State Capacity in Innovation Markets

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What is the role of the Entrepreneurial State?

The popular image of the private vs public sector debate is at times sufficiently extreme that it would be more aptly presented as a caricature than form an academic discussion. Is the public sector led by the enemies of enterprise[1] as the then UK prime minister David Cameron put it in 2011? Or is the private sector focused solely on grinding out personal gain through an ends justifies the means perspective?

The term "Entrepreneurial State" would be deemed by some as an oxymoron, however this term paper looks to form part of a larger project aimed at better understanding the current role of public finance in innovation markets. Technological advances and their merits and demerits dominate both political and social discourse. Does big tech pay enough tax? Why hasn't Europe developed a Silicon valley? Is innovation driving income inequality? The relevance of such questions for policy makers is clear.

Literature

This term paper can be placed within a few larger bodies of literature. The first, is that on state capacity. State capacity in it's purest form has traditionally been defined around an ability to effectively tax citizens, maintain peace and provide public goods (Johnson and Koyama 2017; Besley and Persson 2013; Geloso and Salter 2020). Concurrent to this well established literature is a running debate between state capacity and the literature on economic growth spurred by Barro 1990 and other researchers who demonstrated a negative correlation between increasing government size and economic performance. In response to this belief, Besley and Persson 2009 ask, why then do rich countries have high tax rates?

In their eyes, one justification is that a state's ability to pursue developmental goals is constrained by past investments in state capacity (Besley and Persson 2009). The state must make a conscious choice to invest in their ability to enact fiscal policy which requires a well established tax base. Besley and Persson re-frame the question around state capacity to discuss the ability of the state to support markets while performing their fiscal and state duties. This term paper looks to contribute to this discussion by linking the state capacity concepts to the literature on public finance in innovation.

D. Acemoglu, Moscona, and J. Robinson 2016 demonstrate the role of political institutions in the success of US inventors in the 19^{th} century. They show, using an IV regression method, that the presence of the state predicts a rise in innovative activity. They justify their use of an IV approach by stressing the endogenous relationship between innovation and institutions. Something they believe leading examples from the literature on technological advances and economic growth (e.g. Gordon 2017) in the US have overlooked

[1] https://www.theguardian.com/politics/2011/mar/06/david-cameron-civil-service-enemies

Barro's conclusions on the impact of big government were developed during the endogenous growth theory boom of the 90s. This literature highlighted the role public good provision played in determining economic growth. Romer 1990 categorises a design as a non-rival but partially excludable good, thus only partially qualifying as a public good. The model developed in Besley and Persson 2009 shows how improvements in state capacity are driven through the provision of public goods of common interest. In response a large portion of the classical economic literature dictated that the role of the state is to establish and maintain efficient patenting systems, so as to compensate for this partial excludability.

Claessens and Laeven 2003 develop a model to examine the protection of entrepreneurial assets against the actions of other firms. They argue that firms operating in markets with weak property rights invest more in fixed assets than intangible assets as it is relatively more difficult to protect and make profit from intangibles. Since individuals who have a lower faith in the state to protect their property rights invest sub-optimally in production, leading to output losses (Goldstein and Udry 2008), patenting as a property right is central to prompting optimal innovation.

I present a theory here however, which goes beyond framing the role of the state as an enforcer of patents and property rights, as do Aighon, Dewatripont, and Stein 2008. Their model defines the position of public finance in innovation and proves that it is optimal for early stages of research programs with a sufficiently large number of stages to be conducted in the public sector. They conclude that introducing public finance at the wrong stage of the innovation process can lead to output distortions.

This concept is extended by Akcigit, Hanley, and Serrano-Velarde 2020 who demonstrate that miss allocations in public financing of R&D come not from over or under investing in total quantities but in where the R&D support is targeted. They find that there is an excess of investment in applied research at the cost of basic research. This adds to the results of Romer 1990 whose model predicts under investment in basic research by the private sector. The model developed in Akcigit, Hanley, and Serrano-Velarde 2020 predicts that uniform R&D subsidies are sub-optimal and that the state should target their R&D towards basic research and to interact with the private sector.

Do we give the state enough credit for the current role which public finance plays in the innovation sector? Mazzucato 2013 presents the concept of an entrepreneurial state and highlights the vital role which public finance and support played in key technological advances of recent history. Breakthroughs such as GPS, touchscreen technology and voice recognition are highlighted as examples for which public finance entered earlier than venture capital and supported early seed stage innovation. These technologies have then been successfully commercialised and developed into the products we regularly use today (Mazzucato 2013).

She proceeds to highlight the chronic failure of the state to correctly tax the profits generated by this commercialisation. If the state were to appropriately tax some of techs top performers, they would be able to reinvest and develop their capacity given a strong tax base. This is supported by Besley and Persson 2013 who discuss theoretically, the feedback loop between taxation and economic prosperity.

The public sector is able, through its unique position in the market, to offer patient finance, to supersede the short term-ism of venture capital markets and instead design coordinated innovation strategies. Coordinated in the sense that their interventions harness the cumulative nature of innovation and target key research areas[2]. It is well established that innovation is both cumula-

[2]The recent Covid-19 vaccination is an extreme example of the ability of the state to direct research.

tive and collective (Mazzucato and Lazonick 2013; Sampat and Williams 2019; Filho and O'Neale 2020). These characteristics of innovation, and the availability of quality data on patents, have led to a boom in network approaches to innovation questions.

Daron Acemoglu, García-Jimeno, and J. A. Robinson 2015 develop a network game and find that between local municipalities, state capacity is a strategic complement. They conclude that around 43% of changes resulting from increased local state capacity are due to network effects. They add that ignoring the network context around state capacity is incorrect and can lead to miss-leading results. Furthermore they directly model the role of betweenness centrality on the optimal re-allocation of state capacity. They show through regression analysis that it is optimal to re-allocate state capacity to municipalities as they become more central within the network.

Akcigit, Hanley, and Serrano-Velarde 2020 showed that optimally, government policy in innovation markets is targeted towards key areas. This aligns with König, Liu, and Y. Zenou 2019 who use a network model to identify optimal R&D subsidies. Taking a wider look at the innovation network, D. Acemoglu, Akcigit, and Kerr 2016 show that a stable network is a catalyst for innovation growth. I aim to contribute to this growing literature by examining the role of the connectedness of the state to the private sector and the resulting outcome for innovation rates.

The takeaways are that due to characteristics of public finance, the skills required of the state and the collaborative nature of innovation, a network approach to answering the question is appropriate. Secondly, that the ability of the state to support innovation markets should be framed in the context of state capacity, thus avoiding the assumption that all states are equally able to support innovation and thus endogenise state ability.

Model

I develop here a model in which the network captures one channel through which the state can affect innovation rates and the resulting trade off due to constraints on state capacity. The channel I focus on is that of the state's ability to harness the collective nature of innovation and direct the innovation market through mission led policy (Mazzucato and Semieniuk 2017). The model was motivated by Daron Acemoglu, García-Jimeno, and J. A. Robinson 2015 and is a version of the model presented in Calvó-Armengol, Patacchini, and Yves Zenou 2009.

N = {1, 2, ..., n} is a finite set of firms. These firms make up the innovation network. Collaboration across firms is measured by $\boldsymbol{g} = \mathbb{1}\{\text{firm } i \text{ and } j \text{ are connected}\}$. Collaboration is a reciprocal relationship and therefore the network is directed and $g_{i,j} = g_{j,i}$, normalise $g_{i,i} = 0$.

Each firm faces two endogenous choices, the number of collaborations to make and the level of investment in innovation, $x_i \geq 0$. x_i can capture both tangible and non-tangible investments and enters a firm's innovation production function as,

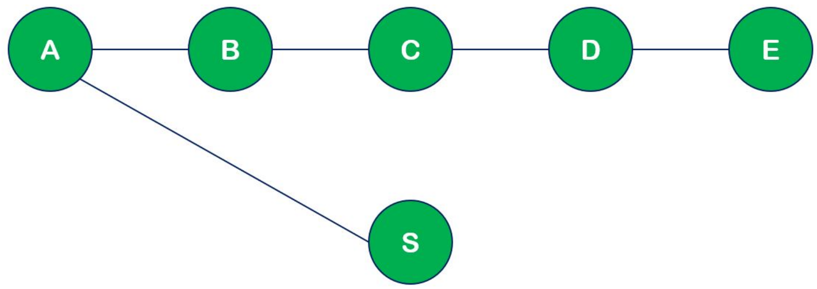
$$I_i = x_i + \sum_{j=1}^{N} g_{i,j}\phi_{i,j} - \frac{1}{2}x_i^2$$

The unique addition of this model is that the contribution of a connection to innovation output is not uniform and is measured by $\boldsymbol{\phi}_i = \sum_{j=1}^{N} g_{i,j}\phi_{i,j}$ where,

$$\phi_{i,j} = \frac{1}{d(i,j)}$$

$d(i,j)$ is the length of shortest path between two firms within network, known in the literature as the geodesic distance. Taking the inverse captures that closer connections, in terms of shorter paths, result in higher quality collaboration and greater marginal change in output. Consider the following example,

Figure 1:



Nodes A-E are firms and S represents the state[3].

$$\begin{aligned}\boldsymbol{\phi_A} &= \phi_{A,B} + \phi_{A,C} + \phi_{A,D} + \phi_{A,E} \\ &= \frac{1}{1} + \frac{1}{2} + \frac{1}{3} + \frac{1}{4} = \frac{25}{12}\end{aligned}$$

I propose that increasing the connectivity of the state can lead to increased innovation output. The network measure which best captures the ability of the state to affect innovation is betweenness centrality. The betweenness of a node counts the number of times a node acts as a bridge along the shortest path between two other nodes [4]. The state can increase $\boldsymbol{\phi_i}$ for a given firm by shortening the distance from them to other firms.

A state can optimally increase their betweenness and increase innovation output through coordinating research efforts which will boost the cumulative nature of innovation. Furthermore Aighon, Dewatripont, and Stein 2008 discuss how publicly funded innovation is more likely to result in new innovation paths and the ability of the state to link together innovative industries will lead to increased entrepreneurial output.

Formally betweenness is defined as,

$$\begin{aligned}B(l) &= \sum_{i \neq l \neq j} \frac{d_{i,j}(l)}{d_{i,j}} \\ &= \sum_{\text{All pairs } i \text{ and } j} \frac{\text{Shortest paths between } i \,\&\, j \text{ that pass through } l}{\text{Total number of shortest paths from } i \text{ to } j}\end{aligned}$$

Returning to the previous example, under figure 1,

$$B(s) = 0$$

[3] ϕ is not calculated for the connection to the state. The state provides other benefits such as patient finance and research freedom which could be captured here however for simplicity I am focusing on just one channel here.

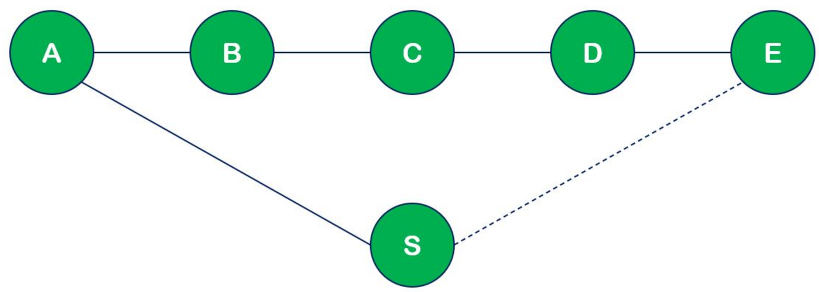
[4] https://sites.google.com/a/umn.edu/social-network-analysis/terminology

Since the state doesn't connect any of the firms together. Formally define the change in path lengths given the state increasing their connectivity as,

$$\hat{\phi_{i,j}} = \frac{1}{d(i,j;state)}$$

Now consider figure 2 and the state increases their betweenness measure by connecting with firm E as shown by the dotted line,

Figure 2:



The betweenness of the state is now,

$$B(s) = \frac{1}{2} + \frac{1}{1} + \frac{1}{2} = 2$$

while,

$$\begin{aligned}\hat{\boldsymbol{\phi}}_{\boldsymbol{A}} &= \hat{\phi_{A,B}} + \hat{\phi_{A,C}} + \hat{\phi_{A,D}} + \hat{\phi_{A,E}} \\ &= \frac{1}{1} + \frac{1}{2} + \frac{1}{3} + \frac{1}{2} = \frac{28}{12} > \frac{25}{12} = \boldsymbol{\phi}_{\boldsymbol{A}}\end{aligned}$$

The state has shortened the distance between firm A and E by increasing it's betweenness level and therefore increased the innovation output of firm A.

This results in the following proposition,

Proposition .1. *The State can increase innovation output by increasing their betweenness centrality within the innovation network*

Literature tells us that assuming that all states are able to enact the desired fiscal policy is mistaken and that we must frame the actions of the state within their capacity to follow policy recommendations such as proposition 1. For simplicity, assume that the state only taxes innovation output before cost deductions and uses all proceeds to directly fund their contribution to the innovation network.

The contribution of the state is welfare improving if innovation output given the taxes and increased connectivity of the state is larger than without. Let $\hat{\boldsymbol{\phi}}_i = \sum_{j=1}^{N} g_{i,j}\hat{\phi}_{i,j}$ measure the return to connections given the state increasing their connectivity. Here notice that I am capturing the change in ϕ given the actions of the state holding all else constant. Therefore defining $\Delta\boldsymbol{\phi} = \hat{\boldsymbol{\phi}} - \boldsymbol{\phi}$, I find the following condition,

$$\hat{I}_i \geq I_i \quad \Leftrightarrow \quad (1-t)\Delta\boldsymbol{\phi_i} \geq t(x_i + \boldsymbol{\phi_i}) \tag{1}$$

The full derivation is included in appendix (1). This condition tells us that the intervention of the state is welfare improving if after taxes, the increase in additional output from connections to other firms exceeds the output losses paid to fund the state increasing their connectedness. Thus providing the second proposition,

Proposition .2. *The capacity for the state to increase innovation output is bounded by the necessary taxes to support increases in their connectedness.*

The scope of this term paper allows me to examine proposition 1. An interesting extension to the model to examine proposition 2 is to include a source of exogenous variation in a state's ability to tax innovation markets, possibly through legislation changes[5]. This would tie both proposition 1 and 2 together however is outside the scope of this paper.

Data

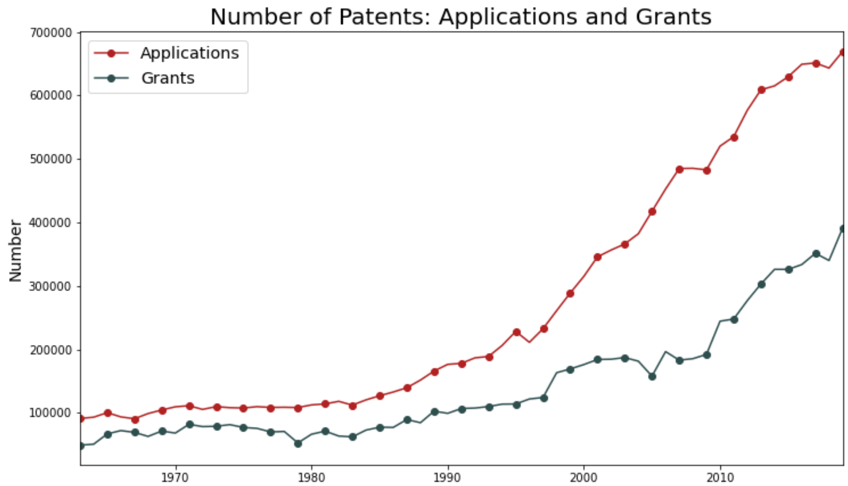
The empirical section will present raw data, network statistics and a system GMM model. As I bring the theoretical model to the empirical network it is important to acknowledge the underlying endogeneity in the question. The empirical model may suffer from reverse causality. If a coefficient on state betweenness is positive, does this capture the state increasing innovation by increasing their connectedness or does an increasingly productive innovation sector attract the state to become more connected. Or vice versa, does the state target starter firms and under developed markets which could lead us to under estimate their potential effect?

The theoretical model has shown that the state can increase innovation output, however to be explicit, the empirical section aims to demonstrate the correlation between state connectivity and innovation. I have taken various steps to tackle endogeneity concerns but I do not claim to prove empirical causality here. The conclusions of this term paper will be extended to look at a causal relationships in the future.

The figure below shows that since the mid 90s the number of patents being awarded has grown significantly[6]. The use of patents as a proxy measure for innovation is the current standard. Despite this, there has been significant debate over whether they are an appropriate measure of innovation. Proponents of the use of patents as a proxy appear to have come out on top (Sampat and Williams 2019; Azoulay, Ding, and Stuart 2009). While I am sympathetic to the idea that simply patenting an idea doesn't guarantee it's usefulness, I have decided to go with patents in line with the current literature. An interesting extension of this paper would be to utilise the information available on citations as a more objective measure of a patent's wider impact.

[5] The EU is currently proposing a wide range of tax reforms to increase the tax paid by large American tech firms, this could provide an interesting avenue through which to test proposition 2 in the future.

[6] Data sourced from https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us$_s$*tat.htm*



Data was collected on 31 US counties over the years 1976-2019, from the US Patent and Trademark Office (USPTO)[7]. This data set is both at once sufficiently large and too small. I am able to achieve reasonably efficient and sensible results however the system GMM model was developed for data with a fixed T and is asymptotically unbiased as $N \to \infty$. Furthermore to create the network and sufficient variation I require that a sufficiently large number of firms are patenting. This means that the data is conditioned on having been taken from the highest frequency patenters which feeds into the endogeneity concerns raised above. However, the 31 counties in question cover over 50% of total patents in the US, therefore I believe enough of the market for patents is covered as to reduce this final concern.

The Network

One graph per county was created for each year. A graph is defined as,

$$\mathcal{G}_{c,t} = \{\mathcal{E}, \mathcal{V}\}$$

for county c in year t and is made up of edges, E, and nodes, V. Each node in the network is an assignee, the owner of a patent, typically a firm. Two nodes are connected by an edge if they both own patents which are credited to the same inventor. This approach is similar to that of Cainelli et al. 2015 and intuitively, firms are sharing knowledge and creating patents through common inventors. The method used to create the network is explained in more technical detail in appendix (2).

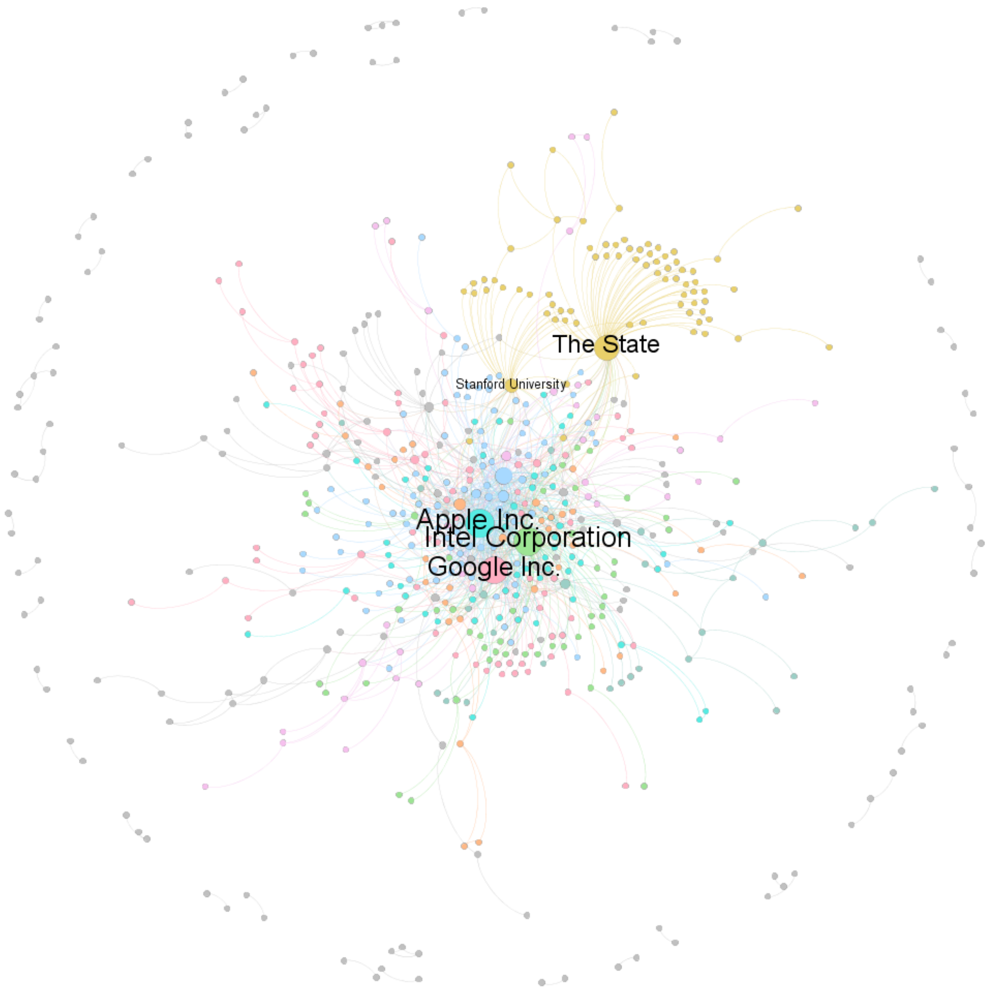
The average degree is the average number of edges on each node and captures how connected the innovation sector is in general[8]. The network is presented below for Santa Clara in 2019 [9]. Santa Clara was chosen since they produce the greatest number of patents, over double that of

[7] https://www.patentsview.org/web/#viz/relationships

[8] All nodes with zero edges were dropped from the graph displayed to show the connected network clearly. They are however included in any network measures such as the average degree since their contribution to the overall network is relevant.

[9] Inner-communities within the network are colour coded by calculating their modularity.

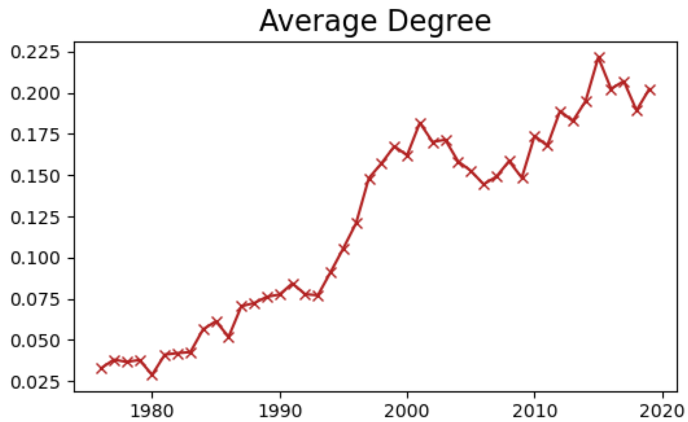
the second place county. It is also home to many of the firms Mazzucato 2013 highlighted as examples of innovation pioneers who were supported by public finance in the early days[10].



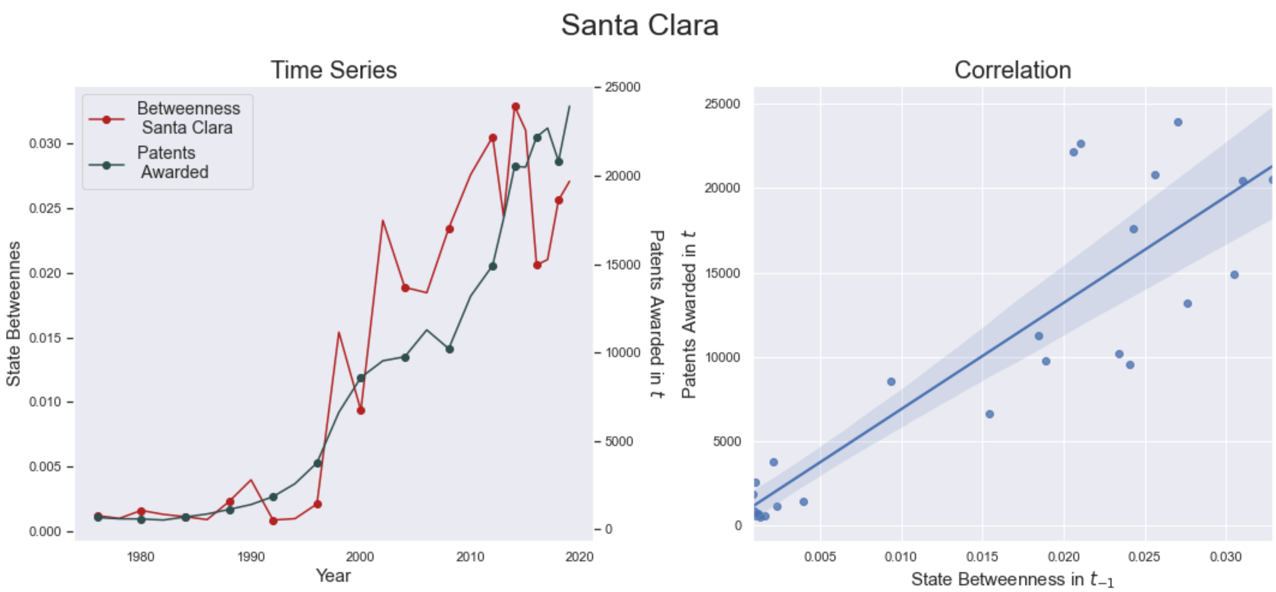
As you can see the innovation network is highly connected in Santa Clara. This supports modelling the level of connectivity into the innovation production function. In addition, the state is well connected to this large body of innovative firms.

Over the period studied the whole network became more connected on average across all counties. Thus controlling for the average degree under the empirical model is necessary. If the average degree is dropped then this may confound results since it will be positively correlated with the quantity of patents produced and the state betweenness if the state are attracted to connect to the growing network.

[10]Mazzucato 2013 highlights key case studies from the iPhone at Apple and Google's initial search engine algorithm.



What is important here is whether the state is becoming increasingly connected to this growing innovation network, or is the distance between the two increasing as the private sector takes off. A time series of the number of patents awarded and the betweenness measure for the state in the same year for Santa Clara is plotted in the left panel below. On the right is a scatter plot of the betweenness measure for the state in $t-1$ and the number of patents in t.



From the left panel we can clearly see that patent growth took off in the 90s and that the connectivity of the state in Santa Clara has kept pace. Both measures move together, showing that the state is increasingly connected to this growing innovation sector. From the right hand panel we see that the betweenness of the state in $t-1$ is positively correlated with the the number of patents awarded in t. While this does not prove proposition (1), it does provide supporting evidence. One reason to be hesitant to place too much weight on these graphs is that we have not accounted for the underlying endogeneity or other heterogeneity in the model, the subsequent analysis section will begin to deal with these issues.

Analysis

To extend the basic graphical analysis I will test the three following scenarios. In all specifications I have controlled for both county and year fixed effects. Unobserved heterogeneity amongst counties can bias results, for example if a county has a number of long standing high level universities then this may cause an upward bias since they are more likely to patent and receive public finance. Time effects will clean out the effects of recessions which in addition to lower patent output, the model has shown would lead to decreased state betweenness due to lower tax receipts.

I have used the within groups estimator to control for η_i and included year dummies. The results are not displayed here but an OLS regression reports a $\beta_{OLS} > \beta_{WG}$ which indicates that the concerns of an upward bias are valid.

Furthermore, the data displays a high level of skewness as shown in histograms included in appendix (4) and so to improve the model fit I took a log transformation of both the dependent and independent variables. As such the coefficients are interpreted as elasticities.

1. The number of patents in period t is a function of the connectivity of the state in $t-1$. Due to the method used to create the network, counting the number of patents on which an assignee is supported by the state, using state betweenness in the current period would lead to further endogeneity. Therefore I only use lagged regressors and the model presented earlier predicts that $\beta > 0$

$$\ln \text{patents}_{it} = \beta \ln \text{state betweenness}_{i,t-1} + \eta_i + \theta_t + \epsilon_{it}$$

2. Next I introduce a control for the average degree of the network. In addition to β, the model predicts that $\gamma_1 > 0$,

$$\ln \text{patents}_{it} = \beta \ln \text{state betweenness}_{i,t-1} + \gamma_1 \ln \text{average degree}_{i,t-1} + \eta_i + \theta_t + \epsilon_{it}$$

3. One attempt to begin to deal with the endogeneity concerns is to include the number of patents in $t-1$ as a regressor. As mentioned before, the model may suffer from reverse causality concerns if the state, in order to maximise return, is increasing their connectivity in areas which already have the largest innovation output. If the coefficient on state betweenness survives controlling for the size of the innovation sector, this will provide stronger support for proposition (1).

   I use a dynamic panel data model, specifically the system GMM model developed by Arellano and Bover 1995 to instrument for variables which become endogenous when using lagged dependent variables, a more in depth justification for why is provided in appendix (3). In addition to β and γ_1, I predict that $\gamma_2 > 0$. The regression equation estimated is,

$$\ln \text{patents}_{it} = \beta \ln \text{state betweenness}_{i,t-1} + \gamma_1 \ln \text{average degree}_{i,t-1} + \gamma_2 \ln \text{patents}_{i,t-1} + \eta_i + \theta_t + \epsilon_{it}$$

Table 1: Regression Results

	(1)	(2)	(3)	(4)
ln Patents$_t$	Within Groups			System GMM
ln State Betweenness$_{t-1}$	0.0135***	0.01**	0.00314	0.0255*
	(0.00453)	(0.00496)	(0.00467)	(0.0134)
ln State Betweenness$_{t-2}$		0.00809*	0.00991**	0.0264*
		(0.00490)	(0.00460)	(0.0157)
ln State Betweenness$_{t-3}$				0.0162
				(0.0116)
ln Average Degree$_{t-1}$			0.104***	-0.0542***
			(0.00775)	(0.0152)
ln Patents$_{t-1}$				0.698***
				(0.0984)
Constant	4.781***	4.818***	5.413***	1.668***
	(0.126)	(0.123)	(0.124)	(0.546)
Observations	1406	1375	1375	495
Adjusted R^2	0.623	0.623	0.669	
Fixed effects:				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Under all four specifications the coefficient β is positive on the majority of lags which supports proposition (1). Introducing further lags causes the coefficient to decrease slightly which may support the theory that public finance is optimally invested at the early stages, thus leading to longer run times until patenting (Aighon, Dewatripont, and Stein 2008).

The most important specification is column (4), which shows that β is reasonably robust to the dynamic model. In fact controlling for the size of the innovation sector increases β two or three times over. For the system GMM model the number of years was restricted and a further lag included due to the relatively low number of counties as to avoid problems of overidentification. That said, all models pass both the Sargan test of over identifying restrictions and the Arellano-Bond test for serial correlation at the 10% level[11],

	Overidentifying Restrictions	AR(1)	AR(2)	AR(3)
Result	$p > \chi^2(550) = 0.364$	0.095	0.11	0.11

The increase in β under the system GMM model may be due to the change in model structure and time range, and should not necessarily be taken as an indication that excluding lagged patents provides a downward bias.

To provide context to the results, the mean number of patents across all counties was 1142 per year. Approximating around one, the coefficients range between a 0.3% to 2.64% increase in the mean yearly patent total given a 1% increase in state betweenness. This corresponds to

[11] Under which the null hypothesis is that the moment conditions are correctly specified and there is not serial correlation.

between 3 and 31 new patents a year. Seeing as one patent can lead to follow on inventions and discoveries (Sampat and Williams 2019) the potential for economic significance is sufficient.

Column (3) shows that the coefficient on state betweenness drops in both size and significance when controlling for average degree. This indicates that increasing overall network connectivity is a significant determinant of patent rates and attracts the state to increase their betweenness. Overall however, the conclusions on average degree are inconsistent. The GMM specification contradicts the model presented earlier and the literature as the coefficient changes sign to negative. Running the model without the log transformation doesn't improve the estimation. This variable may be poorly estimated and is a limitation to these findings.

It could be the case that due to the size of the firms in Santa Clara, Apple, Intel, Google etc. the state is increasingly connected in that county due to the social and political significance of these firms. This along with the exceptionally high connectivity of the innovation network in Santa Clara overall, may cause an upward bias on the results presented above. To mediate this concern I ran a robustness check dropping Santa Clara, the results remain very similar and are presented in the appendix.

Overall, the evidence provided supports proposition (1) that increasing state betweenness increases innovation when proxied by patents. The significance of the coefficients is average but sufficient. The reduced efficiency could be a result of the number of counties used and could be improved by including more.

Conclusions

The literature on both state capacity and determinants of innovation is rich and well developed. I have aimed to contribute to a growing intersection between these two fields by examining the capacity of the state to support innovation.

Applying a network approach to the question I have theoretically shown that the state is capable of increasing innovation rates through increasing their betweenness level. They are able to do so through harnessing collaboration and directing innovation efforts.

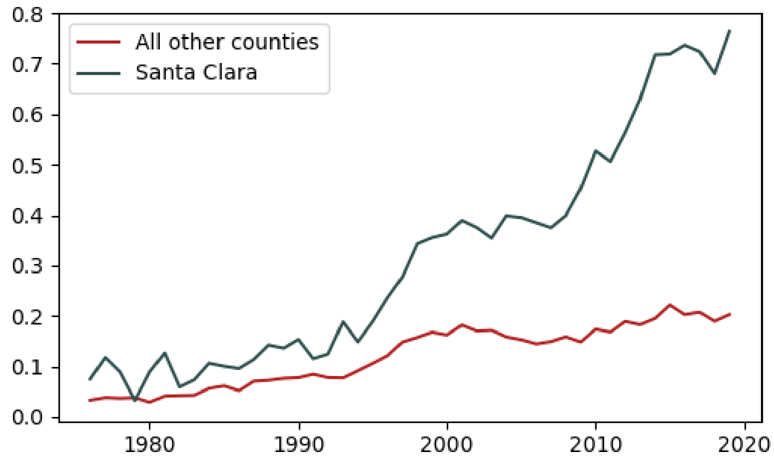
I have then tested the first of two propositions empirically. I believe that the results are sufficient to claim a positive correlation between state betweenness and patent rates. Though I refrain from claiming to have demonstrated causality until further controlling for the endogenous choice of when and how the state supports innovation markets.

The paper has numerous limitations which I have highlighted throughout. The largest being the endogeneity which I have discussed throughout the paper and does limit the strength of the findings. In addition, contradictory results on the affect of increasing the average degree as a measure of overall network connectedness signals that the empirical model likely has specification issues.

I propose improving on these limitations through applying an alternative optimal seeding network approach which identifies the optimal firms within the network to connect with and support and then testing the current performance of the state against this theoretical optimum. Secondly, I would like to extend the model and measure $\hat{\phi}$ explicitly, this statistic could be calculated from the network thus allowing me to directly test proposition (1).

Appendix

Robustness: Dropping Santa Clara



In addition to concerns around endogenous state participation in Santa Clara. I have separated the average degree from the other counties. You can see from the graph that the average degree in Santa Clara is far outgrowing the rest. I have run a robustness check dropping Santa Clara from the data set as to remove the divergent growth of this specific county. The results are robust and change very little.

	(1)	(2)	(3)	(4)
ln Patents$_t$		Within Groups		System GMM
ln State Betweenness$_{t-1}$	0.0140***	0.0103**	0.00335	0.0252*
	(0.00457)	(0.00500)	(0.00469)	(0.0133)
ln State Betweenness$_{t-2}$		0.00854*	0.0105**	0.0261*
		(0.00495)	(0.00462)	(0.0156)
ln State Betweenness$_{t-3}$				0.0158
				(0.0115)
ln Average Degree$_{t-1}$			0.107***	-0.0535***
			(0.00779)	(0.0152)
ln Patents$_{t-1}$				0.695***
				(0.0978)
Constant	4.735***	4.777***	5.398***	1.677***
	(0.129)	(0.127)	(0.127)	(0.542)
Observations	1363	1333	1333	480
Adjusted R^2	0.611	0.611	0.662	
Fixed effects:				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

	Overidentifying Restrictions	AR(1)	AR(2)	AR(3)
Result	$p > \chi^2(550) = 0.274$	0.095	0.11	0.11

1) Full derivations

Note, $\hat{\boldsymbol{\phi}}_i = \Delta\boldsymbol{\phi}_i + \boldsymbol{\phi}_i$

$$
\begin{aligned}
\hat{I}_i &\geq I_i \\
(1-t)\big(x_i + \hat{\boldsymbol{\phi}}_i\big) - \frac{1}{2}x_i^2 &\geq x_i + \boldsymbol{\phi}_i - \frac{1}{2}x_i^2 \\
(1-t)\big(x_i + \hat{\boldsymbol{\phi}}_i\big) &\geq x_i + \boldsymbol{\phi}_i \\
(1-t)\hat{\boldsymbol{\phi}}_i - \boldsymbol{\phi}_i &\geq t x_i \\
(1-t)\big(\Delta\boldsymbol{\phi}_i + \boldsymbol{\phi}_i\big) - \boldsymbol{\phi}_i &\geq t x_i \\
(1-t)\Delta\boldsymbol{\phi}_i &\geq t(x_i + \boldsymbol{\phi}_i)
\end{aligned}
$$

2) Building the network

The code is available online at State Capacity in Innovation, GitHub. The procedure followed is outline below.

Every patent granted contains the following information,

- The assignee: The legal owner of the patent, in most cases a firm
- The inventors: The person or list of people who are credited with the invention
- Government interest: Was the project supported by the government?
- The state and county of the registered assignee (owner)

There are two levels of actors in the main innovation network, assignees and inventors. I transform a two mode network (assignees and inventors) into a one mode network where each node is an assignee and they are linked through the inventors. I then place the state in this network by coding an edge between the state and all assignees which own patents that were supported by the government.

1. Create the innovation network:
   (a) For each individual inventor create a subset of patents which they are credited with
   (b) Under this subset collect all the unique assignee names, this requires cleaning the data set using the Levenshtein distance to clean the data for typos and assignees entered under multiple names.
   (c) Create an edge between these firms that own patents connected by the inventor

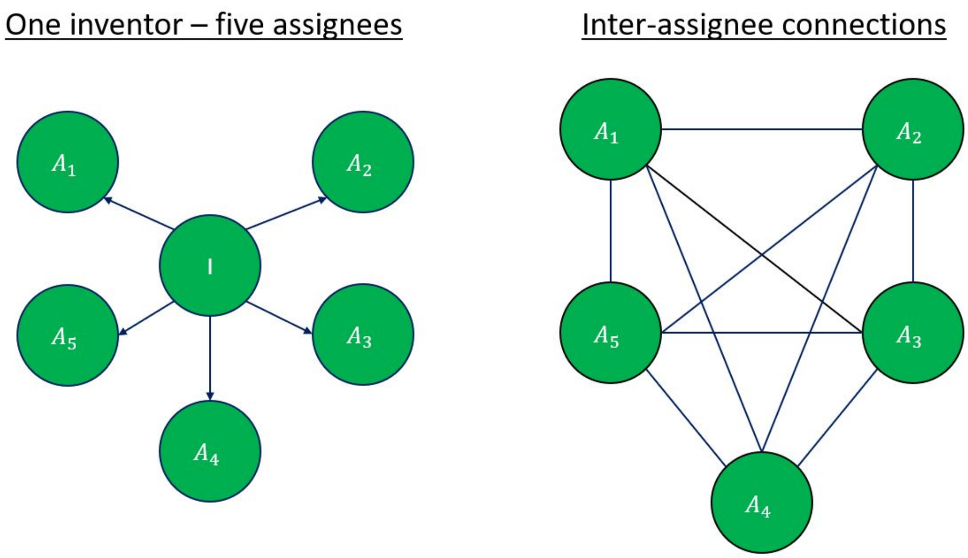


Figure 3: Two mode to one node network

2. Categorise government interest
   (a) Extract all the unique government id values from the data
   (b) Code all patents 0 or 1 if they received government support, where 1 = yes
   (c) Sort data set by inventor id
3. Create the state edges:
   (a) For every unique assignee extract the subset of the patents awarded to this assignee
   (b) Create a link between the state and every unique assignee that appears under government supported patents

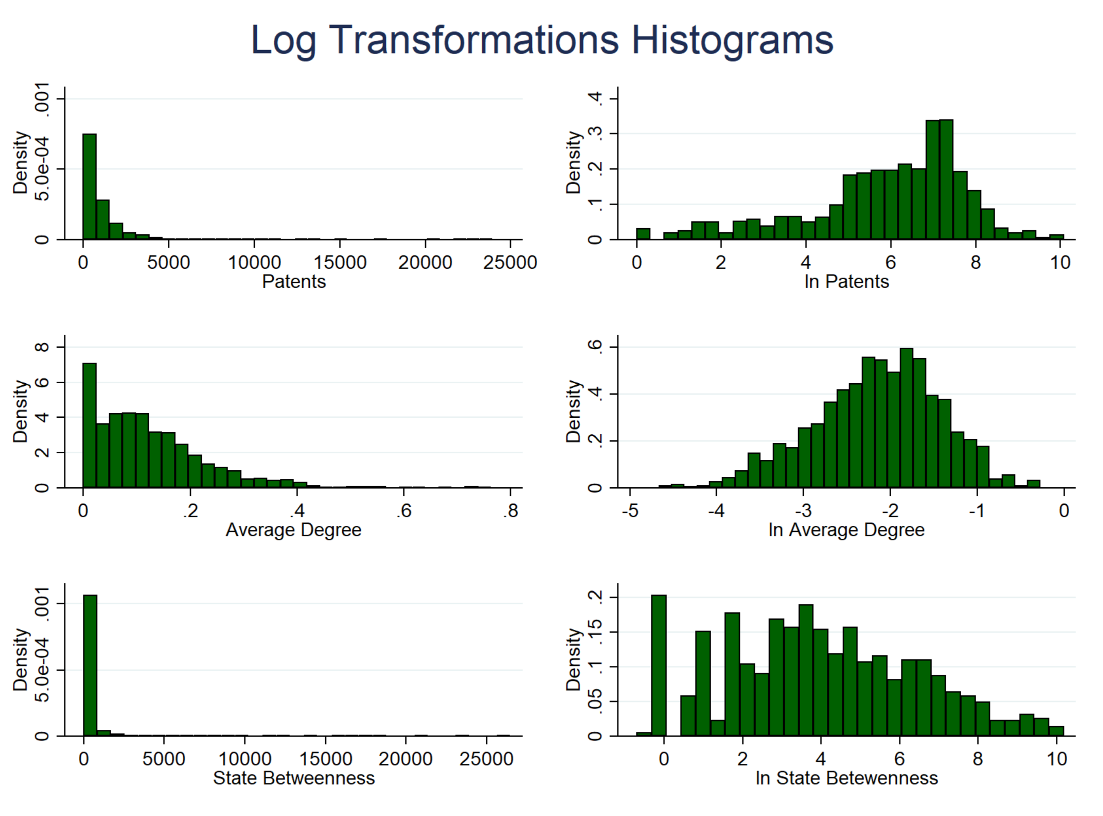
3) System GMM

To run the dynamic panel data model I have used a system GMM model which was developed in Arellano and Bover 1995. A difference GMM model is required when using lagged dependent variables and fixed effects since the within groups estimator is biased. OLS on first differences remains inconsistent since $\mathbb{E}[\Delta y_{it-1}\Delta v_{it}] = -\sigma_v^2 < 0$. $y_{it-2} \ldots y_0$ however, satisfy both the relevance and orthogonality conditions and can be used as valid instruments. The moment conditions are then $\mathbb{E}[Z_i \Delta v_i]$, where Z_i collects all the orthogonal lagged terms and v_i is the vector of first differences on the error term.

The system GMM model[12] improved previous dynamic panel data models as is improves accuracy when the serial correlation between y_t, y_{t-1} is high and reduces small sample bias. Both of these are valid concerns here since firms are not likely to lose their large firm status quickly and due to data collection my sample is currently smaller than ideal.

[12] A clear outline of system GMM and how to implement it in Stata is provided at http://repec.org/bocode/x/xtabond2

4) **Log transformations**



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