# The innovation dividend of fiscal policy: the impact of defense spending on local innovation in U.S*

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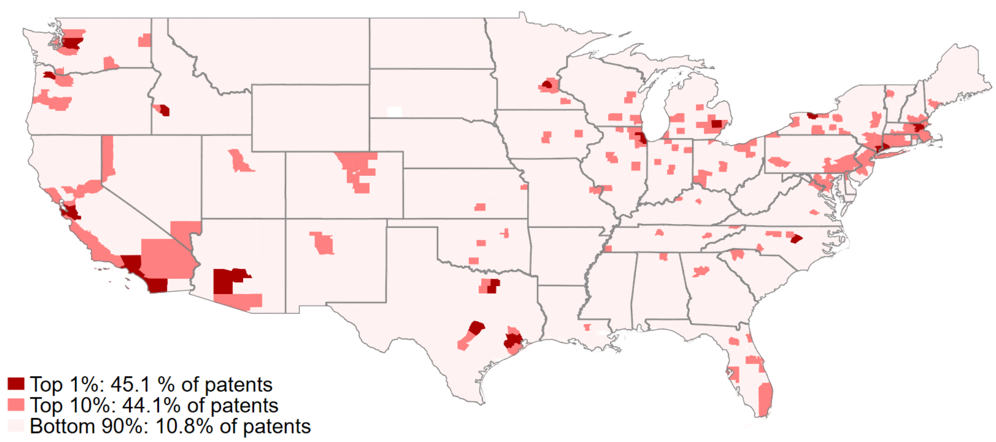
## 1 Introduction

Economic growth in United States has been uneven across the territory. Since 1980s, few super-star cities have been experiencing larger growth rates in employment, investment, and output than the rest of the country. These trends evoked a "*winner-takes-most*" dynamics, where regions left behind are unable to attract investment and create a virtuous circle of economic growth. Some studies have linked this dynamics to the digital technologies and innovation (Atkinson et al., 2019; Eckert et al., 2019). These cities host the bulk of the high-tech clusters, and as consequence develop a significant fraction of U.S. innovation. Figure 1 shows that the top 1% of the U.S counties account for 45.1% of all the patents registered between 2001 and 2013 (7 millions of patents), while the bottom 90% account for only one-tenth of the patenting activities.[1]

Figure 1: Geographic Distribution of Patents by Percentiles




Note: Data are collected from the USPTO. The percentiles are defined based on the the distribution of total number of patent over the period 2001-2013.

The concentration of innovation in super-star cities has been increasing in the last two decades. During 2001-13, the production of patents in the top 30 most innovative counties grew by 75%, while for the bottom 90% of the counties, the growth of patenting has been below 50% (see Figure 2). The increasing trend in output and innovation divergence has been related to other pressing problems like the increase in wage inequality (Moretti, 2013; Eckert et al., 2019),[2] the fall in inter-generational mobility (Bell et al., 2019; Chetty and Hendren, 2018)[3] and the current upsurge of political polarization (Autor et al., 2016).[4]

Place-based policies have been proposed as a policy tool to level the field and boost economic activity and innovation in economic distressed areas. This policies can be justified in the presence of agglomeration economies and spatial misallocation that responds to frictions in the labor and housing market (Kline and Moretti, 2014; Hsieh and Moretti,

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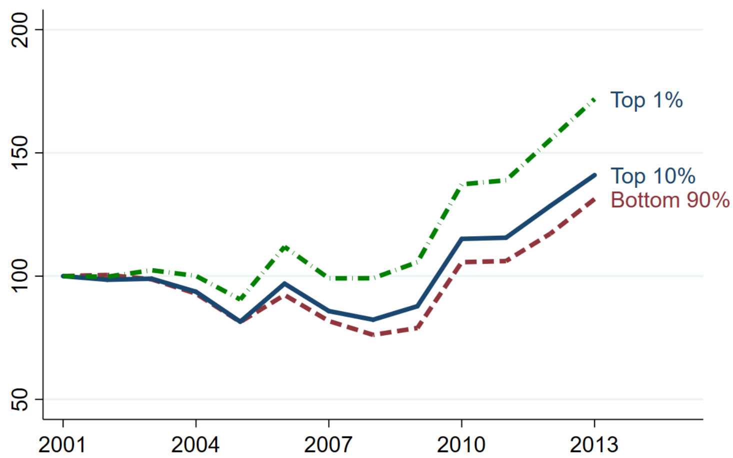
[1] This facts have led to an intensive policy debate by different think tanks such as Brookings (here, here, and here) and the Equitable Growth (here, here, and here).

[2] Eckert et al. (2019) shows that 30% of the increase in wage inequality is due to skilled-tradeable sector in superstar cities.

[3] Chetty and Hendren (2018) finds that the characteristics of the county where you born matters for your adulthood outcomes. In the same vein, Bell et al. (2019) finds that childhood exposure to innovation increase the probability of becoming an inventor.

[4] Autor et al. (2016) finds that local labor markets more affected by import competition from China prefer less moderate candidates, i.e increase the political polarization. Moreover, Rodrik (2018) finds that places that where most affected by globalization shocks have vote more for populist governments in Latin America (left-wing populist) and Europe (right-wing populist).

Figure 2: Growth Rates of Patents by Percentiles




Note: Data are collected from the USPTO. The percentiles are defined based on the 2001 distribution of patents. All values are indexed using the 2001 number of patents of the respective percentile.

2019; Ganong and Shoag, 2017).[5]

However, the rise of the spatial concentration in innovation can be seen as a threat to placed-based policies. Since innovation is the main determinant of long-run economic growth, place-based policies need to incubate innovation outside the super-star cities, otherwise it will be difficult for them to generate a *big push*. National fiscal policy can affect this geographical concentration through spending and taxes. How does federal fiscal policies affect local innovation and long-run economic growth? Can place-based policies reverse the trend of innovation-concentration by generating new innovation clusters? This paper aims to contribute to answer these questions by exploring the effects of a local fiscal stimulus in the form of defense spending on both innovation and economic growth. Defense spending is a large, discretionary and R&D-intensive policy instrument. This fact has been used by the macroeconomics literature to estimate the size of fiscal multipliers. However, with the exception of Akcigit et al. (2017), there is no evidence about how this demand shocks can affect innovation, and subsequently, the persistence of growth after the fiscal resources are gone.

This paper combines several administrative records. First, we collect a rich contract level data on defense spending. It is used to measure the amount and innovation-intensity of defense purchases at county level.[6] Second, we use county-level measures of innovation in terms of outputs (number of patents) and inputs (number of science-related jobs). Based on these measures we will be able to explore trough which channels defense spending affects aggregate innovation.[7] We use GDP, personal income and total employment to evaluate the impacts of defense spending on economic growth. To the best of our knowledge, this project is the first that uses military spending, patenting, and GDP data at a such fine geographic level.

Our identification strategy exploits the quasi-experimental time and cross-sectional variation in defense spending across counties that followed the declaration of the War on Terror in September of 2001. To circumvent some endogeneity concerns in the allocation of military spending across localities we use a shift-share instrument proposed by Nakamura and Steinsson (2014).[8] As any shift-share instrument it creates a predicted defense spending at local level by combining national variation in military spending with a measure of local comparative advantage to receive defense contracts, the latter is parameterized by the share of total military spending that goes to a specific county before 2001.

[5] Agglomeration economies make the social returns of these policies higher than the private returns, this make desirable for the government to invest in places with high agglomeration elasticity. Spatial misallocation implies a dead-weight loss because workers in economical distressed areas can not migrate to productive places and therefore are employed (if lucky enough) in low productivity jobs.

[6] The innovation intensity of government purchases is measured as the share of purchases that demand R&D services, other categories in the data are infrastructure, cleaning services and non-durable goods.

[7] Investigating the role of the extensive (number of researchers) and intensive (number of patents by researcher) margin, is particularly important for the current policy concerns about the decline in research productivity in U.S (Bloom et al., 2017).

[8] This same strategy has been used recently by Auerbach et al. (2019) to estimate fiscal multipliers at CBSA level and by Demyanyk et al. (2019) to measure how consumer debt affect the size of the fiscal multiplier.

The main identification assumption is that the two components used to computed the predicted defense spending are conditionally independent of contemporary and future shocks in our outcomes of interest - innovation and growth.

The defense spending data is suitable to study the effects of local fiscal policies on innovation and economic growth for three reasons: First, defense spending has been a long standing sponsor of innovation worldwide, it funded the creation of internet, GPS, among other path-breaking discoveries. About 15% of defense spending demands R&D, while the rest is spend in infrastructure, services and non-durable goods. Therefore defense spending is a local fiscal policy that affects innovation both directly, by demanding contracting out the research services of the corporate sector, and indirectly by other general equilibrium mechanisms (Moretti et al., 2019; Draca et al., 2012).[9] Second, defense spending is discretionary at aggregate level and responds to geopolitical events rather than to local economic cycles. The weak linkage between local economic cycles and aggregate defense spending alleviates concerns of lack of exogeneity of our instrument due to simultaneity problems (Ramey, 2011). Third the declaration of the War on terror break the aggregate trend in defense spending (it was declining during the whole decade of 90s). Moreover, the fact that defense spending is discretionary leverage a large and unexpected county level variation that we exploit for identification.

**Related literature** This project contributes to three strands of the literature. The first is the literature of place-based policies. A large part of the literature has focused on the effect of those policies in employment and growth without considering outcomes like innovation.[10] The only exception are those papers that have exploited changes in tax rates across U.S states to measure several innovation outcomes like number of inventors and patents Akcigit et al. (2018). Other papers have explored the effect of taxes on R&D, though not strictly under the framework of a place-based policy but a firm-based policy. (Bloom et al., 2002; Dechezleprêtre et al., 2016).[11] We contribute to the analysis of innovation placed based policies by using fiscal stimulus instead of taxes as policy instrument. In spite defense spending does not target specifically innovation, it works as a demand-induced innovation shock due to the amount of purchases of R&D services made by the military sector. This type of shocks may have different effects than the ones found by Akcigit et al. (2018) using tax incentives.

Second, as we focus on innovation as primary outcome and use military spending as approach for a fiscal policy we directly contribute to the literature that studies the effects of military spending on innovation. This literature has focused on understanding the firm level responses to public spending, particularly, they find that it does crowd in corporate investment at firm (Draca et al., 2012), (Slavtchev and Wiederhold, 2016) and international level (Moretti et al., 2019). Our contribution is to focus on aggregate innovation at local level and explore the effects of military spending on creating innovation clusters. Moretti et al. (2019) study this question at national level, our main advantage by using a local level approach is that we are allowed to decompose the aggregate effect into its local and spillover components.

The third contribution is to the literature of relative fiscal multipliers (RFM). This literature tends to use longitudinal data at state or county level to estimate the impact of fiscal policy on local output. A review of Chodorow-Reich (2019) concludes that the bulk of this studies use either military spending or the fiscal policy implemented during the American Recovery Act of 2009 to draw causal inference on the size of the RFM.[12] This paper contributes by asking how the innovation intensity of the military spending matters for the effects of the local fiscal stimulus on the economy. Therefore we contribute by exploring one of the channels trough which fiscal stimulus can affect economic growth. The study more close to ours in this regard is Akcigit et al. (2017) who use the WWII innovation spending as instrument to estimate the effect of patents on economic growth. The policy implications of this project relies at the core of the mission of the Washington Center for Equitable Growth. Our question aim to identify the efficacy of local fiscal stimulus on a key determinant of long-run economic growth, namely, innovation. This will help to design place-based policies that aim to reduce regional disparities that affect U.S today and are deprived many citizens from participating from the dividends of a digital economy.

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[9] Among these mechanisms could be knowledge spillovers, relaxing financial frictions or increasing agglomeration economies.

[10] See Neumark and Simpson (2015) for a literature review on general placed-based policies.

[11] See Bloom et al. (2019) for a excellent review of innovation policies.

[12] Nakamura and Steinsson (2014), Suárez Serrato and Wingender (2016) and Auerbach et al. (2019) focus on contemporaneuos RFM, while other studies use the WWII as natural experiment to estimate long-run RFM (Fishback and Cullen, 2013; Fishback and Jaworski, 2016; Li and Koustas, 2019), most of the long-term studies find no significant results on GDP per capita but significant results on population growth and structural transformation.

## 2 Identification strategy

Our identification strategy exploits a time and spatial variation in military outlays that followed after the declaration of the War on Terror by United States in September of 2001. This event allow us to exploit an unexpected and large increases in defense spending. Before 2001, defense spending was in decline because of several spending cuts that were implemented as a result of the end of the cold war. This makes the rise in defense spending an unexpected event. Moreover the war against Afghanistan and Iraq have been the most expensive military build ups for U.S since WWII. Following Auerbach et al. (2019), we estimate a flexible specification described by equation (1),

$$\frac{Y_{l,t+k} - Y_{l,t-1}}{Y_{l,t-1}} = \beta \frac{G_{l,t+k} - G_{l,t-1}}{GDP_{l,t-1}} + \alpha_l + \delta_{t+k} + \epsilon_{l,t+k}$$

where $l, t$ and $k$ refers to county, time and horizon ($k = 0, 1, 2, 3, 4, 5, 6$). Our outcome variable measures the $k$ period growth rate $\frac{Y_{l,t+k} - Y_{l,t-1}}{Y_{l,t-1}}$ for both innovation and economic growth (e.g output, employment or private earnings). Defense spending is normalized by local output. $\alpha_l$ absorb linear county specific trends and $\delta_{t+k}$ for any mechanical correlation due to secular trends in defense spending and local economic growth.

Still, the realized changes in military spending $G_{l,t+k} - G_{l,t-1}$ may respond to unobserved local shocks that also affect innovation. Private firms located in counties with higher military contracts may have exerted more effort trough lobby and investment in order to bring those contracts home. As long as this firm specific shocks also affect innovation and growth our coefficients will be biased. Also, politicians have an active role in trying to allocate contracts to their constituencies during economic downturns. To circumvent this endogeneity problem we use a shift-share instrument that interacts the nation-wide changes in defense spending ($G_{t+k} - G_{t-1}$) with the share of national defense spending that each locality received during the decade of the 90's. The equation below describes our instrument:

$$G_{l,t+k} - G_{l,t-1} = s_l \times (G_{t+k} - G_{t-1})$$

where $s_l$ can be defined as a predetermined comparative advantage of certain counties to receive military spending and it is defined by the share of total national spending that was allocated to locality $l$ during the decade of the 90s $s_l = \frac{\sum_{t=90}^{00} G_{lt}}{\sum_{t=90}^{00} G_t}$. This identification has been used in the literature before at state level by Nakamura and Steinsson (2014) and at metropolitan area by Demyanyk et al. (2019) and Auerbach et al. (2019).

Since our main regression is in changes and we use locality fixed effects, the conditional variation that is provided by our instrument comes from national level changes in military spending, which is plausible exogenous to local shocks that affect innovation and growth. An emerging literature on Bartik designs provides a new set of test to make more transparent the assumptions behind the use of this type of instruments (Goldsmith-Pinkham et al., 2018; Adao et al., 2019). We will develop their suggested robustness test in future stages of this project, another value over previous approaches.

## 3 Data

### 3.1 Innovation

Microdata for granted patents are publicly released by the United States Patent and Trademark Office (USPTO).[13] Following the USPTO's practice, we classify the patent origin based on the residence of the first-named inventor. Because readily available inventor residence information generally is limited to the city and state at the time of patent grant, we will use the U.S. Post Office zipcode reference file to aggregate the available geographic information by county. We will use this measure as an indicator of innovation activities.

The plain count of number of patents suffers from several measurement issues that are well-established in the literature. The two main issues are: 1) the upward secular trend in patenting; 2) the importance of the different patents.[14] We will complement the empirical analysis by investigating two adjusted measures of innovation. To address the upward trend in patenting, we will adjust the count of patents by implementing the 'fixed-effects' proposed in Hall et al. (2001). To account for the difference in quality and importance among patents, as standard practice in the

[13] We will scrape the data from the following link https://bulkdata.uspto.gov/.

[14] We are aware of other problems with patent data, such as for example, the truncation problem. Due to military expenditures data limitations, we are forced to drop the last few years of the sample. We believe the truncation issue is significantly attenuated.

literature, we will weigh each patent by the number of citations received in a 5-years window after the application year. All information needed for computing the adjustment measures are available in the above mentioned USPTO's files. For the measure of number of researchers see section 3.3.

### 3.2 Defense spending

We will use data on military contracts for the period 1990-2018. Up to now, we have collected and processed data for the sub-period 2001-2013. These data for the recent years is available at USAspending.gov. The data on military contracts for the years before 2001 will be collected from the National Archives and Records Administration-NARA.[15] To our knowledge, our projects is the first that will make a consistent series of military contracts between 1990-2018.[16]

The data allow us to distinguish many characteristics of each contract: i) name and unique identifier of the firms who receive the contract, ii) type of good and service contracted (e.g. missiles, R&D, office supplies, or cleaning services for military bases), iii) geographic location of the primary contractor and where the majority of the work has been performed, iv) duration of the contract, v) the industry classification by 6-digits NAICS of the firm who has received the contract.

### 3.3 Other data

Data on GDP and personal income is taken from the Bureau of Economic Analysis (BEA). GDP data at county level is a new dataset that was just released for first time on December 2019, which allow our project to find and study new stylized facts about growth dispersion in U.S. We use data on employment from County Business Patterns (CBP) from the Census Bureau, this dataset allows us to observe employment for each 4-digits NAICS. We will use this advantage to estimate number of workers in R&D intensive sectors.

## 4 Preliminary results

This section presents the preliminary results of our empirical specification using the instrumental variables strategy. These results are preliminary for three main reasons. First, as explained in the sub-section 3.2, due to the large computation power needed to process the military spending data, we have been processing the data gradually. We expect to conclude the creation of the full dataset by the end of May. Second, the results in this section use the plain count of patents by county. As described in sub-section 3.1, we plan to adjust this measure of innovation along several dimensions. Third, we will explore alternative identification strategies to investigate the robustness of our findings.[17] For all these reasons, the results should be interpreted with a grain of salt.

The data used in this analysis consists of a balanced panel of counties with data on defense spending, patent, GDP and total employment for the period 2001-2013. We keep all counties with more than 1,000 jobs, non-missing values for GDP, DoD spending and non-zero granted patents. Table 1 suggest that expansionary local spending shocks have a strong positive impact on local innovation on impact and in the long run. The results suggest that fiscal stimulus have sizable effects on the number of patents for the average county.

However, we show that there is substantial concentration of patents across counties. Then, the question is if this policy increase innovation in those counties that are lagging behind, i.e. reducing geographical concentration, or the fiscal stimulus boost the concentration of patents in a few counties. To preliminary provide a test for this key policy question, we split counties according to the level of patents in year 2001 (first available). Table 2 suggest that DoD spending seems to have a higher effect on those counties that were in the bottom of the geographic distribution of patents in year 2001.

Preliminary results seems to lead to belief that national government spending can boost local innovation and then local economic growth. Interestingly, the local fiscal stimulus seems to increase innovation in those places that were lagging behind. Placed based policies may help to reduce the differences between counties in terms of what they can offer to firms and workers. This may end up in social gains in terms of spatial equality.

[15] We will follow the harmonization standards recommended in Draca et al. (2012)

[16] We plan to share this data once the project is finished.

[17] See section 5 for details.

Table 1: *Local spending and effects on local innovation*

| | Innovation multiplier | | | |
|---|---|---|---|---|
| | On Impact | 2-year | 4-year | 6-year |
| | (1) | (2) | (3) | (4) |
| Spending | 2.795** | 2.370** | 3.404** | 1.667* |
| | (1.262) | (1.024) | (1.402) | (0.882) |
| County and Time FE | Yes | Yes | Yes | Yes |
| Obs | 11,184 | 9,320 | 7,456 | 5,592 |
| # of Counties | 932 | 932 | 932 | 932 |
| $1^{st}$ Stage F-stat | 28.74 | 22.20 | 13.14 | 12.07 |

***: p<0.01 ;**: p<0.05;*: p<0.1

Table 2: *Heterogeneous effects of spending on local innovation*

| | Innovation multiplier | | | | | |
|---|---|---|---|---|---|---|
| | **Bottom 75%** | | | **Top 25%** | | |
| | On Impact | 2-year | 4-year | On Impact | 2-year | 4-year |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Spending | 2.987** | 2.624** | 3.683** | 0.796 | -0.058 | -0.245 |
| | (1.399) | (1.266) | (1.671) | (0.811) | (0.916) | (1.271) |
| County and Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 8,388 | 6,990 | 5,592 | 2,796 | 2,330 | 1,864 |
| # of Counties | 699 | 699 | 699 | 233 | 233 | 233 |
| $1^{st}$ Stage F-stat | 24.74 | 16.72 | 10.36 | 3.956 | 8.869 | 6.201 |

***: p<0.01 ;**: p<0.05;*: p<0.1

# 5 Timeline and Budget

The next stage of the project can be divided in three parts. The first is the data collection part. We will extend the sample period for DoD spending series to 1990-2018, by downloading and organizing the data from USAspending.gov and NARA. We will scrape USPTO's to add the application year to our county level on patents and also to control for the innovation trends before 2000. We will use the CBP data to estimate science-related jobs and research productivity and include them as outcomes in our estimations. We plan to finish this activity by August of 2020.

The second, is to improve our identification strategy and write down the first draft of the paper. We will add local industry composition to our shift-share instrument, this depends on the quality of the defense contracts to detect DoD national trends at the industry level. Also, we will explore the use of synthetic control methods proposed by Zou (2018). Finally, we will test the robustness of the shift-share instruments following recent econometric guidelines proposed by Goldsmith-Pinkham et al. (2018) and Adao et al. (2019). We plan to finish this activity by December of 2020, additionally by that time we will have the first draft of the paper with all our empirical results.

Third, we will match our empirical results and moments of the data to a endogenous growth model that considers agglomeration economies and spatial heterogeneity. This will allow us to asses the welfare implications of this particular place-based policy on long-run economic growth. Particularly, the model will help us to answer two questions: i) How the spatial dispersion of fiscal policy affects aggregate outcomes of the economy? Is it better to spend equally across the board or concentrate spending in the most productive cities?. ii) How long a fiscal-induced demand shock should stay in order to generate persistent effect over time?. We plan to finish this activity by December of 2021.

We apply to the doctoral grant. The $15,000 will be used for support of the doctoral applicant while he is doing his dissertation which is also related to the topic: fiscal stimulus and firm heterogeneity.

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