity.

The literature most closely related to this paper is that which studies the impact of publicly funded R&D programmes on innovation. The majority of this research focuses on the outcomes of firms or individuals who receive idiosyncratic levels of funding as a result of arbitrary allocation rules ([27], [16], [23], [21]). The question of how systematic public R&D investments impact aggregate outcomes has been a topic of far less focus but has been addressed in a few papers. Most similarly to this paper, Gross & Sampat (2023) [11] show that government funded research during WW2 was crucial to the formation of new technological clusters which have grown and persisted decades later. Focusing on medical research funding, they find that these grants had an especially pronounced effect on research areas which were nascent at the time [12]. Kantor & Walley (2023) [20] find that NASA contracted R&D projects during the Cold-War Space Race led to the formation and persistence of technological clusters. They also provide evidence that the migration of inventors, whilst important, was not the sole mechanism suggesting that R&D funding led to local knowledge spillovers and not simply a reallocation of human capital across the country. Schweiger et al. (2022) [24] study the explicitly place-based approach to encouraging innovation of the Soviet Union during the Cold-War. They find that the establishment of 'Science Cities' had effects on local innovation that persist until today.

The paper also relates to the literature on why innovative activity is so geographically concentrated. Innovative activity in the US is even more concentrated than industrial activity. As discussed in Carlino & Kerr (2015) [8], this is due to agglomeration facilitating the sharing of common inputs, improved labour market matching and the production of local knowledge spillovers. Jaffe et al. (1992) [18] provide evidence for the presence of local knowledge spillovers by showing that patents tend to cite other patents which are produced in the same geographic area. They demonstrate that this cannot be accounted for simply by the clustering of similar innovative activity, thus pointing to the presence of local knowledge spillovers. The evidence has been debated and extended in later papers ([25], [1], [26], [15]). This paper complements this line of research by suggesting that, in the presence of local knowledge spillovers, public R&D programmes lead to the concentration of innovative activity. The paper shows that the effect of public spending on R&D is greatest in counties where competitors are geographically concentrated, suggesting that the effectiveness of public R&D spending is greatest in those counties where other firms can benefit from the local knowledge spillovers. This implies that, even if public R&D spending was equally distributed across counties, the effect would be to concentrate innovation even further in those areas where it is already most concentrated. Furthermore, there is an incentive for the state to promote the concentration of innovation, since it increases the effectiveness of its spending.

Finally, the paper is closely related to the literature which evaluates the effect of defence procurement on innovation. Using firm level defence data from the US and France respectively, Draca (2012) [10] and Moretti et al. (2019) [22] both find evidence of public R&D procurement crowding-in private sector investment. One mechanism, explored in Belenzon and Cioaca (2023) [2], is that public procurement provides 'guaranteed demand' for those who win contracts. This is due to the almost unlimited buying power of the state, especially in the case of the US DoD, and the difficulty of changing military suppliers. This creates strong incentives for firms to co-invest in public R&D to maximise their chances of winning a contract. There has also been a focus on how to optimally design R&D procurement to maximise follow-on innovation. Howell et al. (2023) [17] show that giving firms more flexibility and discretion in the direction in which they innovate improves outcomes. By constructing a model of R&D procurement contests, Bhattacharya (2021) [4] finds a range of policy changes that would improve innovation outcomes within the US Navy programme. Beyond the contractual details of R&D procurement, there is also evidence of the importance of public sector expertise. Decarolis et al. (2021) [9] show that the death of a public procurement officer in the 6-months prior to a DoD award being granted causes a significant decline in follow-on innovation. This paper complements the literature but, instead of considering firm-level outcomes and how to maximise firm-level innovation, it considers county-level outcomes and how to maximise aggregate innovation.

2 Data and Summary Statistics

The analysis combines data on US patenting, Department of Defence procurement spending and county characteristics. Each data source is described and discussed below.

The procurement data comes from the National Archives and Records Administration and contains all contracts awarded from the Department of Defence in the period 1966-2003. The dataset contains detailed information on each contract including the amount spent, the firm which received the contract and the product category. There are 176 different product categories, which are each specified by a four-digit code. These cover a broad range of possible products and services such as R&D contracts, military equipment, maintenance, training and materials. Figure 2 shows the distribution of spending intensity across the US, by categorising each county into quartiles based on the total per capita procurement spending they received over the sample period. Whilst there are some clusters of counties which receive high procurement spending, counties in the highest quartile can be found in every area of the US.

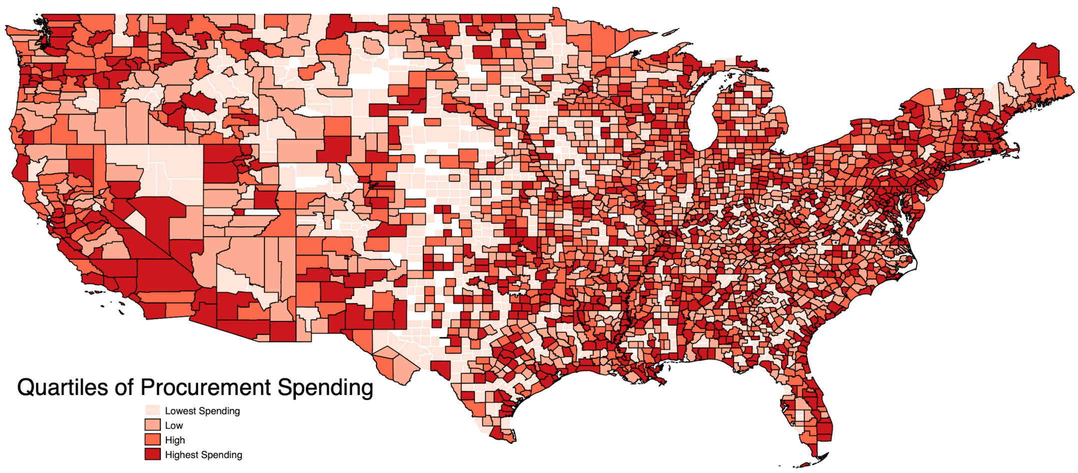

Figure 2: Map of Procurement Spending Intensity by the DoD across US Counties. The county-level measure is the sum of procurement contract dollars received by the county over the entire sample period from 1966 to 2003.

The patent data is from Comprehensive Universe of US Patents [3], which contains the universe of US patents. A citation weighted count is constructed at the US Patent Classification (USPC) sub-class level. It is calculated as the number of citations a patent receives divided by the average number of citations received by a patent in the same technological sub-class, according to the USPC. For each patent, we have the filing year, issue year and the county of the assignee. I use the filing year as this is the best measure of when the innovation was first made. Figure 3 shows the distribution of patenting intensity across the US, where each county has been categorised into quartiles based on the total number of patents per capita produced over the sample period.

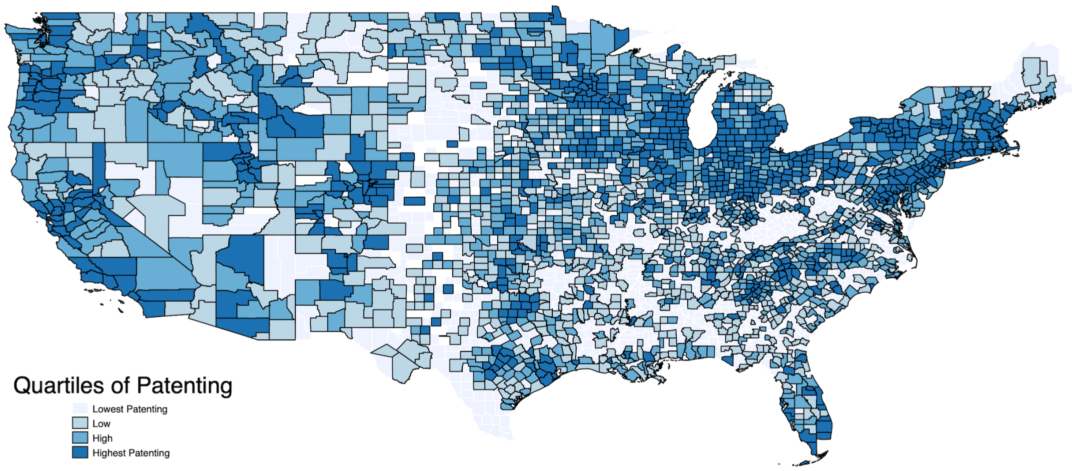

Figure 3: Map of Patenting Intensity by US County. The county-level measure is the total number of patents produced between 1966 and 2003.

The county-level characteristics come from a range of sources. Data on wages come from files published by the Bureau of Labor Statistics, data on population size comes from the National census and data on educational attainment comes from the IPUMS NHGIS (Integrated Public Use Microdata Series National Historical Geographic Information System) database. Summary statistics on the full set of variables used in the analysis are shown in Table 7 in Appendix A.

3 Motivating Evidence

To focus on the unique role of the Reagan military build-up I perform an event-study. The treatment period is set as 1981, when Reagan begins his first Presidential term. The treatment is discretised by comparing the counties which receive the largest growth in procurement spending under Reagan to those which receive lower growth in spending. In particular, for each county I measure the average yearly procurement spending they receive in the five years prior to Reagan's inauguration (1976-1981) and during Reagan's term in office (1981-1989). A county is treated if the absolute increase in average yearly spending it receives between these two time periods in above the median increase across the set of counties. Therefore, 50% of the sample is treated and the treated counties are those which received the largest share of the additional defence spending under Reagan.

The analysis is run using both the number of patents and the number of citation weighted patents. In both cases, the parallel-trends test does not provide evidence of pre-treatment trends which are not parallel between the treatment and control groups. For the respective dependent variables, the p-values of the null-hypothesis of parallel trends are 0.56 and 0.74 and are presented in Table 8 in Appendix B. This confirms that the counties which received the largest increase in spending were not on a different trajectory of innovation prior to Reagan's election.

The presence of parallel trends in the number of patents is shown visually in Figure 4. The observed means show the yearly patenting average in the treated and control groups and the linear-trends model controls for group specific linear trends. As can be seen, the pre-treatment trends in the treatment and control groups follow each other closely. The equivalent figure for the number of citation weighted patents is shown in Figure 8 in Appendix B and confirms the same pattern of parallel trends.

The results from the estimation are presented in Table 1. The estimated treatment effect on the number of patents is 37.23 and is significant at the 1% level. The estimated treatment effect on the number of citation weighted patents is 139.98 and is also significant at the 1% level. The difference in these estimates suggests that the treatment not only increased the number of patents but also the quality of patents, as measured by citations.

The Granger plot for the effect on the number of patents is shown in Figure 5. It

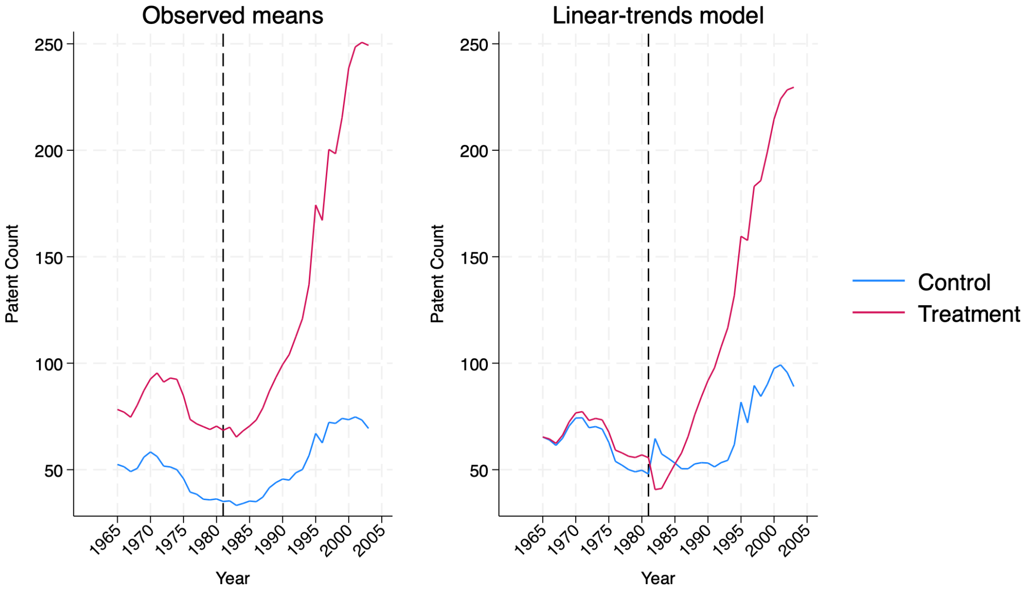

Figure 4: The two tables show evidence of the parallel trends assumption. The y-axis is the number of patents and the x-axis is the years. The first plot shows the mean number of patents produced each year in the counties which are included in the treatment group and those included in the control. The second plot augments the model by including interactions of treatment status with year.

shows the time specific treatment effects by including leads and lags of the treatment indicator. As can be seen, the treatment effect is a precise statistical zero prior to Reagan's inauguration in 1981, confirming the parallel trends assumption. The figure also shows that the treatment effect is statistically significant and that its magnitude increases over time. The Granger plot using the number of citation weighted patents is similar, and is shown in Figure 9 of Appendix B.

The results from the Granger plot emphasise the long-run effect of the treatment.

Table 1: *Difference-in-Differences Estimates*

VARIABLES	(1) Patents	(2) Citation Weighted Patents
Treated * Post-1981	54.42699 *** (20.42682)	139.9752*** (48.37009)
Observations	21,918	16,298
FE	Yes	Yes

Note: The table shows the Difference-in-Differences estimates of the average treatment effect. The first column shows the estimate of the effect of treatment on the number of patents and the second column shows the estimated effect on the log of the citation weighted measure of patents.

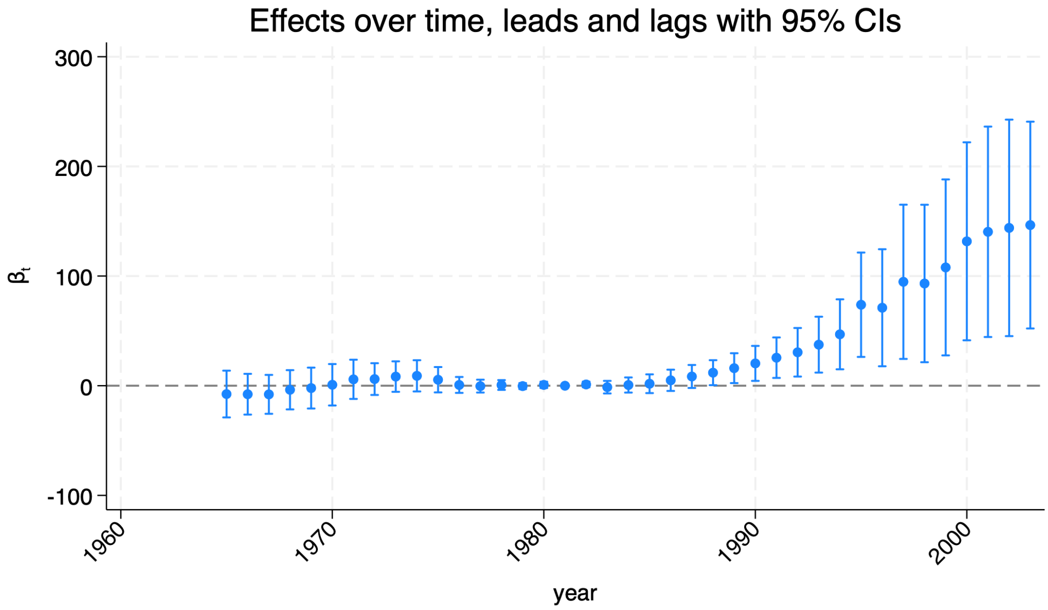

Figure 5: The figure shows the estimated treatment effect on the number of patents in each year. These are the estimated coefficients of treatment status interacted by the leads and lags with respect to the treatment year.

This suggests that the mechanism by which spending stimulates innovation in a county is through the accumulation of local know-how and the agglomeration of industry. This is discussed further in Section 5.2.

Whilst the results provide a strong visual intuition for the trajectory of patenting in counties which received varying levels of defence funding, the estimates cannot reliably be interpreted as causal. The reason is that the counties which received the largest increase in defence spending during Reagan's term, and are therefore treated, are also more innovative to start with, as can be seen from the observed means in Figure 4. It is therefore possible that there was a concurrent shock to innovation in the 1980s whose effect was concentrated amongst the firms which were already the most innovative. In this case, the observed effect would simply be the result of spurious correlation. In addition, it is possible that the treatment effect is larger in counties which are more innovative and are therefore more likely to be treated. In order to overcome these identification problems, it is necessary to isolate a component of exogenous variation in defence spending which is uncorrelated with how innovative a county is. This motivates the use of an instrumental variable strategy in the following section.

4 Empirical Strategy

The paper aims to assess the causal impact of county-level defence procurement spending on county-level innovation. The baseline specification is therefore:

$$\ln \text{Patents}_{i,t} = \alpha_i + \beta \ln \text{Spending}_{i,t} + \chi_{i,t} + f_t + \eta_{s(i),t} + \epsilon_{i,t}$$

where $\ln \text{Patents}_{i,t}$ is the log of the number of citation weighted patents produced in county i in year t and $\ln \text{Spending}_{i,t}$ is the log of procurement spending in county i in year t. The regression includes a vector of time-varying county characteristics, $\chi_{i,t}$, county-fixed effects, α_i, time-fixed effects, f_t, and state-year fixed effects, $\eta_{s(i),t}$, where $s(i)$ is the state of county i.

The OLS regression estimates are likely to be biased for several reasons. The spending treatment is endogenous since counties which receive higher levels of procurement are likely to be more innovative. This is because if a county has a strong industrial base, high levels of human capital and the presence of major universities or research centers then it is both more likely to patent and more likely to receive military procurement contracts. In addition, there is likely to be reverse causality, since if a county is more innovative then it will attract higher levels of procurement for those products in which it has innovated. These sources of endogeneity will contribute to positively biased OLS estimates.

An effective instrument for county-level procurement spending must be uncorrelated to the innovative capacity of counties. I therefore construct a shift-share instrument for county-level procurement spending, exploiting exogenous variation in the spending priorities of the DoD, as in Draca (2013) [10]. Each procured item can be categorised into one of 176 different product types. The share of a county's procurement which comes from each product type in any given year can measured, which captures the county's historical product specialisation. Since these shares are heterogeneous across counties, they imply that counties will be differentially exposed to a common set of shocks. An ideal shock-level experiment would involve the DoD randomly selecting how much to spend in each technological category. Whilst the DoD's spending across different product types is clearly not random, the spending is driven by changing geopolitical priorities and is therefore exogenous to county-level innovation.

The shares used in the instrument, which capture county specialisation across product types, are not exogenous. This is because counties which are more innovative, and thus produce more patents, will have comparatively larger shares of their procurement going towards the product types which are more technologically intensive. This however is not a threat to identification, since a sufficient condition for the exogeneity of the shift-share instrument is the exogeneity of the shocks, as shown in Borusyak et al. (2021) [6].

Let $s_{i,t}$ be the total spending received by county i in year t and let $d_{i,t,k}$ be the total spending received by county i in year t in product type k, such that $s_{i,t} = \sum_{k=1}^{176} d_{i,t,k}$. Then the share of procurement in county i in year t that is spent on product type k is

$$\Phi_{i,t,k} = \frac{d_{i,t,k}}{s_{i,t}}.$$

The instrument uses this measure of county-level product specialisation to capture the differential exposure of counties to a common set of shocks. Letting $D_{t,k}$ be the total national-level procurement spending in year t in category k, the instrument is defined as

$$z_{i,t} = \sum_{k=1}^{176} \Phi_{i,t-5,k} \ln(D_{t,k}).$$

The log is taken of national-level spending in each product category. This is opposed to taking the log of the entire sum since, as discussed in Borusyak et al. (2025) [7], the exogeneity of individual shocks does not imply that the log of a weighted sum of shocks is exogenous. The 5-year lags of the product shares are used to measure past county specialisation. The advantage of using lagged shares over pre-sample fixed shares is that the strength of the instrument is increased. This is especially true within our context since there are product categories which emerge over the sample period and so are lost by only using pre-sample product categories. However, as shown in

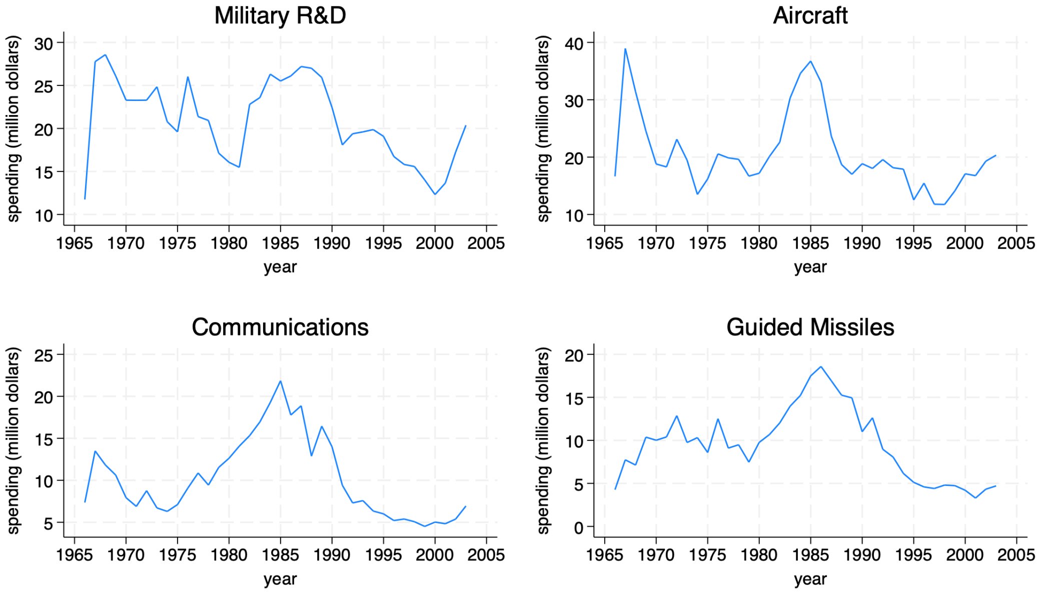

Figure 6: The figure shows the time series of procurement spending from the Department of Defence in the four product categories which receive the most spending over the sample period. In order of highest to lowest spending, the product categories are Military R&D, Aircrafts, Communications/Radar/ECM and Guided Missiles.

Section 5.3.1, the analysis is robust to using pre-sample shares.

4.1 Exogeneity

The exogeneity of the instrument relies on the assumption that national-level spending in individual product categories is exogenous [6]. The plots in Figure 6 show the national-level spending through time for the four product categories which receive most funding over the sample period. Each product category is exposed to small idiosyncratic variation in spending as well as large variation in the rise in spending under Reagan. For example, the yearly spending on aircrafts between 1980 and 1985 rose by almost twice as much as in the other categories shown. Therefore, counties which were specialised in aircrafts were likely to have experienced a larger rise in procurement spending compared to other counties. The variation in spending across product types that is driven by shifting geopolitical priorities and military strategy is uncorrelated with county characteristics across these product types.

Despite there being a component of exogenous variation in national-level spending, there is still the risk of endogeneity. The shocks are exogenous if and only if national-level spending is not systematically different in product categories where county shares in that product category are correlated with innovative capacity. This assumption, however, is threatened by the fact that the DoD spends intensively in product categories which are R&D intensive and the counties which specialise in these product types may have unobservable factors which result in them being more innovative. I account for this threat in three ways.

Firstly, I include county-fixed effects so that the regression measures deviations from a county's mean patenting. This therefore accounts for any potential county unobservable variables which are fixed over time and effect both a county's patenting activity and the value of the instrument.

Secondly, I control for observable time-varying county characteristics which are correlated with the instrument. I regress a range of county-level variables which may be predictors of innovation against the instrument. The variables which are significantly correlated with the instrument are included in the vector of controls $\chi_{i,t}$ in the regression. From the list of variables used, those which were correlated with the instrument are average wages, population and employment. The results from this test are shown in Table 9 in Appendix D.

Finally, I include state-time fixed effects to capture differential trends in innovation between states. It is likely that over the sample period there are time-varying shocks which differ across states. California, for example, was already extremely innovative in the 1960s and will likely have become more innovative at a faster pace compared to other states, independently of whether or not it received military procurement spending. It is therefore important to control for these differential trends.

Another potential risk is that the counties which received the most procurement spending were on a faster trajectory of increasing innovation compared to other counties. Prior to the surge in spending under Reagan this does not seem to have been the case, as shown by the parallel-trends which are tested for in Section 3.

5 Results

5.1 Main Results

The effect of procurement spending on innovation is likely to be heterogeneous across counties. The analysis is therefore run on two different samples of counties. Panel A includes all US counties, whereas Panel B includes the counties which are in the 'semi-intensive margin' of patenting and procurement. In particular, Panel B is composed of those counties which produce a patent in at least 80% of the sample years and receive a procurement contract in at least 80% of the sample years. These are 562 counties out of the original 3042 and are shown on a US map in Figure 11 in Appendix E. These counties account for 97% of all patents produced over the sample period. The reason for not using the pure intensive margin, consisting of only counties which patent and procure every year, is that the sample would be too small.

The results for both panels are presented in Table 2. In all IV regressions, the F-statistics indicate that the instrument is strong. In Panel A, the IV regression with the full-set of controls and fixed-effects estimates that a 1% increase in procurement spending causes a 0.039% increase in citation-weighted patenting. This effect is significant at the 5% level. In Panel B the estimates are larger in both magnitude and significance. Using the full set of controls, a 1% increase in procurement spending is estimated to cause a 0.11% increase in the number of citation-weighted patents. This effect is significant at the 1% level.

The results indicate that the treatment effect is larger in counties which are consistently innovating and receiving procurement contracts over the sample period. This could be due to several reasons. One possible explanation is that the effect is driven exclusively by high-tech procurement, which is concentrated in those counties which are included in the semi-intensive margin. The procurement contracts received in counties which rarely patent are likely to be largely for common items and services, as opposed to military technology, and these are unlikely to cause an increase in innovation.

Another possibility, as discussed in the Introduction, is that the effect of procurement on county innovation depends on the presence of other firms which can benefit from the knowledge spillovers produced. Whilst there may be highly innovative firms in counties which are not in the semi-intensive margin, clusters of highly innovative firms are only likely to be found in counties which are in the semi-intensive margin. If the creation of knowledge spillovers is an important mechanism then the treatment effect will be lower in counties which do not have innovative clusters and are therefore not in the semi-intensive margin. I investigate this possibility further in Section 5.2.

The results show that the IV estimates are significantly larger than the OLS estimates. This has to be accounted for, especially since the OLS estimates are likely to suffer from endogeneity which contributes to a positive bias. One possibility is that the instrument is correlated with unobservable variables which affect patenting, thus leading to positively biased estimates. If the correlation between the instrument and the treatment is low then this positive bias will be inflated. A second reason why the IV estimates may be larger is that the treatment effect could be larger in counties where the instrument is a better predictor of the treatment. The OLS regression estimates the average treatment effect whereas the IV regression estimates a weighted average of marginal effects, where the weights reflect how much procurement is influenced by the instrument [14]. Therefore, we would expect the IV estimate to be larger if the treatment effect is larger in counties for which the instrument is a better predictor of procurement spending. This is likely to be the case, since the DoD's dependence on specific counties is highest in product categories which are more technologically intensive. In particular, an increase in national spending on a general product is unlikely to translate into an increase in spending for counties which are specialised in that good, since the item can be procured from many other counties. In contrast, an increase in national spending in an advanced piece of military equipment is likely to increase spending in a county specialised in its production, since the item cannot be procured from many other counties. Such a county, which is specialised in advanced technology, is likely to experience a larger treatment effect. Therefore, the counties in which the instrument is the best predictor of the treatment are also the counties where the treatment effect is largest.

Table 2: *OLS and IV Estimates for Effect of Spending on Citation Weighted Patents*

VARIABLES	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
ln Spending	0.00427***	0.04177***	0.00347***	0.03395**	0.00410***	0.03857**
	(0.00137)	(0.01390)	(0.00131)	(0.01691)	(0.00128)	(0.01738)
Observations	87,386	87,386	75,982	75,982	75,944	75,944
F-stat.	NA	200.98	NA	119.51	NA	111.81
Panel B: Semi-Intensive Margin						
ln Spending	0.02877***	0.12534***	0.02384***	0.13049***	0.01967***	0.11226***
	(0.00474)	(0.03361)	(0.00448)	(0.03849)	(0.00420)	(0.03695)
Observations	24,476	24,476	21,530	21,530	21,529	21,529
F-stat.	NA	58.99	NA	47.18	NA	45.19
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

I repeat the analysis using the number of non-weighted patents and the results are reported in Table 3. Whilst the effect remains significant at 1% in Panel B, there is a large reduction in the magnitude of the estimated elasticity from 0.11% to 0.068%. The results therefore suggest that an increase in procurement spending increases not only the number of patents produced in a county but also the quality of patents, as measured by citations.

Table 3: *OLS and IV Estimates for Effect of Spending on Number of Patents*

VARIABLES	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
ln Spending	0.00560***	0.01175*	0.00248***	-0.00329	0.00275***	-0.00344
	(0.00095)	(0.00667)	(0.00094)	(0.00997)	(0.00092)	(0.01036)
Observations	114,865	99,705	75,982	75,982	75,944	75,944
F-stat.	NA	305.89	NA	119.69	NA	111.81
Panel B: Semi-Intensive Margin						
ln Spending	0.03811***	0.10283***	0.02855***	0.09440***	0.02199***	0.06773**
	(0.00504)	(0.02564)	(0.00504)	(0.03198)	(0.00481)	(0.03196)
Observations	32,088	27,854	21,530	21,530	21,529	21,529
F-stat.	NA	71.27	NA	47.18	NA	45.56
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on number of patents. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and recieve at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

5.2 Heterogeneity Across Counties

Which county characteristics determine the effectiveness of high-tech procurement at stimulating innovation? In the following section I focus on the role of local firm competition and find that the treatment effect is largest in counties with the highest degree of local competition.

Procurement spending should have a larger effect in counties where there is a higher degree of competition because the knowledge spillovers from innovation will disproportionately benefit county innovation if there are local competitors.[1] When a firm innovates it creates knowledge spillovers through the patent's contents. These knowledge spillovers are not constrained by geography; however, if the innovating firm is surrounded by similar firms then they will be the prime beneficiaries. Therefore, the follow-on innovation induced by the patent will be more geographically con-

[1]A second reason why the treatment effect should be larger in more competitive counties is that the expectation of future procurement contracts stimulates innovation [2]. Military firms engage in risky R&D in order to compete for procurement contracts. If a county contains a cluster of firms producing the same technology then this effect will be geographically concentrated. This channel is however not relevant in the empirical setting of this paper, since the treatment is exogenous and so the treatment effect should not be influenced by expectations of future spending.

centrated. In addition, firm innovation leads to the accumulation of human capital and know-how within the innovating firm. In a county with competing firms, these workers can more easily move between firms creating additional knowledge spillovers.

I test whether this mechanism is consistent with the data by evaluating whether the treatment effect is larger in counties where there is more competition in the pre-sample. To do this, I propose a county-level measure of local concentration of competition. This measure takes the total procurement that a county receives in a given product category and considers how much this procurement is concentrated between a small number of firms. Specifically, I calculate the Herfindahl–Hirschman Index (HHI) for each industry in each county and then aggregate across industries to create a county-level measure. In this definition, each of the 176 different product types are categorised as distinct industries. Since the exogeneity of the shift-share instrument relies on using multiple product categories, it is not possible to analyse the effect of spending in specific industries and therefore the competition index must be aggregated across industries.

The HHI of industry k in county i is defined as

$$HHI_{i,k} = \sum_{f} (MS_{i,k,f})^2$$

where $MS_{i,k,f}$ is the market share of firm f in county i in industry k. To calculate the market share, I define the market-size as the sum of procurement spending in industry k in county i over the years 1965-1980. I only use the years prior to Reagan's election so that the measure of concentration is not affected by the surge in spending that occurred during his term. Importantly, the market-size is calculated only using procurement spending within the county and not at the national level. Since the DoD can procure from any firm across the country, the true relevant market is at the national level. However, defining the relevant market in this way would create a measure which primarily captures how important a county is to national procurement. Instead, this measure captures the extent to which firms in a county are in competition with each other, irrespective of their national importance. This is therefore a modified version of the normal HHI.

I then aggregate the industry specific measures of market concentration, $HHI_{i,k}$, into a single county-level measure of market concentration, HHI_i, defined as

$$HHI_i = \sum_k s_{i,k} HHI_{i,k}$$

where $s_{i,k}$ is the share of procurement spending in county i that goes to industry k between the years 1965-1980. Weighting by the shares $s_{i,k}$ ensures that the measure of market concentration reflects the industries which are most significant to the county.

To test whether the treatment effect depends on the degree of local market concentration, I divide the counties in the semi-intensive margin into four quartiles. The first quartile contains the counties with the lowest values of HHI_i and therefore with the highest degree of local competition in the industries which they are specialised in. Conversely, counties in the fourth quartile have the lowest degree of local competition in the industries which they are specialised in. I restrict the analysis to the semi-intensive margin since this is where the treatment effect is most significant. I modify the regression specification to

$$\ln \text{Patents}_{i,t} = \alpha_i + \sum_{q=1}^{4} \beta_q D_{i,q} \ln \text{Spending}_{i,t} + \chi_{i,t} + f_t + \eta_{s(i),t} + \epsilon_{i,t}$$

where $D_{i,q}$ is a dummy equal to 1 if county i is in quartile q. The regression therefore has four endogenous variables and four instruments, where each instrument is an interaction of the shift-share with a group dummy. There are insufficient observations to include controls for each quartile group; however, I use the full specification which includes county, year and state-year fixed-effects as well as the set of county demographic variables which are correlated with the instrument. The estimated coefficients and 95% confidence intervals for each quartile are presented in Figure 7. The results from the full-specification of the baseline regression using the semi-intensive margin, as shown in Table 2, are also presented.

The results show that the treatment effect is largest in those counties in the first quartile where the market concentration index is lowest and therefore where competi-

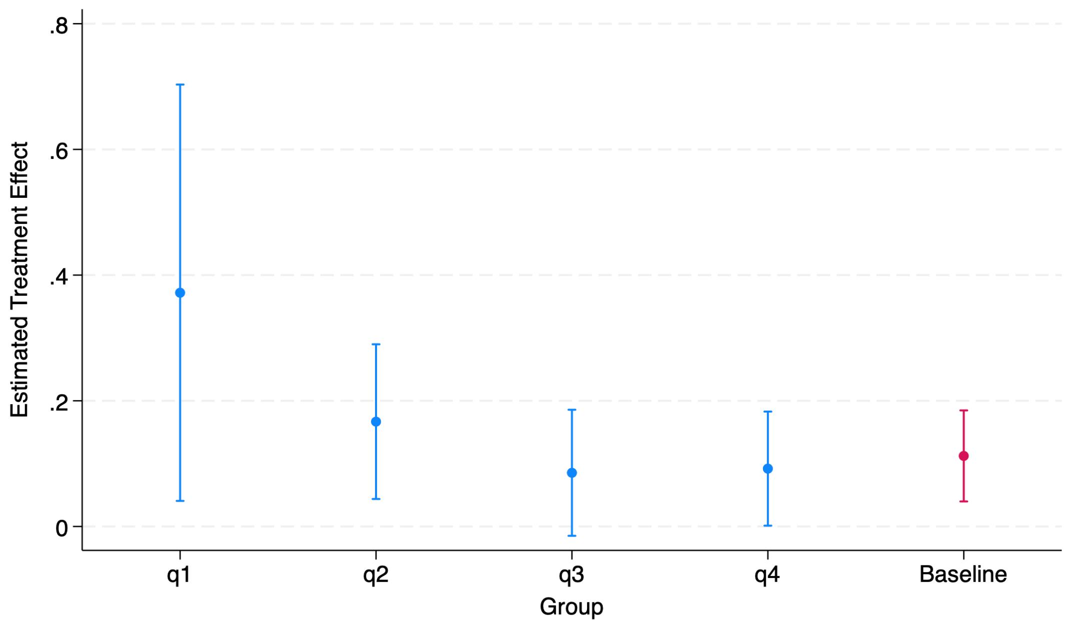

Figure 7: The figure shows the estimated effect of spending on citation weighted patenting for a range of groups, along with 95% confidence intervals. The baseline includes all counties in the semi-intensive margin. Quartiles q1 to q4 are defined over the semi-intensive margin and are defined with respect to the measure of local market concentration described in this section. Counties in lower quartiles have lower levels of local market concentration and therefore higher levels of local competition. All regressions include the full set of fixed effects and controls.

tion is most geographically concentrated. There is also a downward trend in the treatment effect as the local competition decreases. Whilst these results are consistent with the hypothesis that local competition increases the treatment effect, they should not be interpreted as causal. This is because the measure of local competition used is correlated with other county characteristics which are likely to be correlated with innovative capacity. As shown in Appendix F, whilst average wages and the share of employment in technology are relatively constant across quartiles in the pre-sample, the counties in the first quartile have the largest shares of inventors and the largest populations. In the concluding remarks in Section 6, I discuss how future work can establish more convincing evidence that local knowledge spillovers are a relevant mechanism.

5.3 Robustness Checks

5.3.1 Fixed Pre-Sample Shares

A limitation of constructing the instrument using a lag of the shares is that it increases the chances of endogeneity. It is therefore important to check that the results are robust to using fixed pre-sample shares. Using fixed pre-sample shares avoids the possibility of the shares adjusting dynamically in response to changes in the treatment or the outcome.

The main draw-back to using fixed pre-sample shares is that there are many product categories which were introduced over the sample period. This means that the instrument only accounts for spending in the product-categories which already exist in the pre-sample period. Nonetheless, it is important to test the robustness of the results to this choice.

I construct the fixed shares by calculating the total procurement spending that counties receive between 1966 and 1975 and the total procurement spending they receive for each product type over the same period. The share of procurement in county i that goes towards product category k is therefore defined as

$$\Phi_{i,k} = \frac{\sum_{t=1966}^{1975} d_{i,t,k}}{\sum_{t=1966}^{1975} s_{i,t}}.$$

This gives the counties' product specialisation as an average over the pre-sample period. The regressions are run over the period from 1976 to 2003 and the results are presented in Table 4. First of all, notice that the OLS estimates are larger than in the baseline analysis in Figure 2. This is because the baseline regressions also use the period from 1966-1975, where the treatment effect it likely to be lower. The fact that there are fewer observations makes the standard errors larger. This is especially the case for the IV regressions, since the instrument is now weaker as shown by the lower F-statistics. Despite the fact that the standard errors are larger, the estimated coefficients are also larger. The estimated elasticity in Panel B using the full IV specification is 0.21% and this is significant at the 10% level.

Table 4: *OLS and IV Estimates using Fixed Pre-Sample Shares*

VARIABLES	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
ln Spending	0.00428***	-0.16050***	0.00339***	-0.08884**	0.00402***	-0.04677
	(0.00133)	(0.05185)	(0.00127)	(0.04097)	(0.00124)	(0.04890)
Observations	85,008	85,008	74,246	74,246	74,209	74,209
F-stat.	NA	24.08	NA	21.08	NA	15.73
Panel B: Semi-Intensive Margin						
ln Spending	0.03811***	0.26372***	0.03198***	0.24636***	0.02475***	0.20530*
	(0.00641)	(0.09733)	(0.00596)	(0.09095)	(0.00543)	(0.11501)
Observations	15,736	15,736	13,856	13,856	13,805	13,805
F-stat.	NA	19.77	NA	19.03	NA	10.26
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. The regressions use an alternative IV where the shares are fixed and calculated over the pre-sample. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3.2 Leave-One-Out: Product Types

There are several reasons why the estimates could be driven by individual product categories. To address these concerns I run the regressions with specific product types dropped from the sample, such that they are omitted from the treatment and from the construction of the instrument.

The first concern is that the increase in patenting is driven exclusively by R&D spending and not from procurement more generally. To address this concern I drop all R&D procurement contracts. This includes all Military R&D contracts, which is the largest category of spending over the sample period. Among others categories, it includes R&D in Space Science and Aeronautical research, Biomedical research, Manufacturing technology and Physical Sciences. The results can be seen in the first row of Table 5. As expected, the estimated effect is smaller but still remains robust at the 5% level in Panel A and at the 1% level in Panel B.

A second concern is that there are technological shocks which contemporaneously increase the DoD's spending in that product category and also make those counties which are specialised in that category more innovative. For example, during the 1980s there were several key breakthroughs made in Communication/Radar/ECM technologies. This meant that it became increasingly prioritised by the DoD and the spending allocated to it increased. However, these breakthroughs also had the effect of directly increasing patenting independently of there being increased spending from the DoD. Therefore those counties which were specialised in communications technologies would have increased their patenting independently of having received increased public funding. To reduce the influence of such contemporaneous shocks I drop the two product types which experienced the largest growth in procurement spending under Reagan, which were Communication/Radar/ECM and Aircrafts. The sharp rise in spending in these product categories can be seen in Figure 6. These product categories both experienced rapid technological progress during the 1980s and, other than Military R&D, are the product types which received the most spending from the DoD over the sample period. The estimates presented in Table 5 differ from those in the baseline only marginally and maintain the same levels of significance.

Table 5: *Leave-One-Out Analysis: Product Types*

PRODUCTS DROPPED	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
R & D Contracts	0.00398***	0.04213***	0.00341***	0.03633**	0.00406***	0.04057**
	(0.00136)	(0.01423)	(0.00131)	(0.01742)	(0.00128)	(0.01791)
Aircraft & Communication	0.00456***	0.03892***	0.00370***	0.03187*	0.00432***	0.03621**
	(0.00136)	(0.01416)	(0.00131)	(0.01736)	(0.00128)	(0.01783)
Panel B: Semi-Intensive Margin						
R & D Contracts	0.02616***	0.11343***	0.02159***	0.12049***	0.01813***	0.10466***
	(0.00452)	(0.03243)	(0.00425)	(0.03735)	(0.00403)	(0.03623)
Aircraft & Communication	0.02880***	0.12830***	0.02297***	0.13563***	0.01869***	0.11308***
	(0.00473)	(0.03486)	(0.00449)	(0.04067)	(0.00421)	(0.03879)
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. Each row corresponds to a a regression in which the construction of the IV and the treatment omits the product category specified. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

5.3.3 Leave-One-Out: Counties

Another concern is that the results are being driven by a small number of counties. There are two reasons why this may be the case. Firstly, it may be that the results are being driven by a small number of counties which are specialsed in the defence sector and for which the treatment effect is far larger than in other counties. To account for this possibility I drop the three counties which receive the highest amount of procurement spending over the sample period: Arlington (Virgnia), Fairfax (Virginia) and San Diego (California). These three counties are hubs for defence firms due to their strategic locations and their access to high-skilled workers. Arglinton and Fairfax, for example, benefit from their close proximity to the Pentagon.

Secondly, if the instrument is partially correlated with unobservable variables which influence a county's innovative capacity then the results could potentially be driven by a few counties for which the instrument takes a high value and there is a large growth in patenting. I therefore test how the results change by removing the three counties which produce most patents over the sample period: Santa Clara (California), New York County (New York) and Cook (Illinois).

The results are presented in Table 6. The regressions labelled 'Defence Counties' drop the listed counties which are specialised in the defence sector and the regressions labelled 'Innovative Counties' drop the listed counties which are highly innovative. The estimates fall marginally; however, in both cases the significance is the same as in the baseline results.

Table 6: *Leave-One-Out Analysis: Counties*

PRODUCTS DROPPED	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
Defence Counties	0.00422***	0.04159***	0.00347***	0.03383**	0.00410***	0.03852**
	(0.00137)	(0.01390)	(0.00132)	(0.01691)	(0.00128)	(0.01738)
Innovative Counties	0.00429***	0.04179***	0.00347***	0.03371**	0.00411***	0.03841**
	(0.00137)	(0.01390)	(0.00132)	(0.01690)	(0.00128)	(0.01737)
Panel B: Semi-Intensive Margin						
Defence Counties	0.02849***	0.12442***	0.02383***	0.13004***	0.01964***	0.11158***
	(0.00475)	(0.03361)	(0.00448)	(0.03850)	(0.00420)	(0.03690)
Innovative Counties	0.02894***	0.12505***	0.02390***	0.12957***	0.01966***	0.11088***
	(0.00476)	(0.03356)	(0.00449)	(0.03839)	(0.00422)	(0.03685)
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. Each row corresponds to a regression in which a subset of counties have been dropped. The defence counties are Arlington (Virgnia), Fairfax (Virginia), San Diego (California). The innovative counties are Santa Clara (California), New York County (New York), Cook (Illinois). Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

5.3.4 Additional Robustness Checks

I perform a range of other changes to the specification, with tables shown in Appendix G. I test whether the results are robust to clustering at the state-level instead of at the county-level. This is useful since state-level innovation and taxation policies could lead to there being correlation in the error term in counties within the same state. The results are presented in Table 11 and indicate that the results are robust.

Despite the Leave-one-out analysis of counties, there could still be concern that the results are driven by a small number of counties which receive higher levels of procurement spending and produce more patents than other counties. As an alternative test of this possibility, the dependent variable is winsorized. In particular, the top 5% of values taken by the citation weighted patent count are removed from the sample. The results are shown in Table 12. As expected the coefficients fall; however, they fall by a small amount demonstrating that the results are not being driven by these extreme values.

6 Concluding Remarks

In this paper I show that military procurement spending in the US during the Cold-War contributed to the formation of regional innovation clusters. Using a Difference-in-Differences analysis, I provide suggestive evidence that the surge in military spending under Reagan had long-run effects on county patenting. I confirm the effect of spending on county innovation using an instrumental variables strategy exploiting exogenous variation in national-level spending priorities. The results indicate that the effect of procurement spending on innovation is largest in counties where there are high levels of competition, which is consistent with the hypothesis that local knowledge spillovers are a relevant mechanism. The analysis therefore suggests that governments trying to promote innovation should target innovative firms which are located in regional clusters of competing innovative firms. In this way, the spending not only directly benefits the recipient but also indirectly benefits its competitors through the creation of local knowledge spillovers.

Future work should provide clearer evidence on the mechanisms by which county innovation is affected. This can be achieved by combining the analysis in this paper with a firm level analysis to assess what fraction of the increase in county innovation is attributable to firms other than those which received procurement contracts. If a positive effect is identified then an analysis of citations must be used to establish the presence of knowledge spillovers. In particular, one could test whether the patents produced by firms which did not win contracts disproportionately cite the patents produced by firms in the same county which did win contracts. Identifying this precisely would be an interesting challenge which would build on the methodologies introduced in Jaffe et al. (1992) [18]. In addition, the nature of these knowledge spillovers should be studied in order to test to what extent military innovation contributed to innovation for civilian application.

Another key mechanism to test is the migration of inventors. Since procurement spending increases demand for R&D it attracts inventors from other counties. This mechanism implies a reallocation of innovative capacity as opposed to a net increase. As Kantor & Walley (2023) [20] found within the context of NASA contracts, it is likely that migration played an important role but cannot explain the entire effect. Instead, it is likely that inventor migration, industrial agglomeration and local knowledge spillovers are all required to understand the observed effect.

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Appendix A Summary Statistics

Table 7: Summary Statistics

	Mean	Std. Dev.	Min	Max
ln Patents	0.70	1.28	0.00	9.46
ln Cit. Weighted Patents	1.44	1.68	0.00	10.42
ln Spending	5.19	4.35	0.00	17.18
IV	1.96e+06	2.94e+06	0.00	3.67e+07
Average Wages	16601.04	6023.16	548.00	76212.00
Tech Employment Share	0.03	0.05	0.00	1.00
Population	79267.86	260432.71	51.00	9.78e+06
Employment	26496.70	109718.11	1.00	3.87e+06
Observations	115634			

Notes: The Table shows summary statistics on the all the variables used in the analysis.

Appendix B Difference-in-Differences

Table 8: *Parallel Trends Test*

	(1) Patents	(2) Citation Weighted Patents
F-Statistic(1, 496)	0.44	0.52
P-value(Prob > F)	0.5077	0.4725

Note: The Table shows the P-value and F-statistics from testing the hypothesis that the treatment and control groups have parallel trends in the outcome variable prior to the introduction of the treatment. The first column shows the results when the outcome is the number of patents and the second column when the outcome is the log of citation weighted patents.

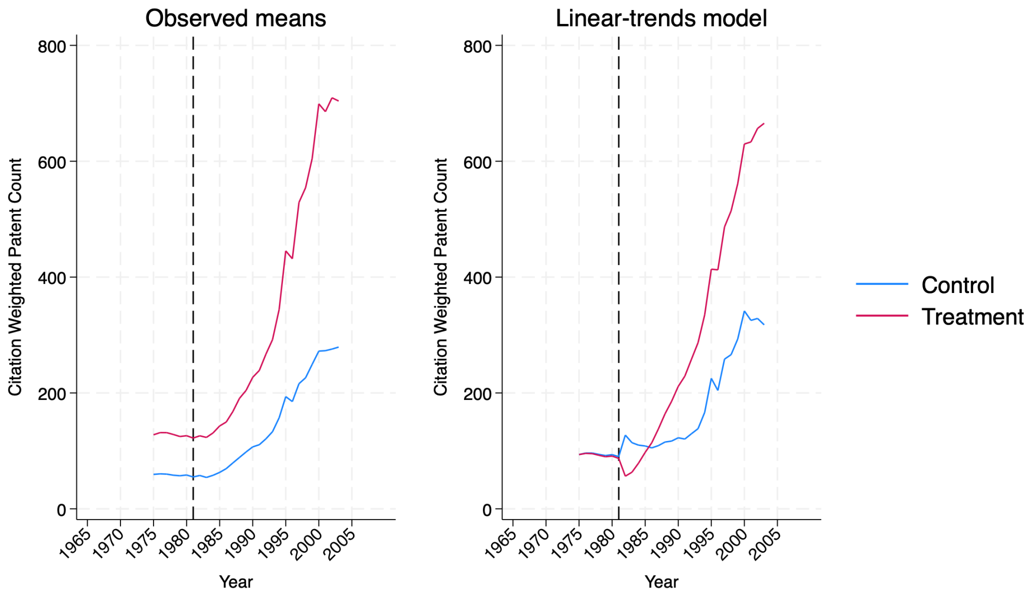

Figure 8: The two figures show evidence of the parallel trends assumption. The y-axis is the number of citation weighted patents and the x-axis shows the years. The plot only starts from 1975 since this is the year from which the citation weighted patent count has been constructed. The first plot shows the mean number of patents produced each year in the counties which are included in the treatment group and those included in the control. The second plot augments the model by controlling for group specific linear trends.

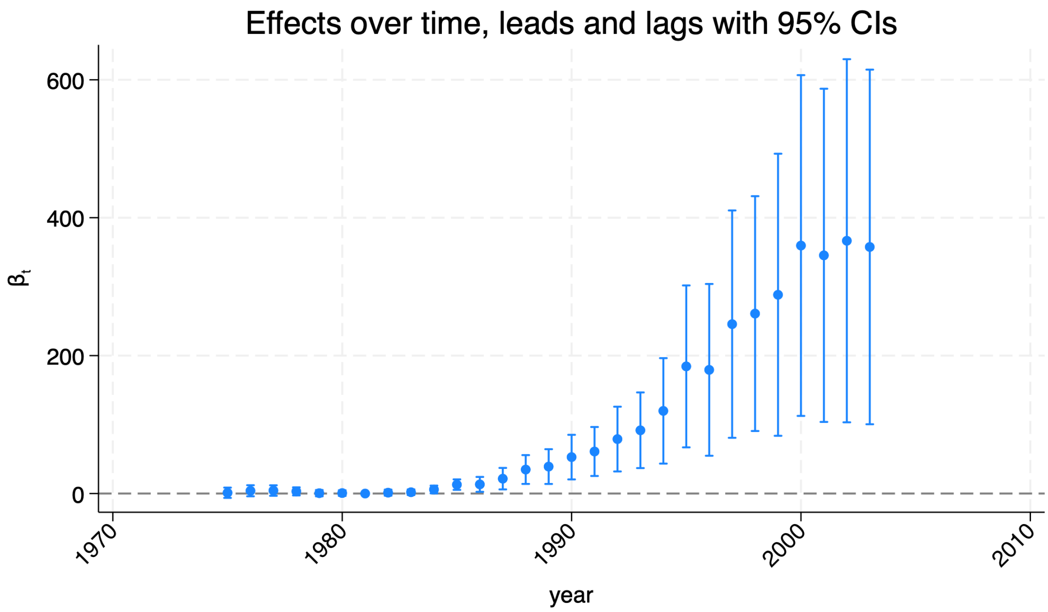

Figure 9: The figure shows the estimated treatment effect on the number of citation weighted patents in each year. These are the estimated coefficients of treatment status interacted by the leads and lags with respect to the treatment year. The plot only begins in 1975 since this is the year from which the citation weighted patent count has been constructed.

Appendix C IV Map

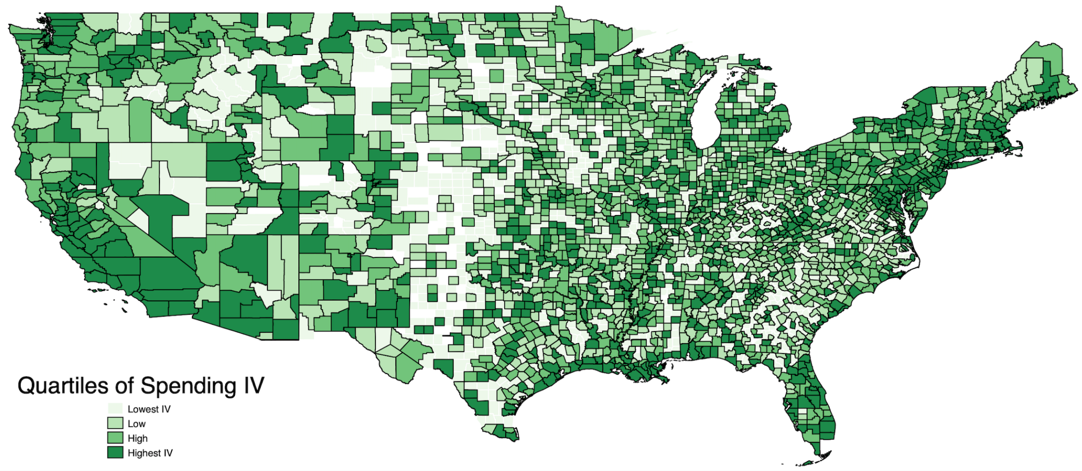

Figure 10: Map of US Counties by quartile value of the IV.

Appendix D Balance Test

Table 9: *Balance Tests*

VARIABLES	(1) Inventor Share	(2) Average Wages	(3) Tech Emp. Share	(4) Pop.	(5) Emp. Share	(6) College Share
Spending IV	-0.00000	-0.00006***	0.00000	-0.00119**	-0.00124***	-0.00000
	(0.00000)	(0.00002)	(0.00000)	(0.00055)	(0.00036)	(0.00000)
Observations	15,736	13,876	15,703	15,736	15,703	838
R-squared	0.90312	0.93555	0.85460	0.98559	0.97638	0.96409

Notes: The Table shows the results of a balance test. Each county-level variable is regressed against the instrument. County and year fixed effects are included. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix E Semi-Intensive Margin

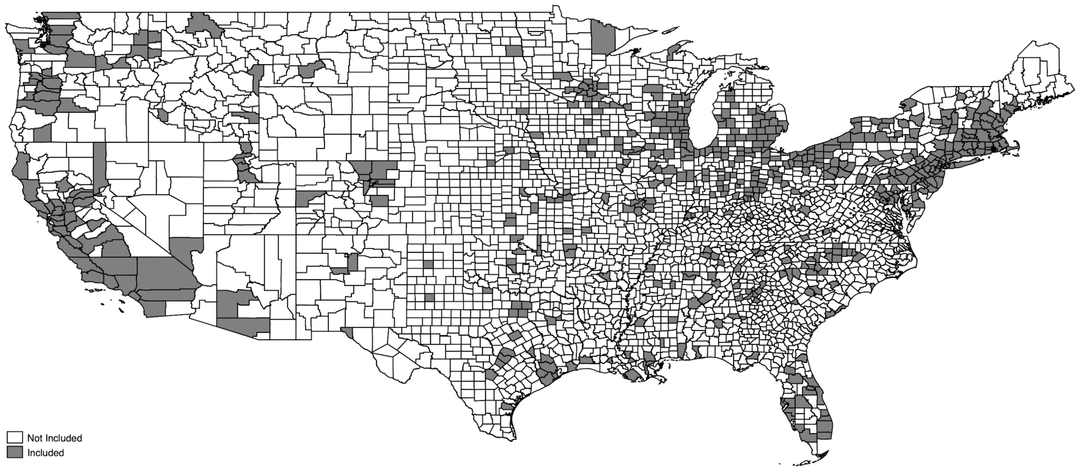

Figure 11: Map of the counties included in Panel B. These are the counties which recieve positive procurment spending and produce at least one patent in over 80% of the years between 1966 and 2003.

Appendix F County Characteristics by Market Concentration

Table 10: Quartile Characteristics

	q1	q2	q3	q4
Inventor Share	0.00204	0.00096	0.00081	0.00059
Tech Employment Share	0.04985	0.05049	0.05275	0.05569
Average Wages	10766.64	10570.24	10522.73	10477.07
Population	377901.9	167928.8	143840	99321.01
Observations	8,065	8,065	8,065	8,065

Notes: The Table shows the group means of the four quartiles for a set of county characteristics over the period from 1966 to 1975. The four quartiles of counties are taken from the semi-intensive margin and defined with respect to the market concentration index defined in Section 5.2. Quartile q1 has the lowest measure of market concentration and therefore the highest degree of local competition and, correspondingly, q4 has the lowest degree of local competition.

Appendix G Additional Robustness Checks

Table 11: *OLS and IV Estimates with state-level clustering*

VARIABLES	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
ln Spending	0.00428**	0.04148***	0.00347**	0.03335*	0.00410***	0.03857**
	(0.00160)	(0.01517)	(0.00168)	(0.01763)	(0.00144)	(0.01877)
Observations	87,299	87,299	75,944	75,944	75,944	75,944
F-stat.	NA	148.18	NA	92.17	NA	104.36
Panel B: Semi-Intensive Margin						
ln Spending	0.02877***	0.12534***	0.02384***	0.13049***	0.01967***	0.11226***
	(0.00467)	(0.03561)	(0.00459)	(0.04350)	(0.00401)	(0.03782)
Observations	24,476	24,476	21,530	21,530	21,529	21,529
F-stat.	NA	44.69	NA	35.25	NA	32.92
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. Instead of county-level clustering, state-level clustering has been used. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 12: *OLS and IV Estimates with Winsorized Dependent Variable*

VARIABLES	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Panel A: All Counties						
ln Spending	0.00407**	0.04480***	0.00347**	0.03759**	0.00401***	0.04193**
	(0.00159)	(0.01495)	(0.00166)	(0.01739)	(0.00147)	(0.01893)
Observations	87,299	87,299	75,944	75,944	75,944	75,944
F-stat.	NA	148.18	NA	92.17	NA	104.36
Panel B: Semi-Intensive Margin						
ln Spending	0.01992***	0.11402***	0.02198***	0.13001***	0.01826***	0.11692***
	(0.00501)	(0.03485)	(0.00512)	(0.04242)	(0.00477)	(0.03923)
Observations	24,476	24,476	21,530	21,530	21,529	21,529
F-stat.	NA	44.69	NA	35.25	NA	32.92
County and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes
State-Year FE	No	No	No	No	Yes	Yes

Notes: The Table shows the OLS and IV estimates of the effect of spending on citation weighted patents. The outcome has been winsorized by dropping the top and bottom 5% of observations. Panel A includes all counties in the United States. Panel B includes the counties which both patent in at least 80% of the years between 1966 and 2003 and receive at least one procurement contract in 80% of the years between 1966 and 2003. Additional controls include average wages, population and employment. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.