Essays in Energy Economics and Entrepreneurial Finance

grant might affect the mean technology quality ($\bar{t}$), the quality variance (σ_T^2), and the signal variance (σ_ε^2). Any value of the grant money that is unrelated to its technology quality is μ_x, where $\mu_n = 0$ and $\mu_g \geq 0$. After the competition entrepreneurs have technology quality $T_{i,x} = \bar{t}_x + \mu_x + \tau_{i,x}$. Now $T_x \sim N\left(\bar{t}_x + \mu_x, \sigma_{T,x}^2\right)$, and the signal error becomes $\varepsilon_x \sim N\left(0, \sigma_{\varepsilon,x}^2\right)$.

Consider two firms i and j with the same noisy signal $\tilde{T}_i = \tilde{T}_j = \tilde{T}_k$, where one won a grant and the other did not. The difference between the two firms' expected qualities is:

$$\mathcal{D} = \mathbf{E}\left(T_i \mid \tilde{T}_i = k, x = g\right) - \mathbf{E}\left(T_j \mid \tilde{T}_j = k, x = n\right) \quad (3)$$

$$= (\bar{t}_g + \mu_g)\left(1 - \frac{\sigma_{T,g}^2}{\sigma_{\varepsilon,g}^2 + \sigma_{T,g}^2}\right) - \bar{t}_n\left(1 - \frac{\sigma_{T,n}^2}{\sigma_{\varepsilon,n}^2 + \sigma_{T,n}^2}\right) + \tilde{T}_k\left(\frac{\sigma_{T,g}^2}{\sigma_{\varepsilon,g}^2 + \sigma_{T,g}^2} - \frac{\sigma_{T,n}^2}{\sigma_{\varepsilon,n}^2 + \sigma_{T,n}^2}\right)$$

The regression discontinuity design in the following section will approximate this situation of two firms possessing the same signal, where one just wins a grant and another just loses. If $\mathcal{D} > 0$, the grant has a positive effect on investment. We can now identify the mechanisms that might drive this equation away from zero.

1. *Certification:* Suppose that the award process separates applicant firms into higher and lower technology quality types, but has no other effect. Now $\bar{t}_g > \bar{t}_n$, while $\mu_g = 0$, $\sigma_{T,g}^2 = \sigma_{T,n}^2 = \sigma_T^2$, and $\sigma_{\varepsilon,g}^2 = \sigma_{\varepsilon,n}^2 = \sigma_\varepsilon^2$. The difference in expected quality for two firms with the same signal $\tilde{T}$ is

$$\mathcal{D} = (\bar{t}_g - \bar{t}_n)\left(1 - \frac{\sigma_T^2}{\sigma_\varepsilon^2 + \sigma_T^2}\right) \quad (4)$$

   If the investor believes the government is choosing superior firms, this expression is positive. From the regression line perspective in equation 2, $\bar{t}_g > \bar{t}_n$ generates two parallel lines (Figure 1.B).

2. *Internal Resources*

   (a) *Equity Channel:* The grant increases the entrepreneur's internal resources, allowing him to maintain a larger share of the firm in exchange for a given external investment. The only difference between grantees and non-grantees, here, is μ. The \$150,000 investment is positive NPV from the investor perspective, but the equity that would need to be transferred would destroy entrepreneurial incentives. This manifests as a mean shifting effect for grantees (Figure 1.B). Now the

spillovers seem absent.

difference is:

$$\mathcal{D} = \mu_g \left(1 - \frac{\sigma_T^2}{\sigma_\varepsilon^2 + \sigma_T^2}\right) \tag{5}$$

(b) *Prototyping:* Suppose the grant permits firms to increase the precision of their signal $\tilde{T}$ by developing a prototype, so $\sigma_{\varepsilon,g}^2 < \sigma_{\varepsilon,n}^2$. The signal is more reliable for grantees. With all else held the same, $\bar{t}_g = \bar{t}_n = \bar{t}$, $\mu_g = 0$, and $\sigma_{T,g}^2 = \sigma_{T,n}^2 = \sigma_T^2$. In this case the difference is:

$$\mathcal{D} = \left(\bar{t} - \tilde{T}_k\right) \left(\frac{\sigma_T^2}{\sigma_{\varepsilon,n}^2 + \sigma_T^2} - \frac{\sigma_T^2}{\sigma_{\varepsilon,g}^2 + \sigma_T^2}\right) \tag{6}$$

The slope of the grantee regression line is steeper (Figure 1.C), because $\frac{\sigma_{T,}^2}{\sigma_{\varepsilon,g}^2+\sigma_{T,}^2} > \frac{\sigma_{T,}^2}{\sigma_{\varepsilon,n}^2+\sigma_{T,}^2}$. If an entrepreneur has a high-type technology ($\bar{t} + \tau_i > \bar{t}$), a signal-precision effect of the grant will be more valuable, whereas it will be harmful to a low-type ($\bar{t} + \tau_i < \bar{t}$).

i. This same effect occurs if grantees perform R&D work that alters their underlying technology quality τ_i such that grantee quality is more variable. Then $\sigma_{T,g}^2 > \sigma_{T,n}^2$, $\sigma_{\varepsilon,g}^2 = \sigma_{\varepsilon,n}^2 = \sigma_\varepsilon^2$ and $\bar{t}_g = \bar{t}_n = \bar{t}$. Now the difference is:

$$\mathcal{D} = \left(\tilde{T}_k - \bar{t}\right) \left(\frac{\sigma_{T,g}^2}{\sigma_\varepsilon^2 + \sigma_{T,g}^2} - \frac{\sigma_{T,n}^2}{\sigma_\varepsilon^2 + \sigma_{T,n}^2}\right) \tag{7}$$

The expression in the last set of brackets is positive, so we are again in Figure 1.C.

ii. In the alternative scenario where firms' underlying quality is pushed toward the mean ($\sigma_{T,g}^2 < \sigma_{T,n}^2$), the expression in the last set of brackets is now negative, and the regression line is steeper for non-grantees.[5]

iii. *Note on Risk Preferences:* This discussion assumes that the expected technology quality enters the VC firm's profit function linearly. If the VC firm is risk-averse, then the variances of the errors are costly. Although VCs pursue high-risk strategies, they often tolerate market risk more readily than technology risk, and seek technology validation prior to investment. With investor risk aversion, the improved signal precision for the grantee shifts its regression line upwards by some risk factor. Within the model, it is indistinguishable

[5] I do not allow the final scenario, where $\sigma_{\varepsilon,g}^2 > \sigma_{\varepsilon,n}^2$, as it seems unlikely that a grant would increase the signal's noise.

from a certification effect.

Given these possible mechanisms, I shift to the government perspective, and connect the model to the empirical design. Entrepreneurs have an ultimate observable quality T_i^O, which is a function of latent quality T_i and resources provided to the entrepreneur. Figure 11 shows the correlation of this outcome with the private government signal $\tilde{T}_i^G$. Applicant firms with $\tilde{T}_i^G$ to the right of the red cutoff line are awardees, while applicants to the left are losers. My regression discontinuity design measures this difference:

$$\mathcal{D} = \mathbf{E}\left(T_i^O \mid \tilde{T}_i^G = k, x = g\right) - \mathbf{E}\left(T_i^O \mid \tilde{T}_j^G = k, x = n\right) \tag{8}$$

First, consider the no-effect case, depicted in Figure 2.A. When the government signal is uninformative about outcomes and the grant has no funds effect, the observed outcome projected on the government signal is a horizontal line; here $\mathcal{D} = 0$.

Second, if the signal is informative about outcomes, the regression line is upward sloping (Figure 2.B).[6] Here, the grant acts as a binary signal about firm quality, which the market learns is informative, so we observe a jump at the discontinuity due to certification ($\mathcal{D} > 0$). Investors are more likely to finance grantees because they have higher mean expected quality ($\bar{t}_g > \bar{t}_n$), even if the money itself has no effect. Figure 2.B, which describes actual investment outcomes as a function of the government signal, maps to Figure 1. B, which shows how the government signal affects investor beliefs.

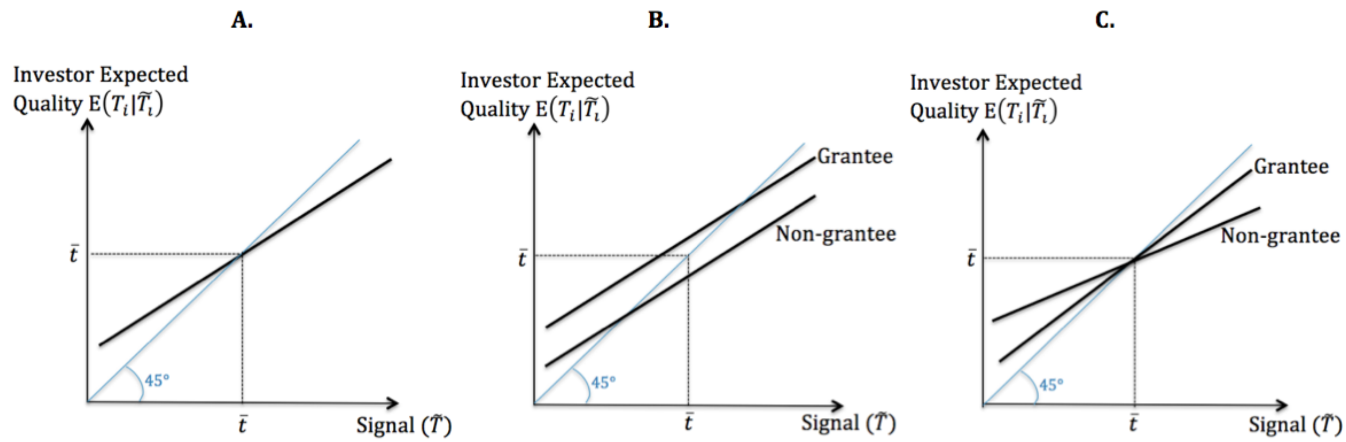
Finally, if $\tilde{T}_i^G$ is uninformative but the grant money itself benefits recipients through either funding or prototyping, we observe a horizontal line with a jump at the discontinuity, shown in Figure 2.C. Because the funding channel is a mean-shifting effect ($\mu_g > 0$), it maps to Figure 1.B from the investor perspective. With only a prototyping channel, the government signal is uninformative (Figure 2.C), but prototyping changes the variance of the signal to investors and so maps to Figure 1.C.

A matrix of hypotheses derived from this model is contained in Table 1. The left-hand column contains the basic questions that I ask in the estimation. In the five columns on the right, I write the answer to the question that best supports they hypothesis in that column. That is, the "Yes" or "No" answer is the one that that supports the hypothesis being the *primary driver* of the grant effect on subsequent VC investment. Multiple mechanisms may

[6] It is possible that the government signal is informative in the other direction; that is, it orders poor quality firms above higher quality firms on average. In this case the line will slope down, and we would expect a downward jump at the discontinuity.

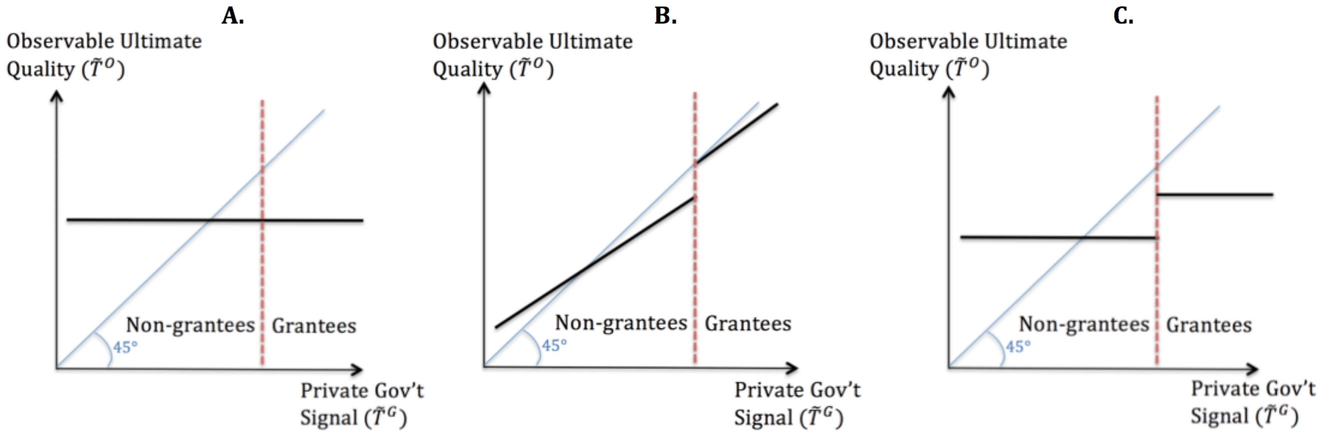
act at once, so my conclusions will be based on the balance of correct answers and the strength of the evidence for a given hypothesis. There are three important assumptions. First, VCs consider only relatively high signal type firms. Second, prototyping can only improve signal precision ($\sigma^2_{\varepsilon,g} \leq \sigma^2_{\varepsilon,n}$). Third, I can only rule out an internal resources hypothesis if I assume that the mechanical alleviation of financial frictions is not decreasing in the size of the award, as is standard in the literature cited above. However, if the relationship is non-monotonic, I cannot distinguish between early stage prototyping effects and an internal resources effect. In the empirical sections below, I argue that my evidence best supports prototyping via reduced signal noise.

Figure 1: Possible grant effects on investor expectations of quality given firms' noisy signal to investors



Note: Figure 11.A shows the investor's expected quality of the entrepreneur (y-axis) as a function of the noisy signal that the investor observes (x-axis). Figure 11.B shows that a certification or valuation effect increases the mean expected quality of grantees relative to non-grantees ($\bar{t}_g > \bar{t}_n$). Figure 11.C shows that a prototyping effect increases the slope of the grantee line relative to the non-grantee line. This occurs because the grant causes the grantee's signal to be more reliable, which for example may occur if prototyping decreases the variance of the noisy signal $\left(\sigma^2_{\varepsilon,g} < \sigma^2_{\varepsilon,n}\right)$.

Figure 2: Possible grant effects on firm outcome given firms' private signal to government



Note: Figure 12.A shows this observable outcome (y-axis) as a function of the signal that the government receives from the firm, which is private to the government (x-axis). In this case, the government signal $\tilde{T}^G$ is wholly uninformative about outcomes, so the line is flat, and there can be no certification effect with rational investors. In Figure 12.A, there is both no certification effect and no effect of the grant money itself, so there is no jump at the discontinuity between non-grantees and grantees. Figure 11.B shows a prototyping or valuation effect increasing outcomes for grantees relative to non-grantees in the absence of certification ($\tilde{T}^G$ uninformative). Figure 11.C. shows the certification case, in which $\tilde{T}^G$ is informative and thus correlated with outcomes. In the absence of a valuation or prototyping effect, we nonetheless observe a jump at the discontinuity as the market accounts for information in the private government signal $\tilde{T}^G$.

Table 1: Tests of Hypotheses for Phase 1 Grant Effect on Subsequent VC

Test	Certification $\bar{t}_g > \bar{t}_n$	Prototyping 1 $\sigma^2_{\varepsilon,g} < \sigma^2_{\varepsilon,n}$	Prototyping 2 $\sigma^2_{T,g} > \sigma^2_{T,n}$	I. Internal Resources
1. Does Phase 1 increase likelihood of subsequent VC?	**Y**	**Y**	**Y**	**Y**
2. Does Phase 2 increase likelihood of subsequent VC?	**Y**	**N**	**Y**	**Y**
3. Does Phase 1 increase subsequent patents?	**N**	**Y**	**Y**	**N**
4. Does Phase 1 increase subsequent citations?	**N**	**N**	**Y**	**N**
5. Do DOE applicant rankings contain positive information about outcomes?	**Y**	**N**	**N**	**N**

Note: This table relates the model in section 2 to empirical tests. Yes (Y) or No (N) is the answer to the Test question that best supports the hypothesis as the primary driver of the grant effect on subsequent VC. Blue indicates the answer my evidence supports, while red indicates the answer that my evidence does not support. The mean firm quality is $\bar{t}$, with individual qualities defined by the variance around this mean σ^2_T. The noise in the signal is cause by a mean-zero error with variance σ^2_ε. g indicates a firm is a grantee, while n indicates the firm is not a grantee.

Appendix B: Geography

This appendix describes the geographic dispersion of applicants and analyzes how the grant acts differently in different regions. Using full addresses, I geocoded the locations of each applicant. Figure 1 shows the overall concentrations by Metropolitcan Statistical Area (MSA). The geography of SBIR applicants corresponds to what we would expect of high-tech firms; the largest clusters by far are Boston and San Francisco, and to a lesser extent New York, Los Angeles, Denver/Boulder, and the greater DC metro area. Black (2004) finds concentrations quite similar in his analysis of overall SBIR grants between 1990 and 1995. He also finds that the geographic pattern of SBIR activity is closely correlated to patent geography, which I do not address here.

The number of applicants by award status from the top ten metro regions with the highest number of applicants in 1995 and in 2012 are in Figure 2. San Francisco moves from 9th place to 1st place, reflecting its growing role in the energy technology sector. LA and Boston are near the top of the list in both years. Bridgeport-Stamford and Baltimore fall completely off the list, while NYC and DC enter. This suggests that the changing agglomerations of SBIR winners over time may reflect cities' lifecycles. Graphs by year, not shown here, suggest that the concentration has not changed much over time except for the San Francisco area, which has increased in importance since the mid-1990s.

Wind and solar applicants are in Figure 3, and oil, gas and coal applicants in Figure 4. It is clear that although both renewable and conventional fuel companies locate in major cities, some clustering relates to the area's resource base. Clusters of coal companies in Pittsburgh, PA and oil and gas companies in Houston, TX contrast with clusters of solar firms in Tampa, FL and Orlando, FL.

Figure 5 shows the location of all wind and solar VC portfolio companies in the ThompsonOne database. Agglomeration in Boston and San Francisco, and to a lesser degree in New York, Denver and Chicago are common to both the SBIR applicants (Figure 3) and the VC portfolio companies (Figure 5) in these clean energy sectors. However, the portfolio companies are more concentrated in the major cities where VC firms are also located. We can see this by examining the location of applicants with at least one VC deal (Figure 7), and comparing to the concentration by MSA of all active VC firms in the Preqin database that, according to Preqin, invest in clean technology (Figure 6). In general, the clustering of both VC firms and VC-funded DOE SBIR applicants aligns fairly closely with the clustering of the overall applicant pool. However, there is clearly considerably more clustering of both

VC firms and VC-funded companies in Boston and San Francisco, especially VC-funded companies that have recieved many VC investment rounds.

Meanwhile, there are far more SBIR applicants from Los Angeles and from the greater DC metro area than portfolio companies. For the subset of firms that focus their resources on govenrment grants and procurement contracts, the DC concentration makes sense. LA, somewhat more surprisingly, seems to also be a long-term hub of government-oriented tech companies. For example, Physical Optics - the largest SBIR winner in my data - is located in Torrance, CA, within the LA MSA. The LA government provides supporting activities, such as regular workshops on applying for SBIR grants and other informational and convening resources through its PortTech Los Angeles program, Los Angeles Regional Small Business Development Center, and others.

The visual evidence of agglomeration suggests a test for whether the Phase 1 grant has different effects in specific regions. As in Chen et al. (2010), I create regions that approximate VC investment areas by combining MSAs for greater San Francisco (SF), New York (NY), Los Angeles (LA), Texas triangle (TX), Boston (BOS), and Washington, D.C. (DC).[1] I regress the indicator for subsequent VC investment (VC_i^{Post}) on dummies for each region and interactions of those dummies with the treatment dummy. The primary takeaways from Table 1 are; (a) the grant effect is much higher for firms in SF; (b) outside of SF, the treatment effect does not vary much by city; and (c) in the absence of treatment firms are more likely to receive VC in in TX and unlikely to receive VC in DC. This is consistent with the concentration of oil and gas firms, for whom I find little grant impact, in Houston. The negative coefficient on DC may reflect the preponderance of firms who survive primarily on government grants and do not seek VC finance. On average, DC firms in my data have 50% more previous non-DOE SBIR awards than SF firms.

Specifically, column I of Table 1 includes the full sample, so that the omitted category is all firms not in any of the six regions. The coefficient on treatment alone (that is, tretament when firms are not in any of the six regions) is 9.6 pp, significant at the 1% level, as in the main specifications. The -8 pp coefficient on being in DC, also significant at the 1% level, indicates that losing (untreated) firms in DC are much less likely to recieve VC relative to firms not in the six regions. The 21.4 pp coefficient on the interaction between treatment

[1] The specific MSAs are as follows. 1) SF: San Francisco-Oakland-Fremont; San Jose-Sunnyvale-Santa Clara. 2) NY: New York-Northern New Jersey-Long Island; Hartford-West Hartford-East Hartford; Bridgeport-Stamford-Norwalk; New Haven-Milford. 3) DC: Washington-Arlington-Alexandria,. 4) TX: San Antonio-New Braunfels; Austin-Round Rock-San Marcos; Dallas-Fort Worth-Arlington; Beaumont-Port Arthur; Houston-Sugar Land-Baytown. 5) LA: Los Angeles-Long Beach-Santa Ana; San Diego-Carlsbad-San Marcos. 6) BOS: Boston-Cambridge-Quincy.

and SF indicates that treated firms in SF do much better than untreated firms or firms in other cities. Columns II and III limit the sample to firms in the six regions. In column II, coefficients are relative to being in LA (the omitted region), while in column III no constant term is included to allow estimates for all region dummies. The coefficients on SF alone indicate that relative to the rest of the country, losing applicants from SF are not measurably more likely to receive VC than firms elsewhere.

Across-region results confirm the large SF effect. The regressions in Table 2 limit the sample to situations when a winner is in one region and the loser in another. When the winner is in SF, the treatment effect is more than 25 pp, but when the loser is in SF, the effect is always under 10 pp (I do not show all permutations, but SF's advantage is consistent). Most other combinations suggest treatment effects roughly equal to my main findings. When the winner is in LA and the loser in NY, the effect is 10 pp, and when roles are reversed, it is 9.7 pp. Grants are consistently useful to firms in SF, regardless of whether they are competing with firms locally or far away.

These within- and across-region effects argue against certification as the primary driver. VC firms typically have more information about nearby companies. If certification is driving the grant's effect, there should be less informational content in the grant when competing firms are located in the same MSA and thus a smaller within-region effect. I find no systematically smaller effect within MSAs than between MSAs. Indeed, the effect is highest in the largest VC cluster (SF).

The SF region is obviously a special cluster of companies and investors. In 2012, total VC investment in companies in SF was $10.9 billion, more than the other five regions combined (Florida 2014). Interestingly, Table 1 reveals that relative to the rest of the country, losing applicants from SF are not measurably more likely to receive VC than firms elsewhere. Large knowledge spillovers may help explain the high grant effect in SF. High-tech employees in California, and especially Silicon Valley, exhibit extreme interfirm labor mobility, as suggested by Saxenian (1994) and shown empirically by Fallick, Fleischman and Rebitzer (2006). Rapid job-hopping can increase agglomeration economies, but it imposes costs on employers who must invest in human capital and expose employees to trade secrets. A grant might be more important for startups in a local economy with greater spillovers from R&D investment. The usefulness of the grant in SF may also reflect more intense competition for venture finance. The notion that the benefits of early stage resources are amplified in SF is consistent with Hochberg, Ljungqvist, and Lu's (2007) finding that network benefits for VC performance is twice as large in California as in the whole U.S.

Motivated by the geographic results thus far, I test whether the grant effect is systematically larger in cities with greater VC investment per unit of city output.[2] For example, SF has about $2 of VC investment for every $100 of regional output. The next highest region is Boston, at $0.90, and third is LA, at $0.22. DC has only $0.11 for every $100 of regional output. I use the amount of VC investment per $100 of MSA output in 2012, for the 20 MSAs with the most VC investment, as a VC intensity index.[3] The left panel of Table 3 interacts the VC intensity index with treatment, and finds a signficant, positive relationship. Below the mean, the grant effect is 7.5 pp, while above it is 17.7 pp. When the regressions are estimated jointly (column VI), the difference is 9.6 pp, significant at the 5% level. This is consistent with the literature. Gans and Stern (2003) conclude that SBIR grantee performance is higher in sectors with high VC capital availability. Lerner (1999) finds that SBIR awardees in the 1980s outperformed a matched set of control firms only in regions with high VC activity.

[2]Calculated using BEA's (2013) statistics on Gross Domestic Product by metropolitan area and Florida's (2014) data on VC investment. A very similar ranking emerges when I use the number of deals, rather than dollar amount.

[3]While I unfortunately do not have data for other years, the ordering of major MSAs by VC and economic activity is likely to be roughly consistent over the time period considered.

Figure 1:

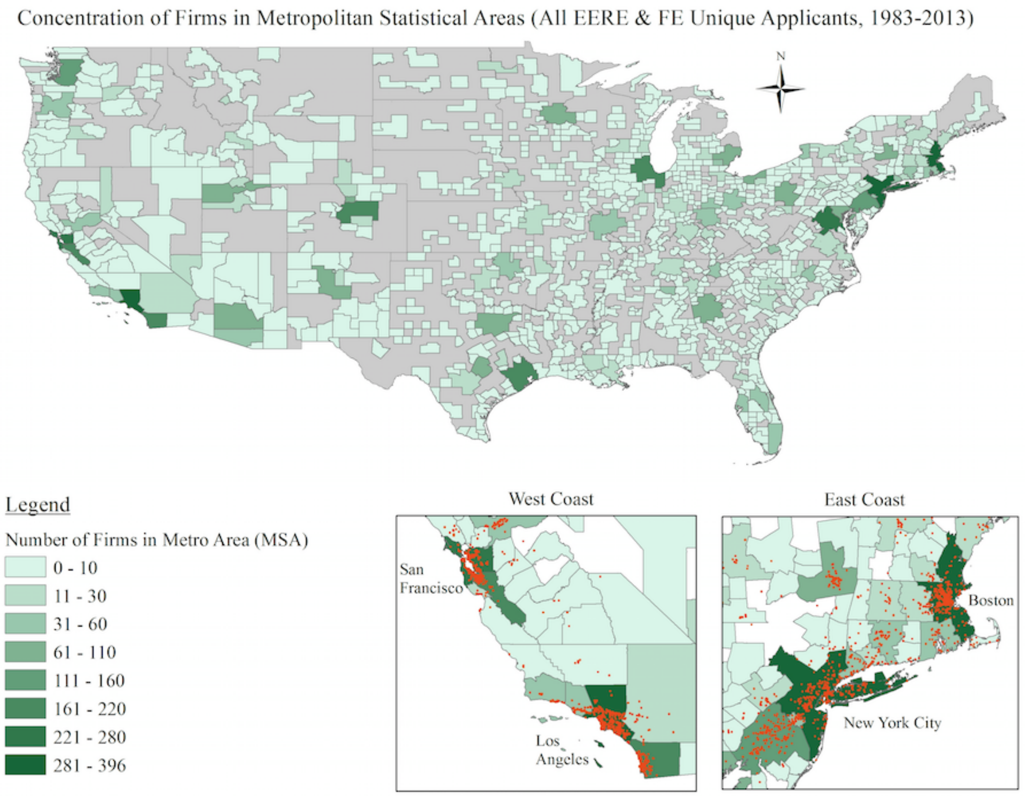

Concentration of Firms in Metropolitan Statistical Areas (All EERE & FE Unique Applicants, 1983-2013)
N
Legend
Number of Firms in Metro Area (MSA)
0 - 10
11 - 30
31 - 60
61 - 110
111 - 160
161 - 220
221 - 280
281 - 396
West Coast
San Francisco
Los Angeles
East Coast
Boston
New York City

Figure 2:

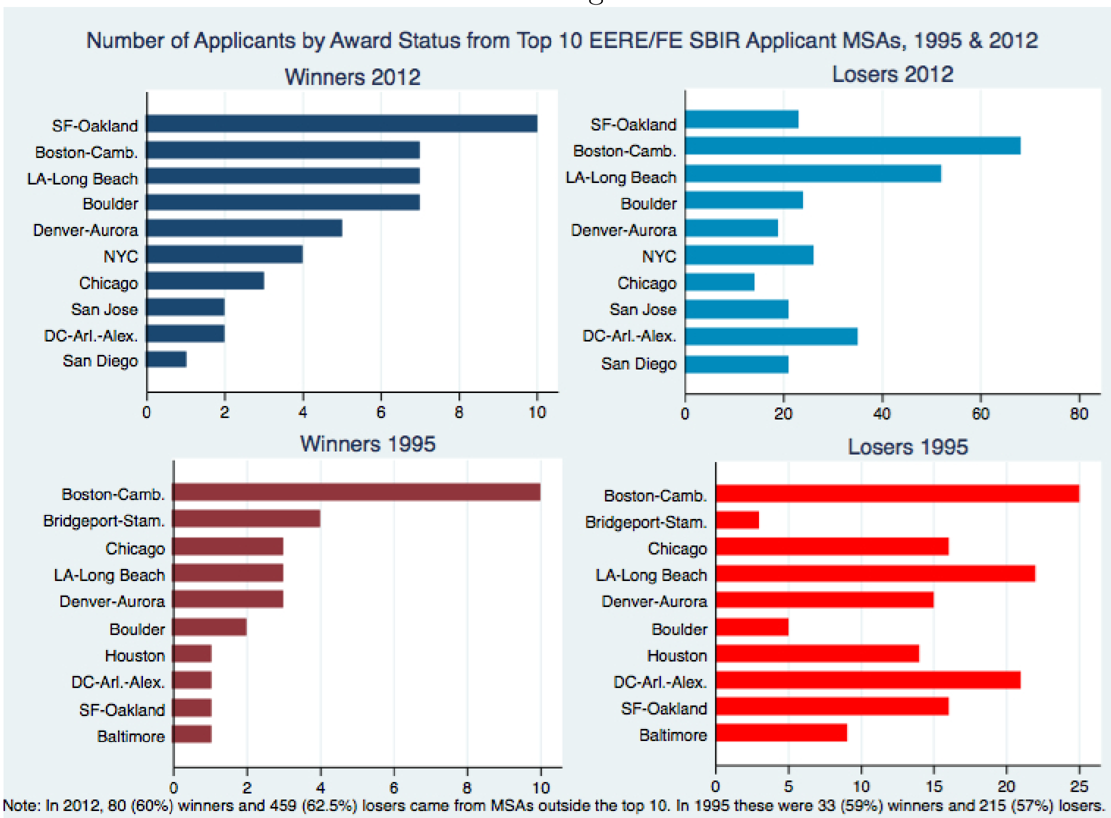
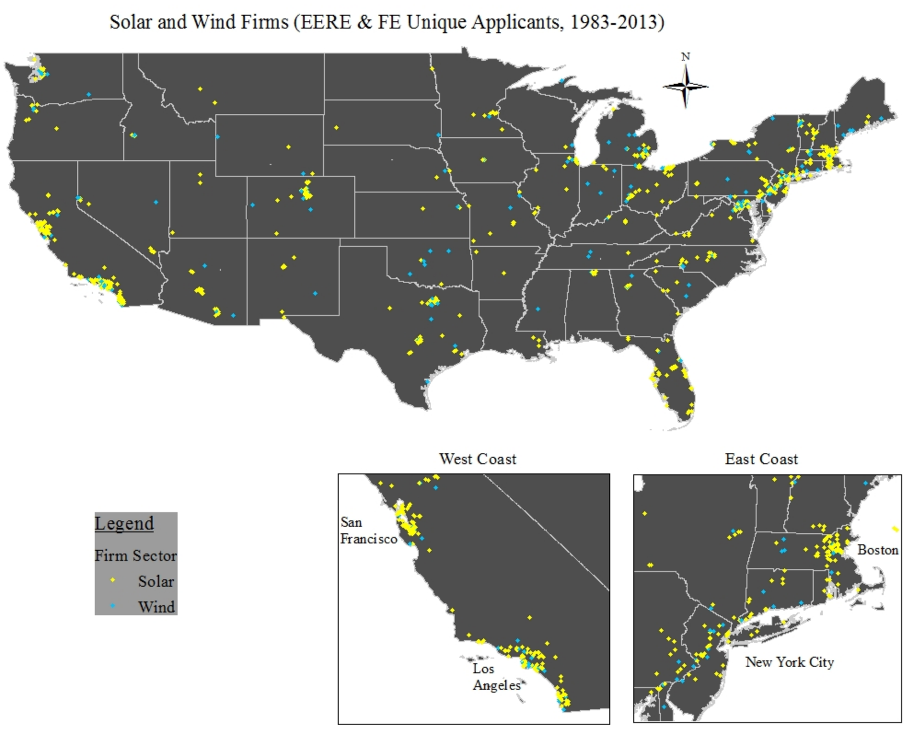


Figure 3:



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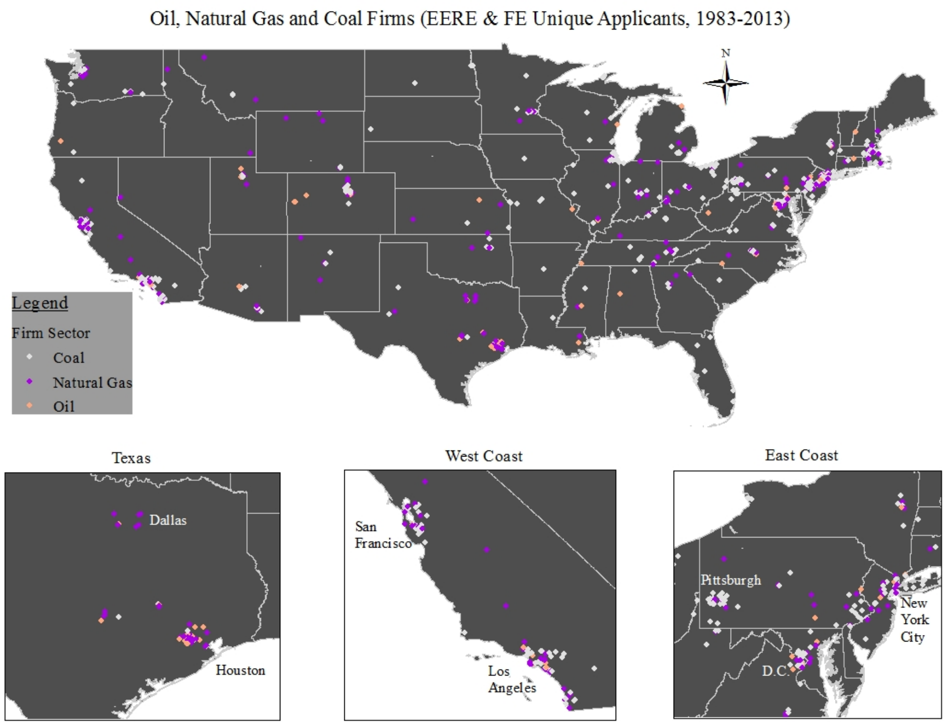

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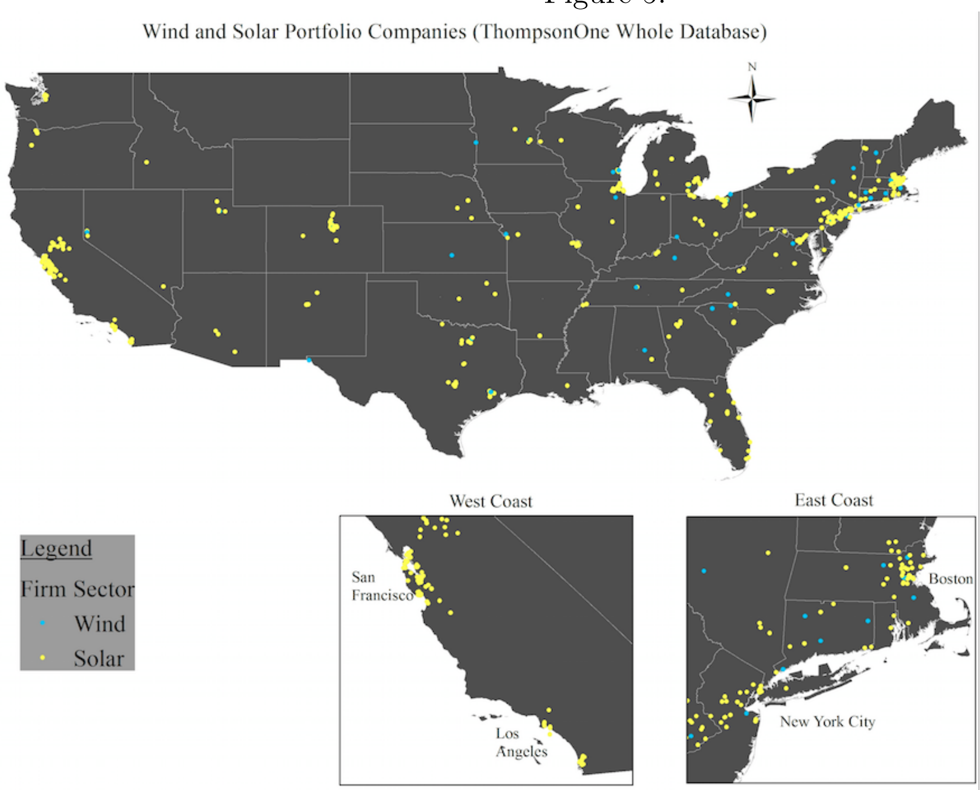

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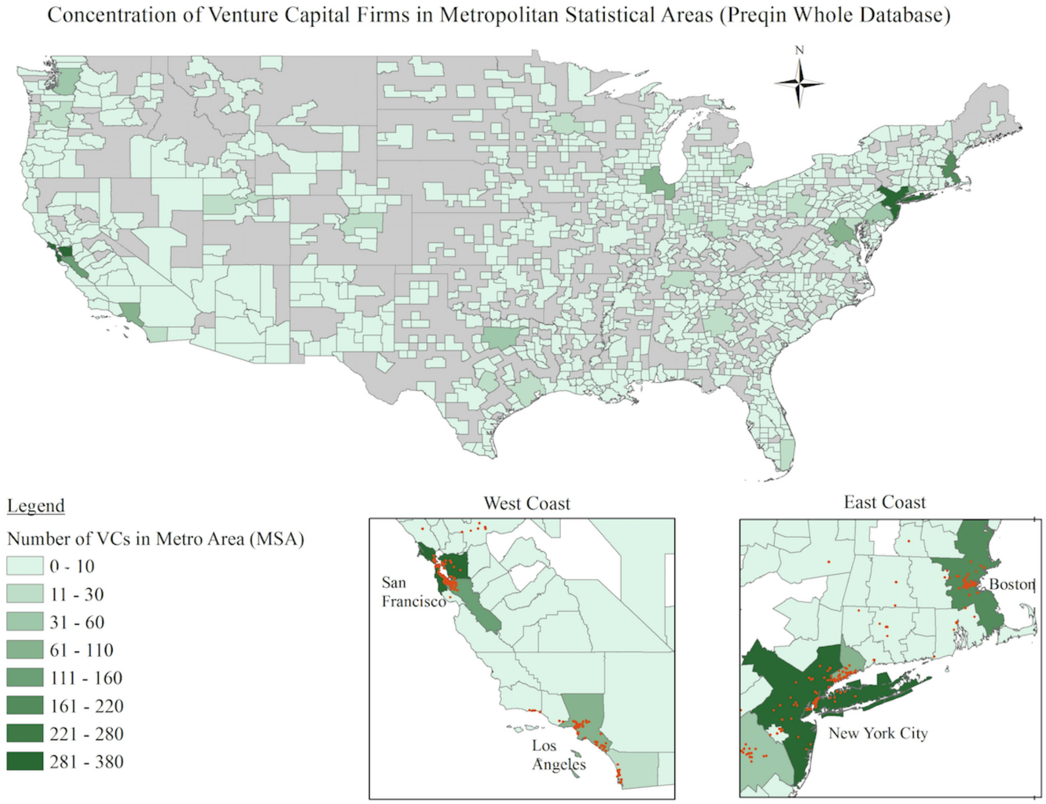

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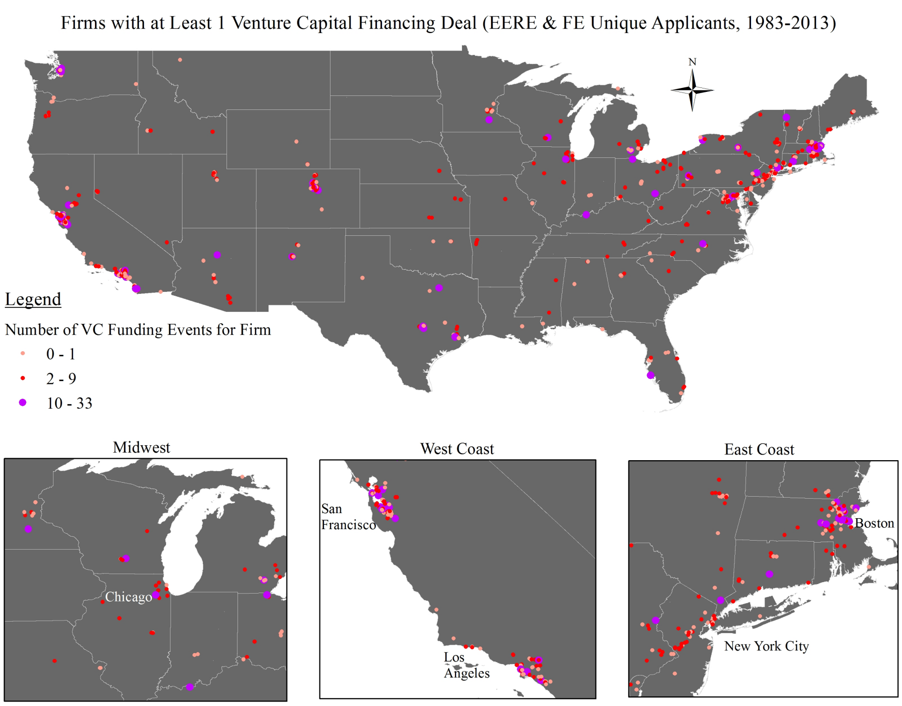


Table 1: Impact of Grant on Subsequent VC for Firms in Six Major Regions

Dependent Variable: VC_i^{Post}	I. Full sample; omitted region is rest of U.S.	II. Sample is 6 regions; no treatment dummy	III. Sample is 6 regions; no constant or treatment dummy
$\mathbf{1} \mid \text{NY}$	0.0285	0.0241	0.197***
	(0.0363)	(0.0615)	(0.0608)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{NY})$	**-0.0797**	**0.0433**	**0.0433**
	(0.101)	(0.156)	(0.156)
$\mathbf{1} \mid \text{SF}$	0.0307	-0.00717	0.166***
	(0.0296)	(0.0472)	(0.0466)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{SF})$	**0.214****	**0.438*****	**0.438*****
	(0.109)	(0.156)	(0.156)
$\mathbf{1} \mid \text{BOS}$	0.0129	-0.0301	0.143**
	(0.0404)	(0.0666)	(0.0699)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{BOS})$	**-0.0132**	**0.139**	**0.139**
	(0.0884)	(0.120)	(0.120)
$\mathbf{1} \mid \text{DC}$	-0.0805***	-0.0963*	0.0771
	(0.0273)	(0.0514)	(0.0516)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{DC})$	**0.0776**	**0.0761**	**0.0761**
	(0.109)	(0.104)	(0.104)
$\mathbf{1} \mid \text{TX}$	0.0651*	0.0289	0.202***
	(0.0346)	(0.0627)	(0.0584)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{TX})$	**-0.0734**	**0.0476**	**0.0476**
	(0.0754)	(0.0865)	(0.0865)
$\mathbf{1} \mid \text{LA}$	0.0288	-	0.173***
	(0.0256)		(0.0343)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid \text{LA})$	**-0.0503**	**0.100**	**0.100**
	(0.0710)	(0.0898)	(0.0898)
$\mathbf{1} \mid R_i > 0$	0.0962***	-	-
	(0.0281)		
VC_i^{Prev}	0.300***	0.286***	0.286***
	(0.0361)	(0.0779)	(0.0779)
$\#SBIR_i^{\text{Prev}}$	0.00107***	0.000932	0.000932
	(0.000262)	(0.000615)	(0.000615)
Competition f.e.	Y	Y	Y
N	3368	1182	1182
R^2	0.353	0.584	0.647

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on subsequent VC by region (see text for definition), using a bandwidth of 3. In column I all coefficients are relative to the firms outside of the six regions. Columns II and III limit the sample to firms in the six regions, and omit the dummy on treatment. Column III does not include a constant term so that all six regional dummies are estimated. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 2: Impact of Grant on Subsequent VC for Firms from Different Regions

Dep Var: VC_i^{Post}	I.	II.	III.	IV.	V.	VI.
Winner Region:	SF	NY	SF	BOS	BOS	DC
Loser Region:	NY	SF	BOS	SF	DC	BOS
$\mathbf{1} \mid R_i > 0$	**0.275*** **	**0.0848**	**0.304*** **	**0.0452**	**0.163*** **	**0.0477**
	(0.0754)	(0.0919)	(0.0781)	(0.0663)	(0.0608)	(0.118)
VC_i^{Prev}	0.277***	0.480***	0.248***	0.485***	0.0498	0.208***
	(0.0795)	(0.0881)	(0.0774)	(0.0901)	(0.0627)	(0.0779)
$\#SBIR_i^{\text{Prev}}$	0.000601	0.000306	0.000358	0.000666	0.000403	0.000207
	(0.000674)	(0.000983)	(0.000370)	(0.000794)	(0.000485)	(0.000294)
Topic f.e.	Y	Y	Y	Y	Y	Y
N	325	330	358	346	231	331
R^2	0.215	0.250	0.173	0.253	0.173	0.105

	VII.	VIII.	IX.	X.	XI.	XII
Winner Region:	NY	BOS	LA	NY	TX	DC
Loser Region:	BOS	NY	NY	LA	DC	TX
$\mathbf{1} \mid R_i > 0$	**0.0774**	**0.0314**	**0.102* **	**0.0972**	**0.109* **	**0.168**
	(0.0846)	(0.0675)	(0.0584)	(0.0802)	(0.0602)	(0.115)
VC_i^{Prev}	0.187**	0.250***	0.294***	0.233***	0.203**	0.0815
	(0.0776)	(0.0816)	(0.0807)	(0.0821)	(0.0807)	(0.150)
$\#SBIR_i^{\text{Prev}}$	0.000406	0.000932	0.00135**	0.00296***	-0.000107	-0.000203
	(0.000349)	(0.000700)	(0.000568)	(0.000850)	(0.000139)	(0.000327)
Topic f.e.	Y	Y	Y	Y	Y	Y
N	346	329	333	493	213	267
R^2	0.108	0.130	0.178	0.152	0.209	0.084

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on subsequent VC by location, where a winner is in one region and a loser in another. These regressions use BW=all, but usually there are only 2 firms per topic. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 3: Impact of Grant on Subsequent Venture Capital by Regional VC Intensity

Dependent Variable: VC_i^{Post}	Treatment interacted with regional VC intensity			Separate regressions around mean regional VC intensity		
	I. BW=2	II. BW=3	III. BW=all	IV. $VC\ Int \leq$ 6.2	V. $VC\ Int >$ 6.2	VI. Diff $VC\ Int \leq 6.2$ & > 6.2
$(\mathbf{1} \mid R_i > 0) \cdot VC\ Int$	**0.0157****	**0.0159*****	**0.0112****			
	(0.00791)	(0.00602)	(0.00480)			
$\mathbf{1} \mid R_i > 0$	0.118**	0.120***	0.0979***	**0.0750****	**0.177*****	0.171***
	(0.0464)	(0.0402)	(0.0343)	(0.0356)	(0.0522)	(0.0343)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid VC\ Int \leq 6.2)$						**-0.0960****
						(0.0456)
VC_i^{Prev}	0.329***	0.322***	0.330***	0.336***	0.345***	0.347***
	(0.0734)	(0.0623)	(0.0444)	(0.0509)	(0.0593)	(0.0341)
$\#SBIR_i^{\text{Prev}}$	0.000341	0.000591	0.000602*	0.00101*	0.000287	0.000326
	(0.000652)	(0.000531)	(0.000334)	(0.000517)	(0.000434)	(0.000238)
$VC\ Int$	0.00000360	-0.000367	0.00178			
	(0.00222)	(0.00165)	(0.00129)			
Competition f.e.	Y	Y	Y	N	N	N
Topic f.e.	N	N	N	Y	Y	Y
Topic f.e. $\cdot (\mathbf{1} \mid VC\ Int \leq 6.2)$	N	N	N	Y	Y	Y
N	1290	1538	2571	1522	1050	2571
R^2	0.536	0.498	0.371	0.286	0.356	0.327

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant $(\mathbf{1} \mid R_i > 0)$ on subsequent VC by regional VC intensity. VC intensity is calculated as 2012 ($ VC investment)/(100$ of GDP) for each of the twenty MSAs with the most VC investment. Each column includes only data from firms in the relevant range of VC intensity. In the difference regression (column VI), all covariates are interacted with a dummy for low VC intensity. Topic-level dummies are used to have adequate firms per fixed effect. Coefficients on $VC_i^{\text{Prev}} \cdot (\mathbf{1} \mid VC\ Int \leq 6.2)$, $\#SBIR_i^{\text{Prev}} \cdot (\mathbf{1} \mid VC\ Int \leq 6.2)$ and $(\mathbf{1} \mid VC\ Int \leq 6.2)$ not reported for space concerns. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Appendix C: Politicization of Awards

There is concern that government grants may be politicized; that is, members of Congress who control the DOE purse may seek to have projects in their districts funded. Previous literature has found that political power in Congress can be used as an instrument for spending. This literature has focused on spending allocated on a state-by-state basis by Congress itself. Knight (2002)'s pioneering study on Federal Highway Grants and Feyrer and Sacerdote (2011)'s estimation of the employment impacts of the ARRA, for example, both use congressional delegation seniority as an instrument for funding to a given state. However, in the case of the SBIR program, decision-making is located in the executive branch. It is also highly dispersed and bureaucratized, conditions that Lerner (2002) suggests should lead to fewer opportunities for capture. My prior is that Congressional political power is unlikely to have an impact on the geography of funding.

I try to predict spending to both the Congressional District (each of which sends one representative to the House) and state (each of which sends two representatives to the Senate). A Congressmember's tenure of service determines her rank, both in the overall chamber and in specific committees on which she sits. Following the political science literature, I use this measure of "seniority," which is the number of terms served in the House and the number of years served in the Senate.

Four congressional committees in each chamber have jurisdiction over the SBIR program. In the House the two primary committees are the Science & Technology and Small Business Committees, but the Energy and Commerce and perhaps most importantly the Appropriations committee are also involved. In the Senate the Small Business Committee has primary jurisdiction, but the Appropriations Committee, the Commerce, Science, and Transportation Committee, and the Energy and Natural Resources Committee are also involved.

I use these four committees and each chamber to develop my committee metrics. Member and committee data is from Charles Stewart III and Jonathan Woon at MIT. This is only available from 1993-2012, so my analysis is limited to this time period.[1] Specifically, the House chamber delegation seniority metrics are for each state ($H\_Sr_g^{\text{State}}$) and district ($H\_Sr_g^{\text{District}}$). The House committee seniority metrics are $H\_C\_Sr_g^{\text{District}}$ and $H\_C\_Sr_g^{\text{State}}$, where seniority is summed over the four committees. For the state variables, seniority is averaged across all representatives from the district. The senate chamber measure is $S\_Sr_g^{\text{State}}$

[1] Available on Stewart's home page: http://web.mit.edu/17.251/www/data_page.html#2

and the committee measure is $S\_C\_Sr_g^{\text{State}}$.

Using full addresses, I geocoded applicant firms by congressional district, and matched congressional districts and application years to the relevant congressional data. The metrics, calculated for a given congress g (where for example the 103rd congress was from January 1993-January 1995) are described in Table B1.

I estimate the following OLS regressions to see whether these metrics are predictive of the total number of annual Phase $x \in [1, 2]$ awards to a given state or congressional district.

$$\begin{aligned} PhxAwards_t^{\text{State}} &= \alpha + \beta_1 S\_Sr_g^{\text{State}} + \beta_2 H\_Sr_g^{\text{State}} \\ &\quad + \beta_3 S\_C\_Sr_g^{\text{State}} + \beta_4 H\_C\_Sr_g^{\text{State}} + \delta_{state} \left[\mathbf{1} \mid \text{State} = \text{State} \right] \end{aligned}$$

$$PhxAwards_t^{\text{District}} = \alpha + \beta_1 H\_Sr_g^{\text{District}} + \beta_2 H\_C\_Sr_g^{\text{District}} + \delta_{district} \left[\mathbf{1} \mid \text{District} = \text{District} \right]$$

Columns I and III of Table B2 suggest that at the state level the strongest predictor of funding is the Senate committee seniority metric. The coefficient implies that an increased year of committee seniority in the Senate yields 0.031 increase in Phase 1 and 0.013 increase in Phase 2 awards to the state. This magnitude is small, as the mean Phase 1 awards to a state is 1.66. Overall House seniority at the state level has a larger, albeit less significant, positive effect of 0.11 for Phase 1 awards, but no apparent effect for Phase 2. The final two variables seem to have no effect.

Columns II and IV show the district level regressions, which support the importance of committee from the state level. While House chamber seniority at the district level has essentially no effect, the average committee seniority for districts' representatives has a positive significant coefficient of 0.0096 for Phase 1 and 0.0053 for Phase 2. Again, the magnitude is quite small. A doubling of mean committee seniority among house representatives yields 0.001 more Phase 1 awards to a district from an average of 0.279.

In sum, I do find surprising positive and significant effects of political power on funding, but the levels are very small. I have no reason to believe that these congressional effects impact my estimates of financial, commercial, and innovation outcomes. In the case of the SBIR program, the grants appear to be too small and the award process too dispersed and bureaucratized to garner substantial lobbying effort, but capture is nonetheless a possibility.

These results are somewhat inconsistent with the previous literature. Knight (2002) and Feyrer and Sacerdote (2011) find that the best variable for predicting spending is mean chamber delegation seniority. However, both use committee metrics that are different from

Table 1: Congressional Data Summary Statistics, 103-112 Congresses (1993-2012)

Variable Name	Variable Meaning	N	Mean*	Std. Dev.
$S\_Sr_g^{\text{State}}$	Mean chamber seniority among senators from given state	893	12.06	7.45
$H\_Sr_g^{\text{State}}$	Mean chamber seniority among House representatives from given state	804	4.64	2.03
$H\_Sr_g^{\text{District}}$	Chamber seniority of House representative from given district	4472	5.54	4.24
$S\_C\_Sr_g^{\text{State}}$	Sum of committee seniority among senators from given state in four committees with SBIR jurisdiction	893	14.16	17.24
$H\_C\_Sr_g^{\text{State}}$	Mean committee seniority among House representatives from given state in four committees with SBIR jurisdiction	804	1.15	1.02
$H\_C\_Sr_g^{\text{District}}$	Sum of committee seniority among House representatives from given district in four committees with SBIR jurisdiction	4472	2.02	3.57
$Ph1Awards_t^{\text{State}}$	Number of EERE/FE Phase 1 awards in year t to given state	893	1.66	3.05
$Ph1Awards_t^{\text{District}}$	Number of EERE/FE Phase 1 awards in year t to given district	4472	0.279	0.621
$Ph2Awards_t^{\text{State}}$	Number of EERE/FE Phase 2 awards in year t to given state	893	0.792	1.61
$Ph2Awards_t^{\text{District}}$	Number of EERE/FE Phase 2 awards in year t to given district	4472	0.123	0.449

*Note: The mean and std. dev. are across state-years or district-years. Of 10,182 applicants between 1993 and 2012, I have state for state for 10,120, and matched 8,799 to congressional districts. Where mean is indicated, the denominator is either the number of senators (2) or the number of congressional districts in a state.

mine (Knight uses proportion of a state's delegation sitting on the transportation committee, and Feyrer and Sacerdote use the number of committee chairs held by the House and Senate delegations). Both also study only the state level whereas I can also exploit Congressional District information.

Table 2: Predictive Power of Congressional Status on Phase 1 and 2 Awards by State and Congressional District

Dep. Var:	I. $Ph1Awards_t^{\text{State}}$	II. $Ph1Awards_t^{\text{District}}$	III. $Ph2Awards_t^{\text{State}}$	IV. $Ph2Awards_t^{\text{District}}$
$S\_Sr_g^{\text{State}}$	-0.0317*		-0.0147	
	(0.0190)		(0.0106)	
$H\_Sr_g^{\text{State}}$	0.116**		0.0258	
	(0.0557)		(0.0310)	
$S\_C\_Sr_g^{\text{State}}$	0.0312***		0.0133**	
	(0.00941)		(0.00523)	
$H\_C\_Sr_g^{\text{State}}$	0.0114		0.00188	
	(0.126)		(0.0701)	
$H\_Sr_g^{\text{District}}$		0.00417*		-0.000437
		(0.00253)		(0.00185)
$H\_C\_Sr_g^{\text{District}}$		0.00962***		0.00526**
		(0.00301)		(0.00220)
State f.e.	Y	N	Y	N
District f.e.	N	Y	N	Y
N	804	4472	804	4472
R^2	0.608	0.041	0.537	0.025

Note: This table uses all applicant data to predict funding by congressional power at the state level (columns I and III) and at the congressional district level (columns II and IV) using both House and Senate seniority metrics. C indicates seniority on committees with SBIR/DOE authority. Year$\geq$ 1993.

Appendix D: Summary Statistics

Figure 1:

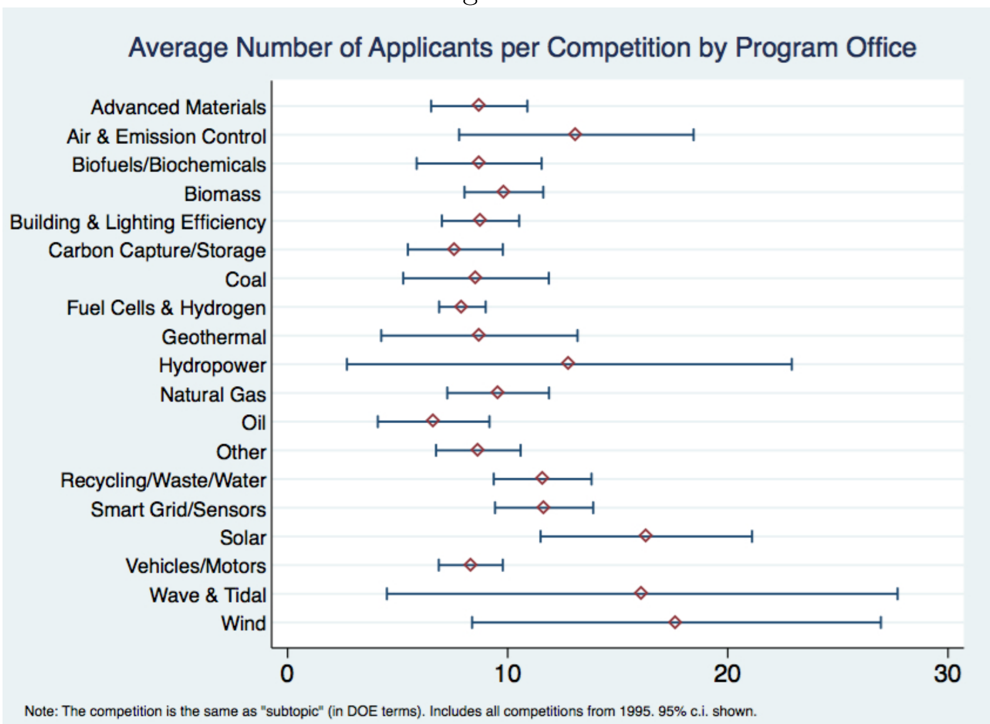


Figure 2:

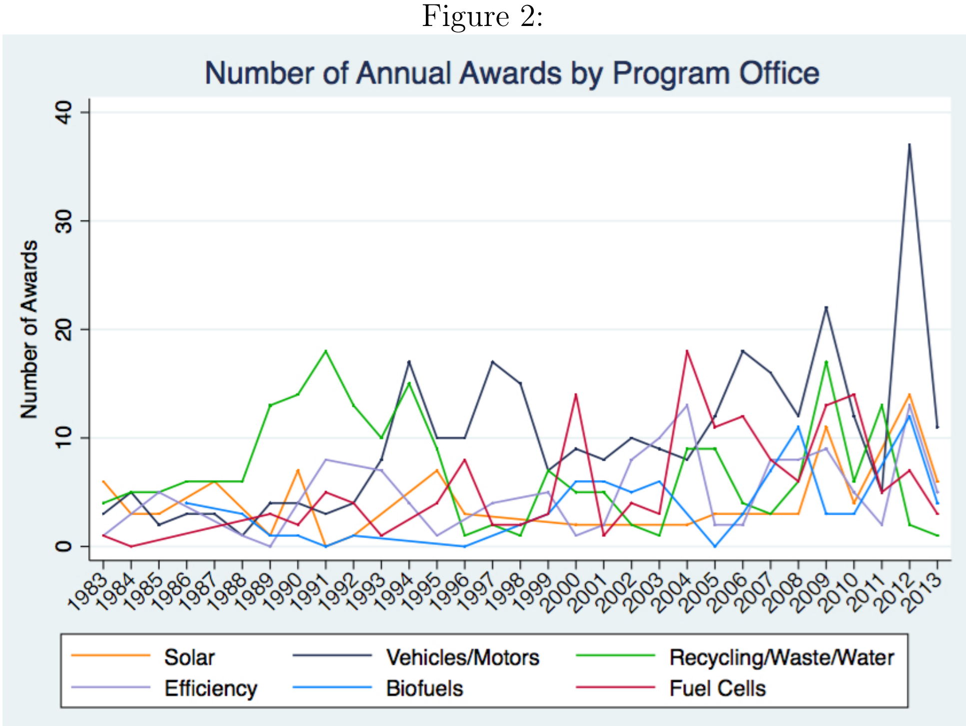


Figure 3:

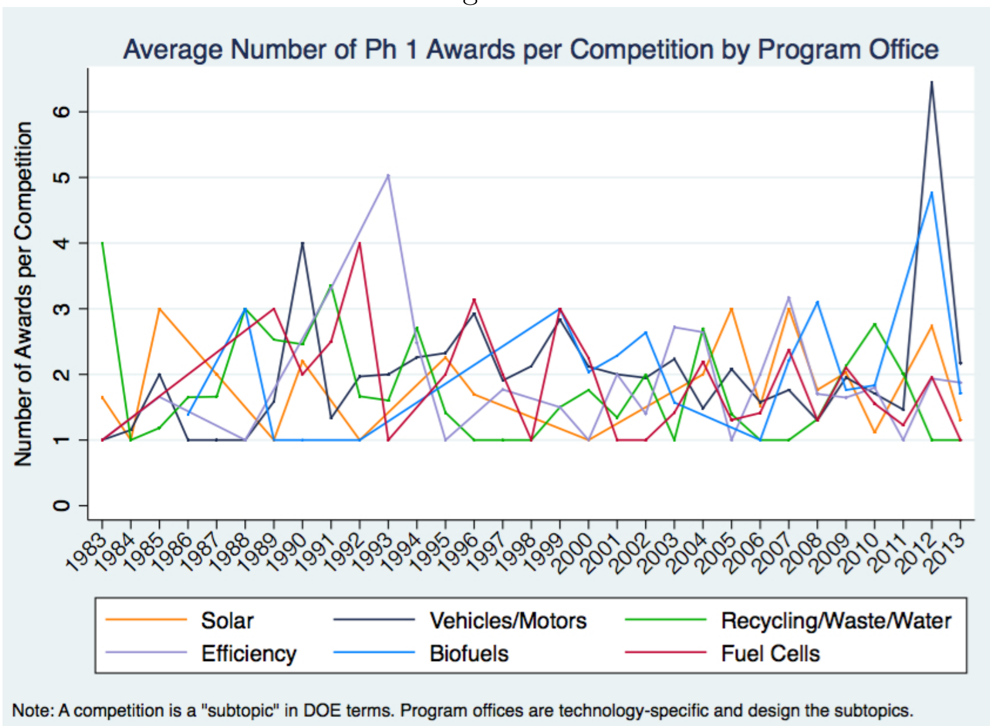
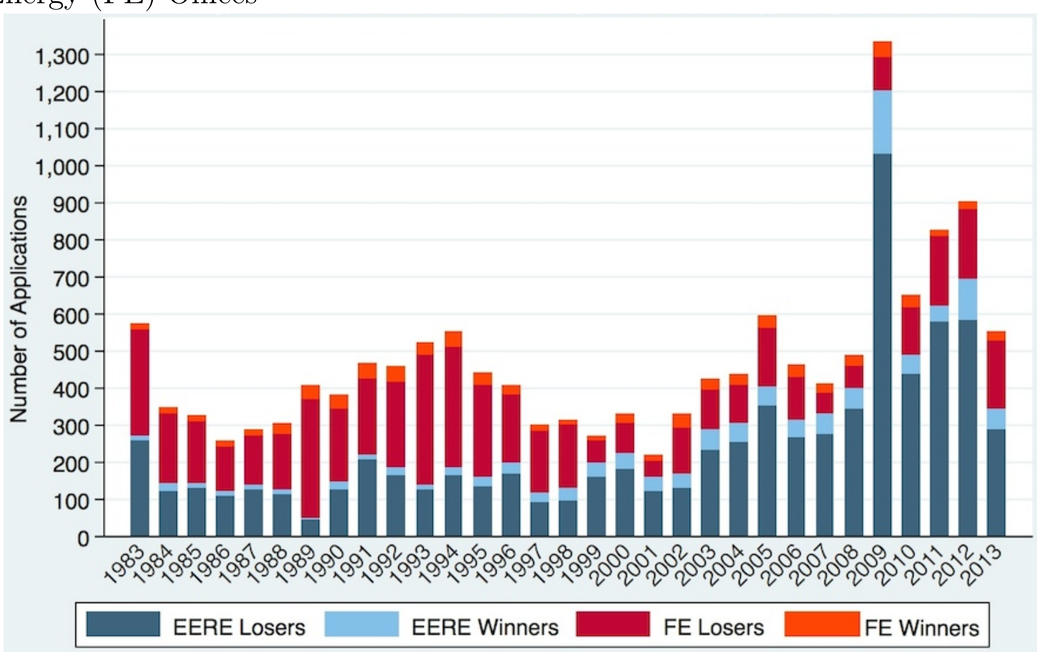


Figure 4: Number of Applicants to Energy Efficiency & Renewable Energy (EERE) and Fossil Energy (FE) Offices



Note: This figure shows the number of losing and winning Phase 1 grant applicants over time. Note that firms may appear more than once. N=14,522.

Figure 5:

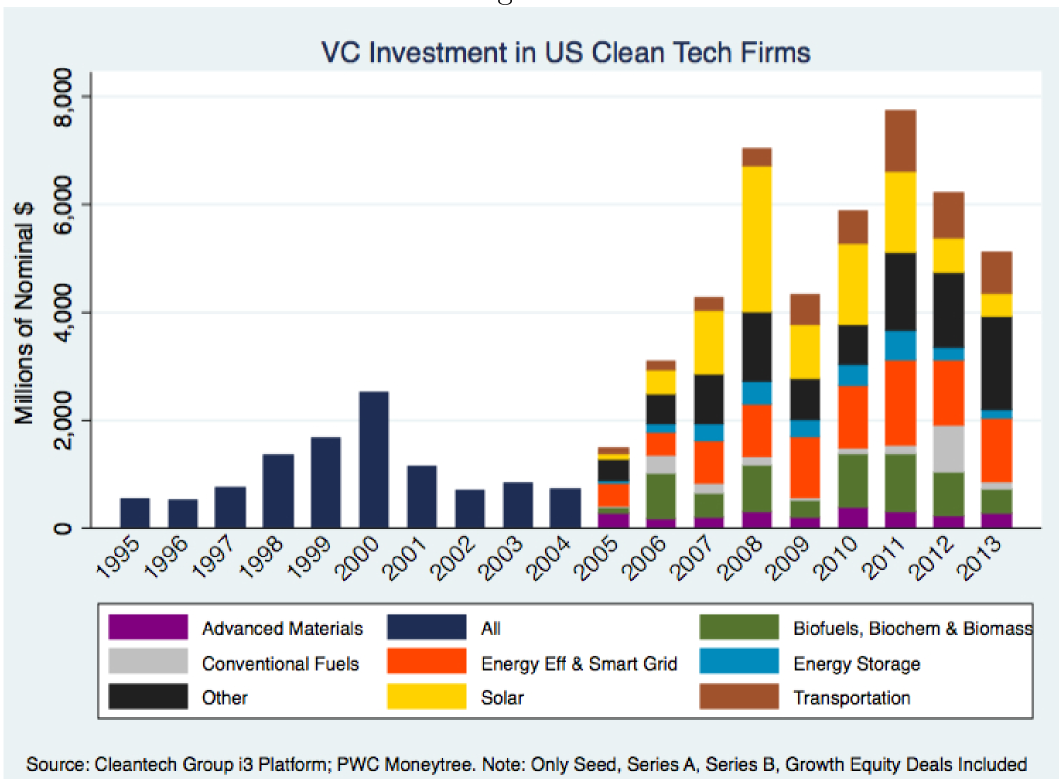


Figure 6:

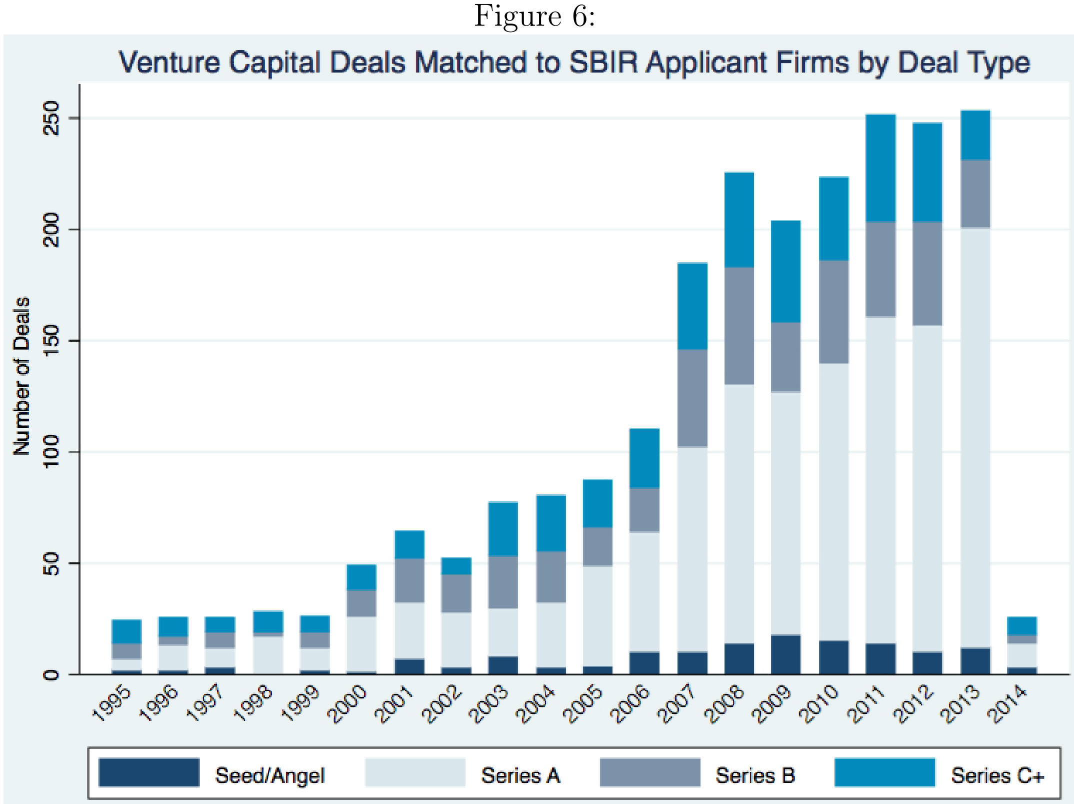


Figure 7:

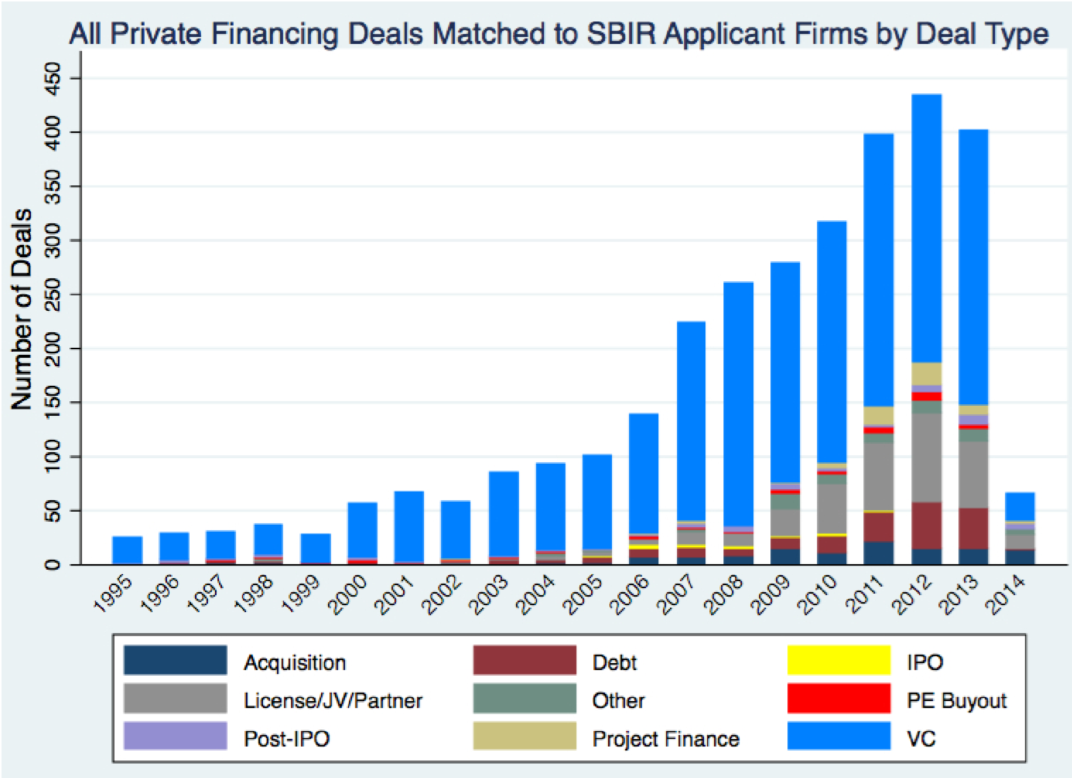


Figure 8:

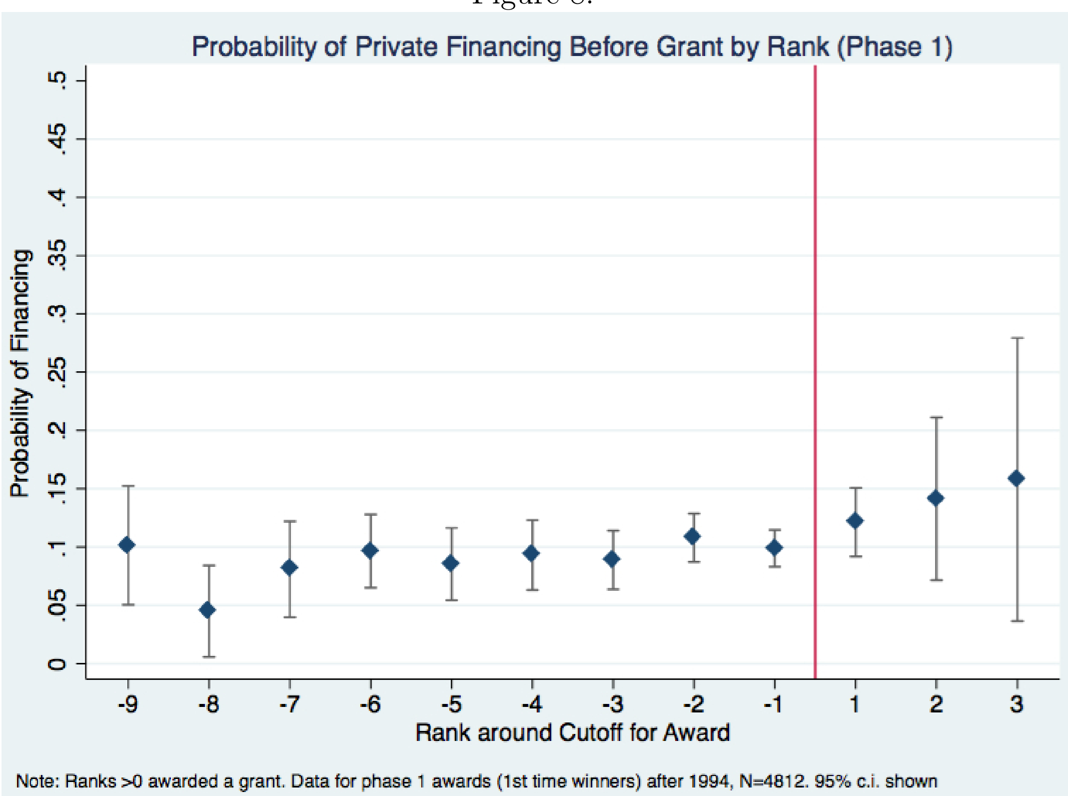


Figure 9:

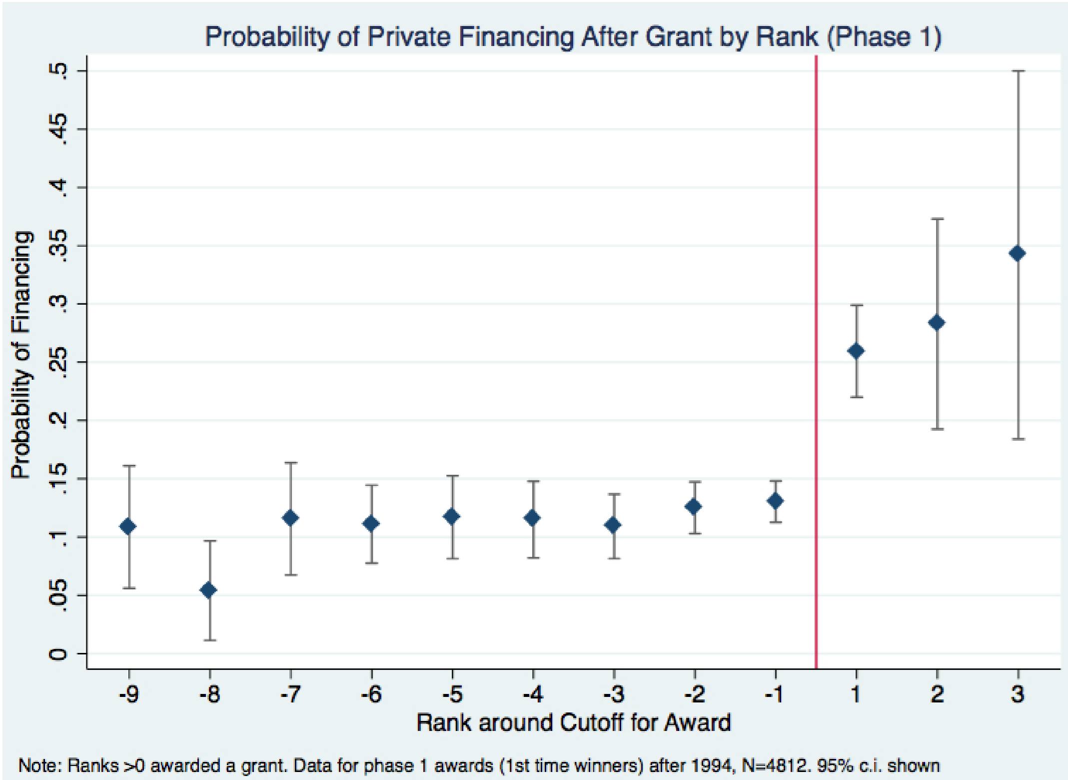


Figure 10:

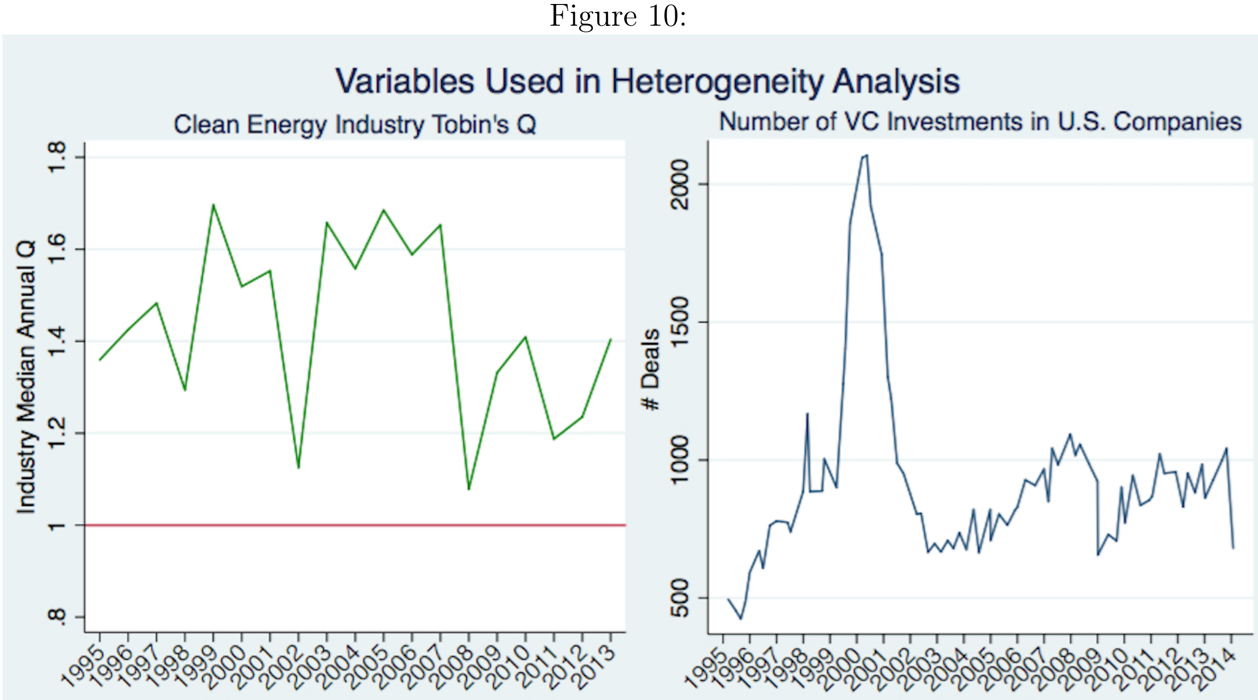


Table 1: Additional Summary Statistics of Dependent Variables

Covariate	N	Variable Type	Mean	Std. Dev.	Min	Max
PF_i^{Post}	5693	0-1	0.14	0.35	0	1
PF_i^{Prev}	5693	0-1	0.095	0.29	0	1
PF # $\text{Deals}_i^{\text{Post}}$	5693	Semi-Cont.	0.45	1.97	0	41
PF # $\text{Deals}_i^{\text{Prev}}$	5693	Semi-Cont.	0.29	1.44	0	30
VC # $\text{Deals}_i^{\text{Post}}$	5693	Semi-Cont.	0.31	1.33	0	17
VC # $\text{Deals}_i^{\text{Prev}}$	5693	Semi-Cont.	0.24	1.27	0	30

Note: First-time winners only. Year$\geq$ 1995

Table 2: Summary Statistics of Private Financing Matches (Number of Deals or Firms)

Applicant firms matched to ≥ 1 PF deal	838
Applicant firms matched to ≥ 1 VC deal	683
PF deals matched to applicant firms (Some companies have multiple funding events)	3,751
VC deals	2,638
Seed/Angel	178
Series A	1,313
Series B	561
Series C+	587
Acquisitions	221
IPOs	27
Debt deals	196
PE Buyout deals	59
Project Finance	61
Unique applicants with ≥ 1 PF deal & 0 grant wins	565
Unique applicants with ≥ 1 VC deal & 0 grant wins	451
Unique applicants with ≥ 1 PF deal & ≥ 1 grant wins	273
Unique applicants with ≥ 1 VC deal & ≥ 1 grant wins	232

Note: PF= all private finance; VC=venture capital (subset of PF). Sources: ThompsonOne VentureSource, Preqin, Cleantech Group's i3 Platform, CrunchBase, and CapitalIQ

Table 4: Summary Statistics of Patent Matching

# Firms matched to ≥ 1 patent (1983-2013)	2,109
Average # Patents	2.06 (9.94)
Average # Patents for firms w/≥ 1 patent (1983-2013)	7.91 (18.25)
# Firms matched to ≥ 1 patent (1995-2013)	1,471
Average # Patents	2.44 (11.69)
Average # Patents for firms w/≥ 1 patent	8.82 (20.42)
Average per patent citations for a firm	9.9 (18)
Average per patent claims for a firm	21.2 (12)
Average total citations for a firm	75.9 (258)
Average total claims for a firm	171.8 (453)
Average total normalized 3-year citations for a firm	3.46 (24.72)
Average total normalized 3-year citations for a firm w/≥ 1 patent	11.80 (44.75)

Source: Berkeley Fung Institute Patent Database

Table 3: Summary Statistics of Revenue and Survival (Number of Applicant Companies)

Reached revenue (commercialization)	2,426
No evidence reached revenue (commercialization)	4,992
Still active (Survival)	3,512
Firm out of business	1,458
Declared bankruptcy	71
Unknown if firm active	2,449

Sources: Primarily web scraping, some from Cleantech Group i3. Data as of May, 2014.

Table 5: NAICS Codes Defining Energy & Clean Energy Sectors for Tobin's Q Calculation

NAICS Code	Clean Energy Sub-Sector
22111	Hydroelectric
221119	Other Renewable
221113	Nuclear
115310	Forest and Reforestation services
115310	Timber cruising, estimating, and valuation services
813312	Environmental advocacy organization
541330	Environmental engineering
541330	Heating and ventilation engineering
541711	Biotechnical research, commercial
562910	Environmental remediation
541690	Energy conservation consultant
541620	Environmental consultant
333111	Windmills for pumping water, agricultural
333611	Windmills, electric generating
334413	Light emitting diodes
334413	Photovoltaic cells, solid state
334413	Fuel cells, solid state
334515	Energy measuring equipment, electrical
334519	Solarimeters
311221	Wet corn milling
311222	Lecithin, soybean
325120	Hydrogen
312140	Ethyl alcohol, ethanol
333414	Solar heaters and collectors
423720	Heating equipment and panels, solar
423730	Air pollution control equipment and supplies
423720	Solar heating equipment

Sources: U.S. Conference of Mayors. 2008. "Green Jobs Report." October; and Iowa http://www.iowaworkforce.org/newenergy/naicscodes.htm.

Table 6: Summary Statistics of Metrics used in Heterogeneity Analysis

	Mean	Std. Dev.	50 pctile
Clean Energy Industry Tobin's Q in 4 Quarters Following Award			
Q_{t+1}	1.288	0.165	1.219
Number of VC Investments in U.S. Companies in 8 Quarters Following Award			
$\#VC_{t+2}$	7575.4	2127.4	7162

Note: All figures are for Year$\geq$ 1995

Appendix E: The Effect of Phase 2 Grants

Roughly a year after receiving a $150,000 Phase 1 award, a firm may apply for a $1 million Phase 2 grant. Successful applicants typically receive their Phase 2 money nearly two years after the Phase 1 award. Figure 1 shows all applicants by office and award status for Phase 2, which is much less competitive. Approximately 45% of applicants receive funding.

The short term nature of the Phase 1 effect on VC - recall that well over half the long term effect occurs within two years - suggests that Phase 2 does not cause the Phase 1 effect. In fact, I find that the Phase 2 grant has no consistently positive effect on subsequent VC. The first column of Table 1 uses the same specification as in the Phase 1 analysis, but estimates the Phase 2 treatment effect. Columns II and III use topic and year instead of competition fixed effects. The coefficients are small and positive, but imprecise. For example, the 95% confidence interval from the column III the coefficient of 4.4 pp ranges from -3 pp to 12 pp. I find smaller coefficients when the dependent variable is all private finance (Table 2).

I also estimate the effects of Phase 1 and 2 together by including an indicator for whether a firm won a Phase 2 award in my primary Phase 1 specification (Table 3). Across bandwidths and fixed effects, I find the same robust Phase 1 effects. Coefficients on Phase 2 range from -3.2 pp to -.1 pp, but have only slightly smaller standard errors than when I estimate Phase 2 alone. The narrowest 95% confidence interval ranges from -7.8 pp to 5.6 pp. I conclude that in contrast to Phase 1, any effect of Phase 2 is not consistently positive. That is, it may be useful for some firms, but is not for others. As with financing, I find no impact of the Phase 2 grant on revenue, survival, or exit, shown in Tables 4-6. The coefficients are small, often negative, and insignificant.

One reason for the absence of a strong measurable Phase 2 effect is adverse selection among Phase 1 winners in the decision to apply to Phase 2. Among Phase 1 winners, 37% *did not apply for Phase 2*. While 19% of the non-applyers received VC investment within two years of their initial award (column I), only 9%(8%) of firms who applied and lost(won) Phase 2 did (see Table 7). A t-test of the difference of means strongly rejects the hypothesis that non-appliers and appliers have the same mean probability of VC investment within two years, with a t-statistic of 5.44. In interviews, grantees told me that the grant application and reporting processes are so onerous that once they receive external private finance, it is often not worthwhile to apply for additional government funding. Similarly, Gans and Stern (2003) hypothesize that private funding is preferred to SBIR funding. For startup Oscilla

Power (introduced above), the Phase 2 grant of $1 million was significant in relation to what the firm sought to raise from private sources. Had Oscilla raised a $10 million VC round, CEO Shendure said, applying to Phase 2 would not have been worthwhile.

Now I turn to the set of firms that did apply to Phase 2. In the "Standard Sample" regressions (columns I-III of Table 1), there are only 410 observations, which is roughly half the total number of Phase 2 applicants. The other half are omitted because they are not first-time Phase 1 winners. The SBIR mills always apply to Phase 2, which is why the sample with only first-time winners is small. Column IV expands the sample to all firms, and finds a statistically insignificant effect of 0.2 pp. Column V considers only firms with more than one previous win, and finds a large negative coefficient, also insignificant.

The concentration of SBIR mills in the Phase 2 applicant sample may help explain the absence of a strong Phase 2 impact, but it does not cause the imprecision. The fraction of Phase 2 winners and losers who receive VC are quite similar, at 22% and 24% (columns II and IV of Table 7). These percentages are large; despite the SBIR mills, the Phase 2 applicants more broadly are only adversely selected relative to the population of Phase 1 winners.[1] It seems that the Phase 1 grant enables venture funding for high-quality firms whose prototyping reveals positive information. There is sufficient information about the firms at the Phase 2 stage that the grant no longer serves to mitigate information asymmetries.

It is natural to imagine that the very small Phase 1 grant enables access to VC finance because of the expected value of the Phase 2 effect. To the contrary, Table 8 shows that the Phase 1 grant effect on subsequent VC is *stronger* than in the whole sample both for Phase 1 winners who choose not to apply (Panel A), and for Phase 1 winners who lose Phase 2 or choose not to apply (Panel B). For firms who opt not to apply (Panel A), the long term effect of Phase 1 on VC is twice as large as in the whole sample within two years of winning the grant (i.e. before the firm could in theory have gotten a Phase 2 had they applied) and in the long term. Specifically, column II shows that the effect within two years is 14 pp, significant at the 1% level, whereas the effect in the whole sample from Table 7 in the main text is 7.5 pp. In the long term, column IV reveals an effect of 16.2 pp, also significant at the 1% level. This again is roughly twice the whole sample effect from Table 3 in the main

[1] One example of such a firm is FloDesign Wind Turbine, which received a Phase 2 award in 2010, and over the following two years raised money from Kleiner, Perkins Caufield and Byers, Goldman Sachs, Technology Partners and VantagePoint Venture Partners. A second example is American Superconductor, which received a Phase 2 award in 1996 after many rounds of VC investment from the likes of Bessemer Venture Partners and Venrock Associates. After the award, it received funding in 2012 from Hercules Technology Growth Capital. These two companies were at quite different stages when they won their Phase 2 grants and illustrate the variety underlying a "success" ($VC_i^{\text{Post}} = 1$) in my data.

text.

In contrast to the results thus far, I do find a positive effect of the Phase 2 grant on patenting *and* citations. The effect on patents is, however, much smaller than the Phase 1 effect. The Phase 2 award leads a firm to generate 1.5 times the patents it would otherwise (Table 9), about half the Phase 1 effect. The average patents for this sample is 2.2. Including applicants with previous DOE SBIR wins, I find the effect declines (columns II and III), suggesting decreasing returns in the number of Phase 2 grants to a firm. The same pattern occurs with citations (Table 10). The first stage indicates that for first-time winners (column Ia) the odds of positive citations for grantees are 85% higher than the odds for non-grantees, significant at the 5% level.[2] Among the Phase 2 applicants, the probability of positive subsequent citations is 0.31, so the population odds are 0.44. The second stage (regression within observations with positive citations, column Ib) finds small and insignificant coefficients. As with patents, the first stage effect declines substantially and becomes insignificant when firms have more than one previous win (column III).

Thus the Phase 2 grant acts on the extensive margin of innovation quality, but not the intensive margin. That is, among firms with positive citations and among firms with at least one previous win, the grant has no measurable effect. A policy implication is that if the government's objective is to generate R&D (measured by patents and more highly cited patents) rather than leverage private financing, then Phase 2 awards are beneficial when awarded to firms without previous patenting or citation histories.

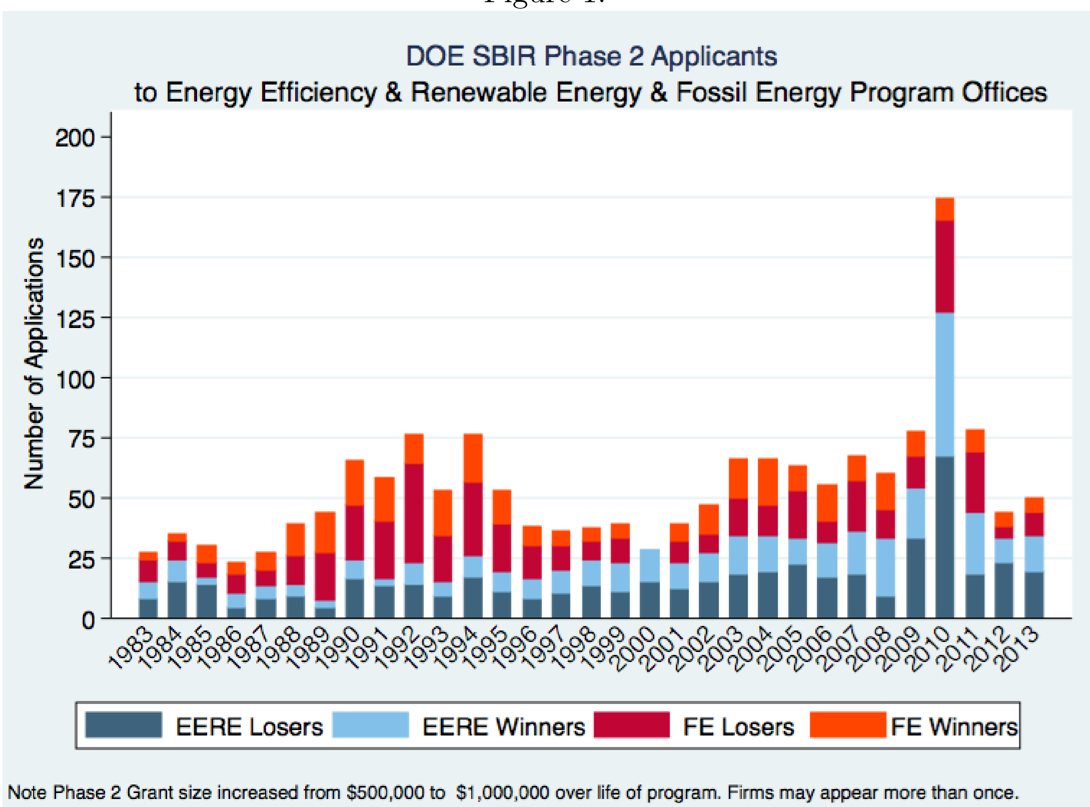
The principal research underlying the technology at the Phase 1 stage may have occurred before the firm applied for a grant. The Phase 1 award generates testing and demonstration (prototyping) which sometimes yields additional patents but generally does not represent a fundamental change to the firm's technology (thus no effect on citations). The Phase 2 grant, in contrast, allows the firm to undertake new inventive activity. This interpretation is consistent with previous literature that has found investment in R&D and patenting to occur simultaneously (Pakes 1985, Hall, Griliches and Hausman 1986; Gurmu and Pérez-Sebastián 2008). The large effect of Phase 2 on citations suggests that Phase 2 may affect the entrepreneur's technology quality (σ_T^2). This Phase 2 R&D work does not, however, likely generate the Phase 1 financing result, because (a) the impact of the award on VC is short term, mostly occurring between two and four years after the award; and (b)

[2]Logit coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable. This odds ratio is calculates as $OR = e^{\beta}$, where β is the logit coefficient. Odds are the probability of success divided by probability of failure.

many firms who win Phase 1 and receive VC do not apply to Phase 2.

Since the SBIR program spends vastly more on Phase 2 than Phase 1, the absence of a consistently positive Phase 2 effect is important from a policy perspective. At the high end of the confidence intervals, the impact of Phase 2 is still much weaker per public dollar than Phase 1. For example, suppose that the true effect of Phase 2 on the likelihood of subsequent VC is 12 pp. Then the effect of Phase 1 per grant dollar is six times that of Phase 2.[3] Consider the following thought experiment. In 2012 DOE spent $111.9 million on 111 Phase 2 grants and $38.3 million on 257 Phase 1 grants. If all the Phase 2 money were reallocated to Phase 1, DOE could have provided 750 additional firms with Phase 1 grants, increasing by a factor of 2.5 the "return" in additional VC funding probability.[4]

Figure 1:



[3]Specifically, at this high end of the confidence interval, the effect of Phase 2 per $100,000 in grant money is 1.2 pp. My preferred estimate of 9 pp for Phase 1 corresponds to 6 pp per $100,000.

[4]The calculation is as follows, where all numbers are per $100,000 of grant spending: The effect of Phase 2 is 1.2 pp, andthe effect of Phase 1 is 6 pp. Actual Phase 2 2012 spending was 111.9, and actual Phase 1 spending was 383. The "return" in percentage points of increased VC funding probability was 3,640. If instead Phase 2 spending were 0, and Phase 1 spending were 1,502, then the counterfactual "return" would be 9,011, which is 2.48 times the actual "return."

Table 1: Impact of Phase 2 Grant on Subsequent VC

Dependent Variable: VC_i^{Post}					
	Standard sample			≥ 1 previous Ph. 1 Wins	> 1 previous Ph. 1 wins
	I.	II.	III	IV.	V
$\mathbf{1} \mid R_i^{Ph2} > 0$	**0.0389**	**0.0255**	**0.0443**	**0.00220**	**-0.144**
	(0.141)	(0.0584)	(0.0363)	(0.0848)	(0.234)
VC_i^{Prev}	0.679***	0.505***	0.461***	0.396***	0.125
	(0.217)	(0.128)	(0.0756)	(0.132)	(0.304)
$\#SBIR_i^{\text{Prev}}$	0.000115	0.000352	0.000520	0.000301	0.000337
	(0.00105)	(0.000697)	(0.000429)	(0.000205)	(0.000374)
Competition f.e.	Y	N	N	Y	Y
Topic f.e.	N	Y	N	N	N
Year f.e.	N	N	Y	N	N
N	410	410	410	868	460
R^2	0.773	0.546	0.191	0.634	0.734

Note: This table is an RD estimating via OLS the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on subsequent VC using BW=1. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 2: Impact of Phase 2 Grant on Subsequent Private Financing

	Standard sample			≥ 1 previous Ph. 1 Wins	> 1 previous Ph. 1 wins
Dep Var: PF_i^{Post}; BW=1	I.	II.	III	IV.	V
$\mathbf{1} \mid R_i > 0$	**-0.000950**	**-0.0000022**	**0.0279**	**-0.0295**	**-0.140**
	(0.174)	(0.0730)	(0.0403)	(0.0922)	(0.232)
PF_i^{Prev}	0.621***	0.484***	0.422***	0.401***	0.205
	(0.173)	(0.121)	(0.0712)	(0.113)	(0.270)
$\#SBIR_i^{\text{Prev}}$	0.000195	0.000644	0.000450	0.000253	0.000323
	(0.00109)	(0.000695)	(0.000405)	(0.000208)	(0.000370)
Competition f.e.	Y	N	N	Y	Y
Topic f.e.	N	Y	N	N	N
Year f.e.	N	N	Y	N	N
N	410	410	410	868	460
R^2	0.776	0.526	0.164	0.638	0.742

Note: This table is an RD estimating via OLS the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on all subsequent private finance. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 3: Impact of both Phase 1 and Phase 2 Grants on Subsquent Venture Capital Financing with No Rank Control and Varying Fixed Effects

Dependent Variable : VC_i^{Post}	Topic f.e.				Competition f.e.		Year f.e.	
	I. BW=1	II. BW=2	III. BW=3	IV. BW=all	V. BW=3	VI. BW=all	VII. BW=3	VIII. BW=all
$\mathbf{1} \mid R_i^{Ph1} > 0$	**0.106*** **	**0.103*** **	**0.113*** **	**0.114*** **	**0.110*** **	**0.114*** **	**0.111*** **	**0.106*** **
	(0.0272)	(0.0233)	(0.0236)	(0.0230)	(0.0274)	(0.0254)	(0.0213)	(0.0214)
$\mathbf{1} \mid R_i^{Ph2} > 0$	**-0.0261**	**-0.0169**	**-0.0108**	**-0.0141**	**-0.0321**	**-0.0168**	**-0.0101**	**-0.0105**
	(0.0495)	(0.0399)	(0.0380)	(0.0369)	(0.0475)	(0.0428)	(0.0343)	(0.0342)
VC_i^{Prev}	0.305***	0.337***	0.322***	0.332***	0.307***	0.324***	0.335***	0.338***
	(0.0472)	(0.0335)	(0.0312)	(0.0269)	(0.0363)	(0.0290)	(0.0283)	(0.0249)
$\#SBIR_i^{\text{Prev}}$	0.00117***	0.000989***	0.00100***	0.000895***	0.00105***	0.000871***	0.000987***	0.000897***
	(0.000302)	(0.000253)	(0.000233)	(0.000207)	(0.000270)	(0.000236)	(0.000200)	(0.000186)
N	1872	2836	3368	5021	3368	5021	3368	5021
R^2	0.299	0.237	0.212	0.179	0.345	0.268	0.132	0.124

Note: This table is an RD estimating via OLS the both impact of the Phase 1 grant ($\mathbf{1} \mid R_i^{Ph1} > 0$) and Phase 2 grant ($\mathbf{1} \mid R_i^{Ph2} > 0$) on subsequent VC with no rank controls. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 4: Impact of Phase 2 Grant on Revenue

Dependent Variable: $Revenue_i$					
	Standard sample			≥ 1 previous Ph. 1 Wins	> 1 previous Ph. 1 wins
	I.	II.	III	IV.	V
$\mathbf{1} \mid R_i^{Ph2} > 0$	**-0.00385**	**0.0292**	**0.0581**	**-0.0129**	**-0.0470**
	(0.165)	(0.0834)	(0.0464)	(0.0737)	(0.219)
VC_i^{Prev}	0.128	0.0932	0.189***	0.164*	0.138
	(0.200)	(0.0895)	(0.0543)	(0.0923)	(0.242)
$\#SBIR_i^{\text{Prev}}$	0.000619	0.000962	0.00103***	-0.000583***	-0.000728***
	(0.00118)	(0.000731)	(0.000309)	(0.000149)	(0.000279)
Competition f.e.	Y	N	N	Y	Y
Topic f.e.	N	Y	N	N	N
Year f.e.	N	N	Y	N	N
N	410	410	410	868	460
R^2	0.785	0.522	0.118	0.678	0.770

Note: This table is an RD estimating via OLS the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on reaching revenue using BW=1. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 5: Impact of Phase 2 Grant on Survival

Dependent Variable: $Survival_i$					
	Standard sample			$\geq$ 1 previous Ph. 1 Wins	$>$ 1 previous Ph. 1 wins
	I.	II.	III	IV.	V
$\mathbf{1} \mid R_i^{Ph2} > 0$	**-0.00240**	**0.0447**	**0.0668***	**0.0374**	**0.0693**
	(0.139)	(0.0702)	(0.0372)	(0.0735)	(0.180)
VC_i^{Prev}	0.118	-0.0122	0.0954**	-0.0213	-0.106
	(0.149)	(0.0714)	(0.0430)	(0.101)	(0.226)
$\#SBIR_i^{\text{Prev}}$	0.0000976	0.000571	0.000469**	0.000276	0.000290
	(0.000776)	(0.000581)	(0.000235)	(0.000314)	(0.000663)
Competition f.e.	Y	N	N	Y	Y
Topic f.e.	N	Y	N	N	N
Year f.e.	N	N	Y	N	N
N	390	390	390	778	388
R^2	0.776	0.528	0.099	0.692	0.799

Note: This table is an RD estimating via OLS the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on firm survival using BW=1. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 6: Impact of Phase 2 Grant on Exit (IPO or Acquisition)

Dependent Variable: $Exit_i^{\text{Post}}$					
	Standard sample			≥ 1 previous Ph. 1 Wins	> 1 previous Ph. 1 wins
	I.	II.	III	IV.	V
$\mathbf{1} \mid R_i^{Ph2} > 0$	**-0.0275**	**-0.0282**	**0.00234**	**-0.0542**	**-0.122**
	(0.123)	(0.0519)	(0.0259)	(0.0526)	(0.106)
VC_i^{Prev}	-0.112	-0.106	-0.133***	-0.138	-0.208
	(0.172)	(0.0719)	(0.0416)	(0.0872)	(0.312)
$\#SBIR_i^{\text{Prev}}$	0.117	0.0864	0.128**	0.241**	0.314*
	(0.191)	(0.0719)	(0.0560)	(0.102)	(0.184)
Competition f.e.	0.000556	0.000611	0.000165	-0.0000217	-0.000149
Topic f.e.	(0.00102)	(0.000558)	(0.000335)	(0.000104)	(0.000134)
Year f.e.	Y	N	N	Y	Y
N	N	Y	N	N	N
R^2	N	N	Y	N	N

Note: This table is an RD estimating via OLS the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on exit using BW=1. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 7: Relationship between Phase 2 application and subsequent VC financing

	Number of Phase 1 winners (% of column)			
Phase 2 Status:	I. Did not apply	II. Applied and lost	III. Applied and won	IV. Applied and won (VC from time of Ph 2 award)
$VC_i^{\text{Post}} = 0$	366 (69%)	400 (78%)	297 (73%)	308 (76%)
$VC_i^{\text{Post}} = 1$	164 (31%)	111 (22%)	111 (27%)	100 (24%)
$VC_i^{\text{0-2 yr Post}} = 1$	102 (19%)	50 (9%)	33 (8%)	44 (11%)

Note: This table uses all Phase 1 winners and analyzes the relationship between whether a firm did or did not apply for Phase 2 and VC financing status. Year$\geq$ 1995

Table 8: Impact of Grant on VC for Firms who did not Apply to or did not Win Phase 2

Panel A: Firms who did not apply to Phase 2				
Dependent Variable:	$VC_i^{\text{0-2 yr Post}}$		VC_i^{Post}	
	I. BW=2	II. BW=3	III. BW=2	IV. BW=3
$\mathbf{1} \mid R_i > 0$	**0.122*** **	**0.140*** **	**0.142*** **	**0.162*** **
	(0.0334)	(0.0373)	(0.0417)	(0.0422)
VC_i^{Prev}	0.269***	0.273***	0.285***	0.281***
	(0.0406)	(0.0371)	(0.0417)	(0.0398)
$\#SBIR_i^{\text{Prev}}$	0.0000192	0.0000465	0.00117***	0.00118***
	(0.000263)	(0.000212)	(0.000333)	(0.000296)
Competition f.e.	Y	Y	Y	Y
N	2460	2968	2460	2968
R^2	0.468	0.400	0.419	0.364
Panel B: Firms who lost Phase 2 or did not apply				
Dependent Variable:	$VC_i^{\text{0-2 yr Post}}$		VC_i^{Post}	
	V. BW=2	VI. BW=3	VII. BW=2	VIII. BW=3
$\mathbf{1} \mid R_i > 0$	**0.0740*** **	**0.0919*** **	**0.103*** **	**0.114*** **
	(0.0225)	(0.0235)	(0.0279)	(0.0276)
VC_i^{Prev}	0.300***	0.294***	0.310***	0.292***
	(0.0387)	(0.0351)	(0.0399)	(0.0381)
$\#SBIR_i^{\text{Prev}}$	-0.0000802	-0.0000423	0.00104***	0.00106***
	(0.000261)	(0.000209)	(0.000330)	(0.000293)
Competition f.e.	Y	Y	Y	Y
N	2670	3190	2670	3190
R^2	0.450	0.395	0.408	0.353

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC, where dependent variable ${VC^{\text{Post}}}_i = 1$ if the company ever received VC after the award. The bandwidth around the cutoff varies. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 9: Impact of Phase 2 Grant on Patenting (Negative Binomial)

Dependent Variable: $\#Patent_i^{\text{Post}}$			
	I. Standard sample	II. ≥ 1 previous Ph. 1 Wins	III. > 1 previous Ph. 1 wins
$\mathbf{1} \mid R_i > 0$	**0.417****	**0.303****	**0.189**
	(0.200)	(0.130)	(0.135)
$\#Patent_i^{\text{Prev}}$	0.735***	0.614***	0.666***
	(0.110)	(0.0608)	(0.0654)
VC_i^{Prev}	0.689**	0.576***	-0.0194
	(0.333)	(0.219)	(0.211)
$\#SBIR_i^{\text{Prev}}$	0.00320***	0.000803**	0.000535**
	(0.00112)	(0.000313)	(0.000246)
Year f.e.	Y	Y	Y
N	410	868	458
Pseudo-R^2	0.077	0.073	0.098
Log Likelihood	-794.7	-2094.3	-1241.3

This table is an RD estimating via a negative binomial model the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on the firm's patent count after award using BW=1. Columns I-III use the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column IV includes all Phase 2 applicants, while column V includes only firms with more multiple DOE Phase 1 wins. Note: Standard errors robust. *** $p < .01$. Year$\geq$ 1995

Table 10: Impact of Phase 2 Grant on Normalized Citations (Two-Part)

Dependent Variable: $Citation_i^{\text{Post}}$						
	I. Standard sample		II. ≥ 1 previous Ph. 1 wins		III. > 1 previous Ph. 1 wins	
	Ia. Logit	Ib. Regress	IIa. Logit	IIb. Regress	IIIa. Logit	IIIb. Regress
$\mathbf{1} \mid R_i > 0$	**0.627****	**1.522**	**0.427*****	**2.723**	**0.347**	**4.800**
	(0.260)	(15.09)	(0.147)	(5.828)	(0.245)	(5.863)
$Citation_i^{\text{Prev}}$	0.0645	1.362	0.0136***	0.400***	0.0157***	0.393***
	(0.0485)	(1.155)	(0.00459)	(0.0845)	(0.00538)	(0.0743)
VC_i^{Prev}	-0.231	23.24	0.0222	11.63	-0.334	-0.968
	(0.470)	(29.69)	(0.319)	(12.73)	(0.415)	(11.14)
$\#SBIR_i^{\text{Prev}}$	0.00521*	-0.0215	0.00312***	0.00458	0.00274***	0.0112
	(0.00287)	(0.0340)	(0.000830)	(0.0135)	(0.000817)	(0.0127)
Year f.e.	Y	Y	Y	Y	Y	Y
N	386	128	860	338	428	210
Pseudo-R^2 Logit	0.188		0.223		0.252	
R^2 Regress		0.137		0.142		0.292
Log lik.	-892.6		-2222.1		-1275.1	

Note: This table is an RD estimating via a two-part (logit plus regression) model the impact of the Phase 2 grant ($\mathbf{1} \mid R_i > 0$) on the firm's normalized citation count after award using BW=1. The logit portion of estimates zero vs. positive citations (extensive margin), and then the regress part estimates the impact of the grant on observations with positive citations (intensive margin). Column I uses the sample from the Phase 1 analysis, where no previous DOE winners are included (only the Phase 1 win that made the firm eligible to apply for Phase 2 is allowed). Column II includes all Phase 2 applicants, while column III includes only firms with more multiple DOE Phase 1 wins. Standard errors robust. *** $p < .01$. Year$\geq$ 1995

Appendix F: The Grant Impact for SBIR "Mills"

A small subset of the firms in my data apply more than once. Of the 7,436 applicant firms, 71% applied only once, and a further 14% applied twice. Within my data, seven companies each submitted more than 50 applications. Figure 1 shows the frequency of firms by their number of awards, omitting firms with less than four awards. These companies who win many SBIR awards, sometimes termed "SBIR mills," have raised concerns since the early years of the SBIR program (GAO 1992, Wallsten 2000). Appendix G Table 1 shows the relationship between applicant rank and previous non-DOE SBIR wins. DOE program officials appear to be ranking firms higher that have more previous wins from other agencies. Firms with more previous wins are likely more skilled appliers. They have more application experience and may dedicate more resources to accessing government funding.

Implications for firms with a few awards may be more ambiguous. For example, Oscilla Power (introduced in the main text) had two Phase 1 SBIRs from other agencies prior to applying for its DOE SBIR. For Oscilla, all three Phase 1's funded useful testing work.

These firms, often employing specialized grant application staff, seem unlikely candidates for venture finance. Ineed, I find evidence of decreasing returns to previous non-DOE SBIR awards. Table 1 finds that among firms with no previous SBIRs, an award increases a firm's probability of subsequent VC investment by 14.8 pp, significant at the 1% level. For firms with at least one previous SBIR, the effect is halved to 7.5 pp, also significant at the 1% level. However, the difference betwen these coefficients is insignificant. The left panel of Table 2 interacts treatment with previous awards and finds negative coefficients, although in two of the three models they are significant only at the 10% level. The imprecision could be due to opposing forces: additional SBIRs may produce valuable prototyping, but a significant portion of firms with previous SBIRs are "mills" and not seeking private finance.

When a firm has just one previous non-DOE SBIR award, the Phase 1 impact on reaching revenue drops precipitously - even more so than with financing. Table 2 (right panel) interacts treatment with previous awards and finds strong and highly significant negative effects. Table 3 shows that among firms with no previous SBIR wins, a grantee is 19 pp more likely to reach revenue than a loser (column I), significant at the 1% level. When regressions using zero and positive SBIR wins are estimated jointly, the difference in the coefficients is 14.7 pp, significant at the 1% level (column III). The effect declines further along the intensive margin. Table 4 shows that there may be a similar precipitous drop for patents by previous SBIR wins, but the coefficients are much more imprecise. This SBIR mill effect accords with Link and Scott's (2010) conclusion that mills are less likely to commercialize their projects, and with Lerner (1999)'s finding that multiple awards are not associated with increased performance for SBIR awardees.

Figure 1:

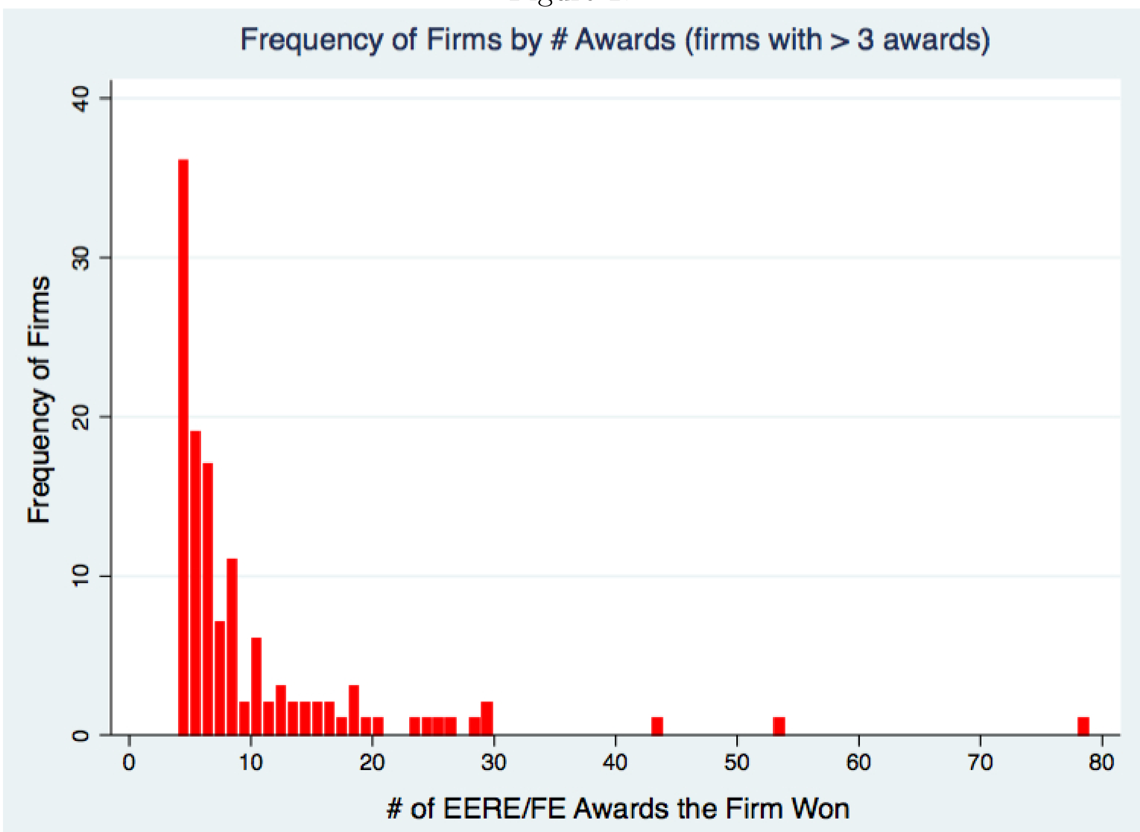


Table 1: Impact of Grant on Subsequent VC by Number of Firm's Previous SBIR Awards

Dependent Variable: VC_i^{Post};	I. $\#SBIR_i^{\text{Prev}} = 0$	II. $\#SBIR_i^{\text{Prev}} > 0$	III. Diff I & II	IV. $\#SBIR_i^{\text{Prev}} < 5$	V. $\#SBIR_i^{\text{Prev}} \geq 5$	VI. Diff IV & V
$\mathbf{1} \mid R_i > 0$	**0.148*** **	**0.0748*** **	0.0746***	**0.0872*** **	**0.0601**	0.0601
	(0.0380)	(0.0260)	(0.0263)	(0.0247)	(0.0385)	(0.0371)
VC_i^{Prev}	0.298***	0.359***	0.358***	0.360***	0.333***	0.333***
	(0.0630)	(0.0506)	(0.0512)	(0.0473)	(0.0626)	(0.0603)
$\#SBIR_i^{\text{Prev}}$		0.000166	0.000177*	0.00555***	0.000145	0.000145
		(0.000102)	(0.000103)	(0.00162)	(0.000115)	(0.000111)
$\mathbf{1} \mid R_i > 0 \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$			**0.0724**			**0.0270**
			(0.0452)			(0.0449)
$VC_i^{\text{Prev}} \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$			-0.0598			0.0267
			(0.0823)			(0.0777)
$\#SBIR_i^{\text{Prev}} \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$						0.00541***
						(0.00166)
$\left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$			-0.0749***			0.136***
			(0.0175)			(0.0151)
Topic f.e.	Y	Y	Y	Y	Y	Y
Topic f.e. $\cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$	N	N	Y	N	N	Y
N	1099	1615	2714	1654	1060	2714
R^2	0.395	0.294	0.335	0.373	0.336	0.367

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on subsequent VC by number of previous non-DOE SBIR awards (from other gov't agencies, e.g. DOD, NSF), using BW=3. Each column includes only data from firms with the relevant number of wins. In the difference regressions (columns V-VI), all covariates are interacted with a dummy for low SBIRs. Column VI only includes firms with 0 or at least 5 SBIRs. The coefficients on ($\mathbf{1} \mid R_i > 0$) do not precisely match columns III-IV because SBIRs are not controlled for in column I (there are none). Topic dummies permit sufficient within-group observations. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 2: Impact of Grant on VC & Reaching Revenue Interacted with Number of Firm's Previous SBIR Awards

Dependent Variable:		VC_i^{Post}			$Revenue_i$	
	I. BW=2	II. BW=3	III. BW=all	IV. BW=2	V. BW=3	VI. BW=all
$(\mathbf{1} \mid R_i > 0) \cdot \#SBIR\_d_i^{\text{Prev}}$	**-0.0408***	**-0.0359***	**-0.0411****	**-0.0779*****	**-0.0843*****	**-0.0865*****
	(0.0232)	(0.0202)	(0.0170)	(0.0234)	(0.0219)	(0.0179)
$\mathbf{1} \mid R_i > 0$	0.121***	0.131***	0.146***	0.120***	0.128***	0.158***
	(0.0187)	(0.0177)	(0.0160)	(0.0204)	(0.0189)	(0.0161)
$\#SBIR\_d_i^{\text{Prev}}$	0.0633***	0.0651***	0.0700***	0.00544	0.00965	0.00953
	(0.0179)	(0.0163)	(0.0125)	(0.0199)	(0.0187)	(0.0153)
Competition f.e.	Y	Y	Y	Y	Y	Y
N	3916	4572	7332	3916	4572	7332
R^2	0.285	0.252	0.181	0.262	0.227	0.158

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant $(\mathbf{1} \mid R_i > 0)$ on reaching revenue by number of previous non-DOE SBIR awards (from other government agencies, e.g. DOD, NSF) using BW=1. Here the $\#SBIR_i^{\text{Prev}}$ variable has been demeaned and divided by 100 for clarity. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 3: Impact of Grant on Reaching Revenue by Number of Firm's Previous SBIR Awards

Dependent Variable: $Revenue_i$			
	I. $\#SBIR_i^{\text{Prev}} = 0$	II. $\#SBIR_i^{\text{Prev}} > 0$	III. Diff I & II
$\mathbf{1} \mid R_i > 0$	**0.190*** **	**0.0448**	0.0446
	(0.0445)	(0.0272)	(0.0275)
VC_i^{Prev}	0.289***	0.0986**	0.0973**
	(0.0571)	(0.0428)	(0.0432)
$\#SBIR_i^{\text{Prev}}$		-0.000475***	-0.000463***
		(0.0000824)	(0.0000840)
$\mathbf{1} \mid R_i > 0 \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$			**0.147*** **
			(0.0535)
Topic f.e.	Y	Y	Y
Topic f.e. $\cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$	N	N	Y
N	1099	1615	2714
R^2	0.327	0.238	0.294

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on reaching revenue by number of previous non-DOE SBIR awards (from other government agencies, e.g. DOD, NSF) using BW=1. Each column includes only data from firms with the relevant number of wins. To estimate the difference regressions, all covariates are interacted with a dummy that, for example in Column VIII, takes a value of 1 if the firm has 0 SBIR wins, and 0 if at least 5. The coefficients on treatment ($\mathbf{1} \mid R_i > 0$) in columns VII and VIII do not precisely match because I do not control for previous SBIRs when there are none (column I). Coefficients on $VC_i^{\text{Prev}} \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$, $\#SBIR_i^{\text{Prev}} \cdot \left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$ and $\left(\mathbf{1} \mid \#SBIR_i^{\text{Prev}} \leq X\right)$ not reported for space concerns. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 4: Impact of Phase 1 Grant on Subsequent Patenting within 3 Years by Number of Firm's Previous SBIR Awards (All Gov't) (Negative Binomial)

Dependent Variable: $\#Patent_i^{\text{3 yrs Post}}$	I. $\#SBIR_i^{\text{Prev}} < 2$	II. $\#SBIR_i^{\text{Prev}} < 5$	III. $\#SBIR_i^{\text{Prev}} > 0$	IV. $\#SBIR_i^{\text{Prev}} \geq 2$	V. $\#SBIR_i^{\text{Prev}} \geq 5$
$\mathbf{1} \mid R_i > 0$	**0.896***	**0.805***	**-0.405**	**0.120**	**-0.257**
	(0.531)	(0.481)	(0.369)	(0.444)	(0.576)
$\#Patent_i^{\text{Prev}}$	0.479***	0.451***	0.183***	0.158***	0.145***
	(0.0506)	(0.0452)	(0.0201)	(0.0196)	(0.0204)
VC_i^{Prev}	1.210***	1.062***	0.544***	0.647***	0.737***
	(0.251)	(0.238)	(0.170)	(0.170)	(0.191)
$\#SBIR_i^{\text{Prev}}$	0.0330	0.0438***	0.00586***	0.00503***	0.00479***
	(0.0242)	(0.0118)	(0.000827)	(0.000770)	(0.000738)
$R_{i,-}$	0.176***	0.157***	0.0949**	0.0305	0.0444
	(0.0608)	(0.0567)	(0.0476)	(0.0493)	(0.0519)
$R_{i,+}$	0.913*	0.854*	0.827***	0.460	0.339
	(0.483)	(0.441)	(0.298)	(0.385)	(0.569)
$R_{i,-}^2$	0.00717**	0.00581*	0.00287	-0.00275	-0.00148
	(0.00358)	(0.00347)	(0.00324)	(0.00318)	(0.00336)
$R_{i,+}^2$	-0.184**	-0.137	-0.0602	-0.0120	0.0130
	(0.0922)	(0.0835)	(0.0372)	(0.0490)	(0.0733)
Year f.e.	Y	Y	Y	Y	Y
N	4249	4651	1879	1444	1042
Pseudo-R^2	0.097	0.098	0.093	0.096	0.101

Note: This table is an RD estimating via a negative binomial model the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the firm's patent count within three years after grant award by number of previous non-DOE SBIR awards (from other government agencies, e.g. DOD, NSF), using BW=all. Each column includes only data from firms with the relevant number of wins. Unfortunately I could not estimate difference equations due to non-convergence of the Poisson maximum likelihood. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Appendix G: Continuity of Covariates & Additional Specifications

Figure 1: Applicant Baseline Covariates by Rank (Phase 1)

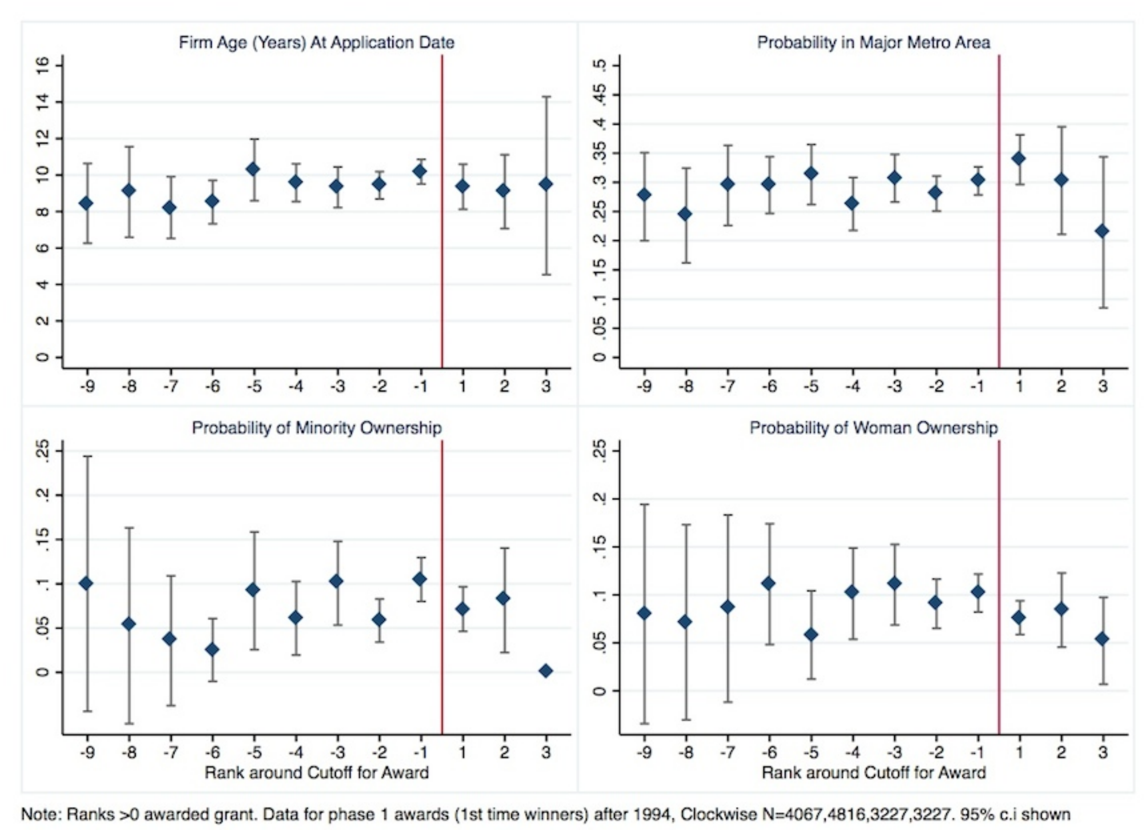


Figure 2: Number of Phase 1 All-Gov't SBIR Awards Before Grant by Rank (Phase 1)

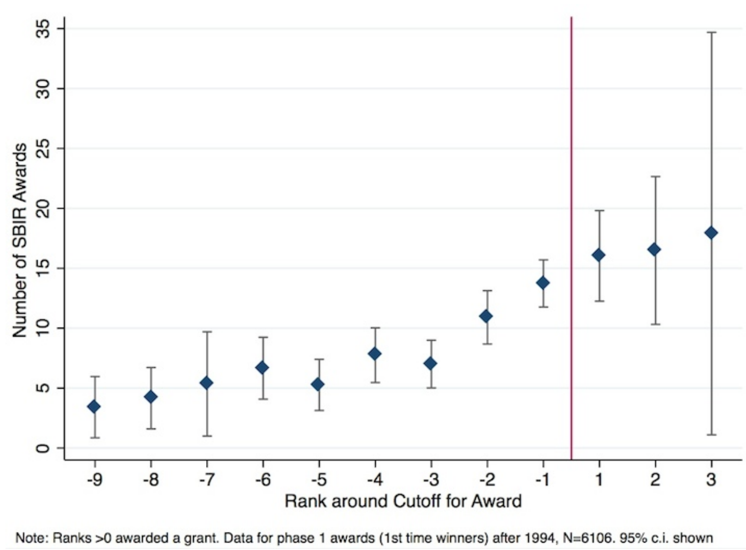


Figure 3: Phase 1 Grant Effect on VC Regression Predictive Margins by Rank

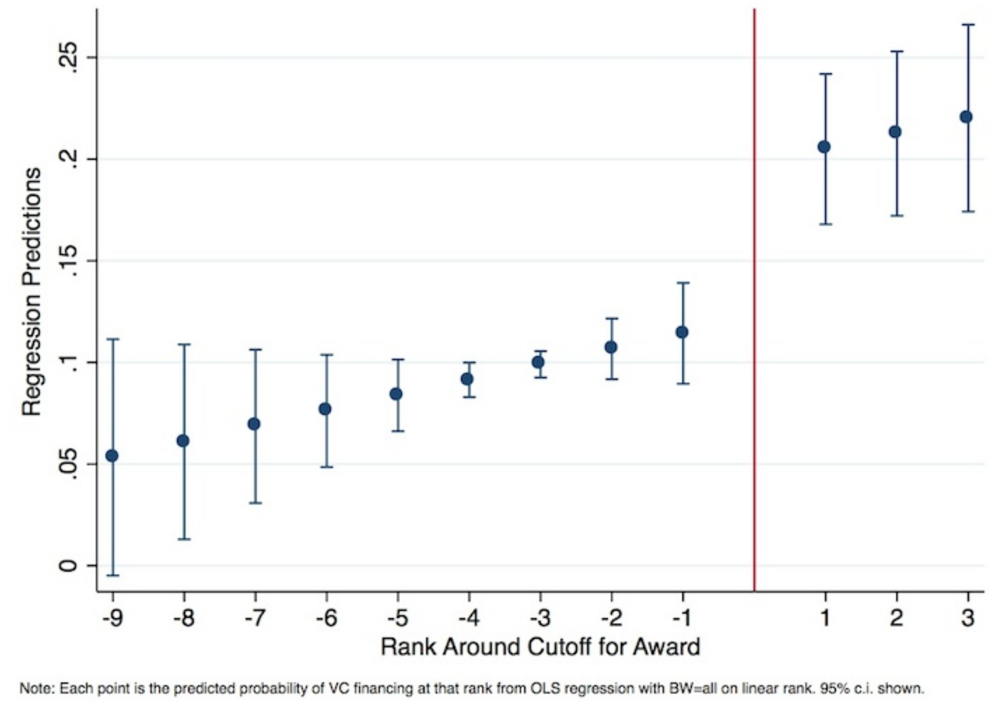


Figure 4: Cox Proportional Hazard Model Predicted Probability of IPO or Acquisition by Years from Award

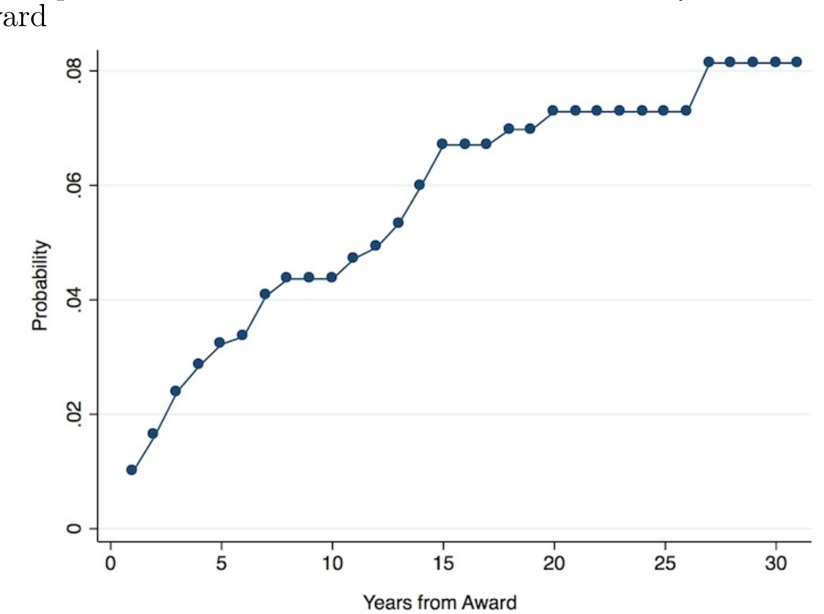


Table 1: Rank Production Function

Dependent Variable: R_i	I. All Covs	II. Select Covs
VC_i^{Prev}	0.0498	0.0717**
	(0.0321)	(0.0304)
$\#SBIR_i^{\text{Prev}}$	0.00212**	0.00256***
	(0.000950)	(0.000827)
MSA_i	0.165	0.121
	(0.137)	(0.0971)
Age_i	-0.00141	
	(0.00345)	
$Exit_i^{\text{Prev}}$	0.124	
	(0.211)	
$Patent_i^{\text{Prev}}$	0.0368	0.0895
	(0.117)	(0.0797)
$Citation_i^{\text{Prev}}$	0.0730	0.0438
	(0.102)	(0.0715)
Competition f.e.	Y	Y
N	3871	5848
R^2	0.606	0.629

Note: This table reports regression estimates of the effect of the baseline covariates on the Phase 1 rank. Column I includes all observables while column II uses only variables available for the full dataset. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 2: Impact of Grant on Subsequent VC with Linear and Quadratic Control Functions on Either Side of Cutoff

Dependent Variable: VC_i^{Post}				
Bandwidth:	I. 1	II. 2	III. 3	IV. All
$\mathbf{1} \mid R_i > 0$	**0.0984*** **	**0.167** **	**0.232*** **	**0.113** **
	(0.0319)	(0.0776)	(0.0892)	(0.0564)
VC_i^{Prev}	0.274***	0.318***	0.304***	0.320***
	(0.0566)	(0.0378)	(0.0360)	(0.0293)
$\#SBIR_i^{\text{Prev}}$	0.00125***	0.00102***	0.00106***	0.000841***
	(0.000336)	(0.000291)	(0.000268)	(0.000239)
$R_{i,-}$		-0.0101	0.0201	0.0142**
		(0.0214)	(0.0555)	(0.00722)
$R_{i,+}$		-0.0551	-0.227***	-0.0353
		(0.0592)	(0.0863)	(0.0480)
$R_{i,-}^2$			0.00181	0.000344
			(0.0137)	(0.000348)
$R_{i,+}^2$			0.0655***	0.00410
			(0.0193)	(0.00667)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	5021
R^2	0.473	0.393	0.349	0.270

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC. The specifications are variants of the model in Equation 1. The dependent variable $VC^{\text{Post}}{}_i$ is 1 if the company ever received VC after the award decision, and 0 if not. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 3: Impact of Grant on Subsequent VC with Percentile Rank Control (Quartiles)

Dependent Variable: VC_i^{Post}				
Bandwidth:	I. 1	II. 2	III. 3	IV. All
$\mathbf{1} \mid R_i > 0$	**0.0984*** **	**0.0891*** **	**0.0888*** **	**0.0898*** **
	(0.0319)	(0.0306)	(0.0299)	(0.0254)
VC_i^{Prev}	0.274***	0.319***	0.306***	0.321***
	(0.0566)	(0.0378)	(0.0362)	(0.0289)
$\#SBIR_i^{\text{Prev}}$	0.00125***	0.00101***	0.00104***	0.000850***
	(0.000336)	(0.000295)	(0.000271)	(0.000240)
$R_i{}^{\text{Q2}}$		-0.0146	-0.0264	-0.0115
		(0.0294)	(0.0255)	(0.0175)
$R_i{}^{\text{Q3}}$		0.0355	0.00302	-0.0439**
		(0.0393)	(0.0299)	(0.0184)
$R_i{}^{\text{Q4}}$		-0.0480	-0.0540	-0.0406*
		(0.0524)	(0.0339)	(0.0244)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	5021
R^2	0.473	0.393	0.346	0.269

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC. The specifications are variants of the model in Equation 1. The dependent variable $VC^{\text{Post}}{}_i$ is 1 if the company ever received VC after the award decision, and 0 if not. Ranks are transformed into the applicant's percentile rank within his competition. The highest quartile is omitted. Columns I-IV vary the bandwidth. Standard errors are robust and clustered at topic-year level. The top quartile dummy is omitted. *** $p < .01$. Year$\geq$ 1995

Table 4: Impact of Grant on Subsequent Private Finance with Linear and Quadratic Control Functions

Dependent Variable: PF_i^{Post}							
Bandwidth:	1	2		3		All	
	I.	II.	III.	IV.	V.	VI.	VII.
$\mathbf{1} \mid R_i > 0$	**0.124*** **	**0.117*** **	**0.227*** **	**0.132*** **	**0.287*** **	**0.121*** **	**0.105*** **
	(0.0366)	(0.0283)	(0.0623)	(0.0268)	(0.0509)	(0.0225)	(0.0368)
PF_i^{Prev}	0.317***	0.352***	0.353***	0.344***	0.345***	0.362***	0.362***
	(0.0510)	(0.0350)	(0.0349)	(0.0337)	(0.0338)	(0.0281)	(0.0286)
$\#SBIR_i^{\text{Prev}}$	0.00147***	0.00118***	0.00119***	0.00119***	0.00118***	0.00106***	0.00102***
	(0.000350)	(0.000298)	(0.000298)	(0.000267)	(0.000274)	(0.000202)	(0.000234)
R_i			-0.0447**		-0.116***		0.00512
			(0.0216)		(0.0289)		(0.00813)
R_i^2					0.0335***		0.0000719
					(0.00852)		(0.000593)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y
N	1872	2836	2836	3368	3368	5021	5021
R^2	0.468	0.394	0.396	0.353	0.361	0.277	0.289

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all private finance. The specifications are variants of the model in Equation 1. The dependent variable $PF^{\text{Post}}{}_i$ is 1 if the company ever received PF after the award decision, and 0 if not. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 5: Impact of Grant on Subsequent Private Financing with Linear and Quadratic Control Functions on Either Side of Cutoff

Dependent Variable: PF_i^{Post}				
Bandwidth:	I. 1	II. 2	III. 3	IV. All
$\mathbf{1} \mid R_i > 0$	**0.124*** **	**0.235*** **	**0.389*** **	**0.105***
	(0.0366)	(0.0824)	(0.117)	(0.0611)
PF_i^{Prev}	0.317***	0.353***	0.344***	0.360***
	(0.0510)	(0.0350)	(0.0342)	(0.0282)
$\#SBIR_i^{\text{Prev}}$	0.00147***	0.00119***	0.00123***	0.00104***
	(0.000350)	(0.000298)	(0.000261)	(0.000203)
$R_{i,-}$		-0.0422*	0.0145	0.0143**
		(0.0241)	(0.0542)	(0.00627)
$R_{i,+}$		-0.0537	-0.361***	-0.0148
		(0.0636)	(0.130)	(0.0553)
$R_{i,-}^2$			0.00521	0.000506
			(0.0134)	(0.000380)
$R_{i,+}^2$			0.0975***	0.00245
			(0.0348)	(0.00707)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	5671
R^2	0.468	0.396	0.359	0.278

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all private finance. The specifications are variants of the model in Equation 1. The dependent variable ${PF^{\text{Post}}}_i$ is 1 if the company ever received PF after the award decision, and 0 if not. The highest quartile is omitted. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 6: Impact of Grant on Subsquent Private Financing with Percentile Rankings (Quartiles)

Dep Var: PF_i^{Post}	I. BW=2	II. BW=3	III. BW=all
$\mathbf{1} \mid R_i > 0$	**0.114*** **	**0.123*** **	**0.101*** **
	(0.0337)	(0.0315)	(0.0243)
PF_i^{Prev}	0.353***	0.344***	0.360***
	(0.0348)	(0.0339)	(0.0280)
$\#SBIR_i^{\text{Prev}}$	0.00116***	0.00118***	0.00104***
	(0.000302)	(0.000270)	(0.000205)
R_i Q2	-0.0312	-0.0242	-0.0134
	(0.0289)	(0.0259)	(0.0170)
R_i Q3	0.0665	0.0212	-0.0523***
	(0.0414)	(0.0315)	(0.0192)
R_i Q4	-0.0908*	-0.0793**	-0.0566**
	(0.0491)	(0.0332)	(0.0257)
Competition f.e.	Y	Y	Y
N	2836	3368	5671
R^2	0.397	0.354	0.278

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all subsequent private finance with ranks transformed into the applicant's percentile rank within his competition. The highest quartile is omitted. Standard errors robust and clustered at topic-year level. The top quartile dummy is omitted. *** $p < .01$. Year$\geq$ 1995

Table 7: Impact of Grant on Subsquent Private Financing with Percentile Rankings (Quintiles)

Dep Var: PF_i^{Post}	I. BW=2	II. BW=3	III. BW=all
$\mathbf{1} \mid R_i > 0$	**0.132*** **	**0.137*** **	**0.102*** **
	(0.0384)	(0.0346)	(0.0253)
PF_i^{Prev}	0.353***	0.344***	0.360***
	(0.0350)	(0.0339)	(0.0280)
$\#SBIR_i^{\text{Prev}}$	0.00117***	0.00118***	0.00104***
	(0.000302)	(0.000272)	(0.000205)
R_i Q2	0.0105	0.00143	-0.00671
	(0.0329)	(0.0299)	(0.0186)
R_i Q3	0.0484	0.0373	-0.0293
	(0.0466)	(0.0362)	(0.0215)
R_i Q4	0.0395	-0.00708	-0.0566**
	(0.0531)	(0.0390)	(0.0240)
R_i Q5	-0.0646	-0.0772*	-0.0728**
	(0.0616)	(0.0428)	(0.0313)
Competition f.e.	Y	Y	Y
N	2836	3368	5671
R^2	0.395	0.354	0.279

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all subsequent private finance with ranks transformed into the applicant's percentile rank within his competition. The highest quintile is omitted. Standard errors robust and clustered at topic-year level. The top quintile dummy is omitted. *** $p < .01$. Year$\geq$ 1995

Table 8: Impact of Grant on Subsequent Venture Capital by Sector Maturity 2007-2013

Dependent Variable: VC_i^{Post}			
	I. Mature	II. Immature	III. Diff I & II
$\mathbf{1} \mid R_i > 0$	**0.101**	**0.245*****	0.101
	(0.0664)	(0.0561)	(0.0651)
VC_i^{Prev}	0.346***	0.384***	0.346***
	(0.0829)	(0.0476)	(0.0813)
$\#SBIR_i^{\text{Prev}}$	-0.000581*	-0.000706**	-0.000581*
	(0.000342)	(0.000296)	(0.000335)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid Imm.)$			**0.144***
			(0.0862)
$VC_i^{\text{Prev}} \cdot (\mathbf{1} \mid Imm.)$			0.0385
			(0.0950)
$\#SBIR_i^{\text{Prev}} \cdot (\mathbf{1} \mid Imm.)$			-0.000125
			(0.000438)
$(\mathbf{1} \mid Immature)$			0.158***
			(0.0290)
Topic f.e.	Y	Y	Y
Topic f.e.$\cdot$ $(\mathbf{1} \mid Imm.)$	N	N	Y
N	482	1229	1711
R^2	0.232	0.243	0.240

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant $(\mathbf{1} \mid R_i > 0)$ on subsequent VC by sector maturity using BW=3 and data only from 2007-2013. See text for definition of maturity. In columns I and IV, $Immature = 0$. In the difference regressions (columns III and VI), all covariates are interacted with $Immature$. Topic dummies permit sufficient within-group observations. Standard errors robust and clustered at topic-year level. *** $p < .01$.

Table 9: Impact of Grant on Subsequent Financing with Sector Dummies

BW=all; Dep Var:	I. VC_i^{Post}	II. PF_i^{Post}
Advanced Materials	**0.0939*** **	**0.0766*** **
	(0.0209)	(0.0271)
Biofuels/Biochemicals	**0.00576**	**0.0124**
	(0.0224)	(0.0347)
Biomass Production/Generation	**0.0605*** **	**0.0645** **
	(0.0206)	(0.0313)
Building/Lighting Efficiency	**0.0877*** **	**0.0887*** **
	(0.0276)	(0.0339)
Carbon Capture & Storage	**0.0493* **	**0.0834** **
	(0.0298)	(0.0375)
Coal	**0.0352**	**0.0439**
	(0.0348)	(0.0467)
Fuel Cells/Hydrogen	**0.0757*** **	**0.0717** **
	(0.0227)	(0.0295)
Geothermal	**0.128*** **	**0.140** **
	(0.0419)	(0.0567)
Hydropower/Wave/Tidal	**0.0795*** **	**0.122*** **
	(0.0225)	(0.0303)
Natural Gas	**-0.00109**	**-0.0124**
	(0.0211)	(0.0297)
Oil	**-0.0619*** **	**-0.0965*** **
	(0.0163)	(0.0236)
Other	**0.0228**	**0.00256**
	(0.0225)	(0.0287)
Recycling/Waste to energy/Water	**0.0615*** **	**0.0509* **
	(0.0228)	(0.0298)
Smart Grid/Sensors/Power Converters	**0.0568*** **	**0.0620** **
	(0.0157)	(0.0247)
Solar	**0.103*** **	**0.0923*** **
	(0.0273)	(0.0349)
Vehicles/Batteries	**0.0979*** **	**0.0999*** **
	(0.0208)	(0.0271)
Wind	**0.0119**	**0.00361**
	(0.0245)	(0.0316)
Year f.e.	Y	Y
N	6324	6324
R^2	0.128	0.141

Note: This table is an RD estimating via OLS the relative likelihood of sectors of Phase 1 applicants to receive subsequent VC and all private finance, without controlling for treatment. The base dummy is Air & Emissions. Std errs robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 10: Impact of Grant on Subsequent VC Investment by Technology Type

Dependent Variable: VC_i^{Post}				
	I. Solar	II. Coal	III. Natural Gas	IV. Vehicles/Batteries
$\mathbf{1} \mid R_i > 0$	**.25****	**.024**	**.06**	**.12****
	(.11)	(.053)	(.074)	(.06)
Year f.e.	Y	Y	Y	Y
N	421	108	255	726
R^2	.17	.20	.21	.17
	V. Geothermal	VI. Wind	VII. Adv. Materials	VIII. Air/Emissions
$\mathbf{1} \mid R_i > 0$	**.56***	**.11****	**.11**	**.025**
	(.24)	(.039)	(.071)	(.035)
Year f.e.	Y	Y	Y	Y
N	51	194	435	300
R^2	.36	.23	.19	.097
	IX. Recycling/Waste to energy/Water	X. Biomass Production/ Generation	XI. Building/Lighting Efficiency	XII. Smart Grid/Sensors/Power Converters
$\mathbf{1} \mid R_i > 0$	**.045**	**.085**	**.14****	**.045**
	(.053)	(.067)	(.057)	(.053)
Year f.e.	Y	Y	Y	Y
N	549	308	370	634
R^2	.2	.22	.36	.2
	XIII. Carbon Capture & Storage	XIV. Fuel Cells/ Hydrogen	XV. Hydro/ Wave/Tidal	XVI. Biofuels/ Biochemicals
$\mathbf{1} \mid R_i > 0$	**.2****	**.077**	**.51****	**.014**
	(.091)	(.0723)	(.19)	(.054)
Year f.e.	Y	Y	Y	Y
N	211	400	181	176
R^2	.31	.18	.35	.33

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC by technology (sub-sector) using BW=all. The specifications are variants of the model in Equation 1. The dependent variable $VC^{\text{Post}}{}_i$ is 1 if the company ever received VC after the award decision, and 0 if not. Each specification includes only competitions whose topics fall within the specific technology. The "Other" and "Oil" technologies are omitted due to few observations. Control coefficients are not reported for brevity. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995.

Table 11: Heterogeneity of Grant Impact on Subsequent VC with Clean Energy and Energy Tobin's Q

Dependent Variable: VC_i^{Post}			
Time Series Variable:		Q	
	I. $Q_{t+1} < 50$pct	II. $Q_{t+1} > 50$pct	III. Diff $Q_{t+1} < 50$pct & > 50pct
$\mathbf{1} \mid R_i > 0$	**0.152*** **	**0.0596*** **	0.0596**
	(0.0383)	(0.0278)	(0.0242)
VC_i^{Prev}	0.354***	0.241***	0.241***
	(0.0458)	(0.0556)	(0.0473)
$\#SBIR_i^{\text{Prev}}$	0.000174	0.00151***	0.00151***
	(0.000481)	(0.000307)	(0.000241)
$\mathbf{1} \mid R_i > 0 \cdot (\mathbf{1} \mid Q_{t+1} < 50\text{pct})$			**0.0922*** **
			(0.0382)
Competition f.e.	Y	Y	Y
Competition f.e.$\cdot$ $(\mathbf{1} \mid Q_{t+1} < 50\text{pct})$	N	N	Y
N	1673	1694	3368
R^2	0.363	0.342	0.362

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on subsequent VC in different Q and VC flow environments using BW=3. To estimate the difference regressions, all covariates are interacted with a dummy that, for example in Column III, takes a value of 1 when Q is below its median, and 0 above. Coefficients on the other interactions and the dummy for the low region of the time series variable omitted for space concerns. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 12: Impact of Grant on Firm Reaching Revenue

Dep Var: $Revenue_i$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.112*** **	**0.0988***	**0.0950*** **	**0.0654**
	(0.0380)	(0.0574)	(0.0436)	(0.0521)
VC_i^{Prev}	0.167***	0.171***	0.174***	0.226***
	(0.0503)	(0.0378)	(0.0333)	(0.0244)
$\#SBIR_i^{\text{Prev}}$	0.00170***	0.00172***	0.00180***	0.00192***
	(0.000277)	(0.000220)	(0.000218)	(0.000191)
R_i		-0.00341	-0.0241	0.00752
		(0.0214)	(0.0190)	(0.0183)
R_i^2			0.0143**	0.00208
			(0.00690)	(0.00203)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	4816
R^2	0.407	0.332	0.297	0.232

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the firm's likelihood of reaching revenue (commercializing its technology). This variable is not date-specific. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 13: Impact of Grant on Firm Reaching Revenue

Dep Var: $Revenue_i$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.112*** **	**0.0964** **	**0.156***	**0.0717**
	(0.0380)	(0.0441)	(0.0864)	(0.0462)
VC_i^{Prev}	0.167***	0.172***	0.174***	0.226***
	(0.0503)	(0.0380)	(0.0332)	(0.0245)
$\#SBIR_i^{\text{Prev}}$	0.00170***	0.00172***	0.00181***	0.00192***
	(0.000277)	(0.000219)	(0.000218)	(0.000191)
$R_{i,-}$		-0.0141	-0.0471	0.00779
		(0.0265)	(0.0585)	(0.0230)
$R_{i,+}$		0.00370	-0.0479	-0.0000581
		(0.00443)	(0.0824)	(0.000371)
$R^2_{i,-}$			-0.0179	-0.00202
			(0.0135)	(0.00243)
$R^2_{i,+}$			0.0135	0.00344
			(0.0169)	(0.0138)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	4816
R^2	0.407	0.332	0.297	0.232

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the firm's likelihood of reaching revenue (commercializing its technology). This variable is not date-specific. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 14: Impact of Grant on Firm Survival

Dep Var: $Survival_i$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0722** **	**0.0712**	**0.0820** **	**0.0401**
	(0.0356)	(0.0561)	(0.0411)	(0.0416)
VC_i^{Prev}	0.0863*	0.108***	0.0964***	0.0997***
	(0.0470)	(0.0306)	(0.0283)	(0.0201)
$\#SBIR_i^{\text{Prev}}$	0.000715***	0.000726***	0.000775***	0.000773***
	(0.000245)	(0.000189)	(0.000166)	(0.000140)
R_i		-0.0100	-0.0321**	-0.00344
		(0.0202)	(0.0160)	(0.0131)
R_i^2			0.00913	0.00158
			(0.00633)	(0.00137)
Competition f.e.	Y	Y	Y	Y
N	1750	2660	3160	4537
R^2	0.385	0.324	0.282	0.232

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the probability of survival as of May, 2014. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 15: Impact of Grant on Firm Survival

Dep Var: $Survival_i$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0722****	**0.106**	**0.160****	**0.0979**
	(0.0356)	(0.0698)	(0.0722)	(0.0760)
VC_i^{Prev}	0.0863*	0.108***	0.0959***	0.0986***
	(0.0470)	(0.0306)	(0.0284)	(0.0201)
$\#SBIR_i^{\text{Prev}}$	0.000715***	0.000719***	0.000776***	0.000772***
	(0.000245)	(0.000188)	(0.000167)	(0.000140)
$R_{i,-}$		0.00240	0.00467	0.00899
		(0.0257)	(0.0498)	(0.0189)
$R_{i,+}$		-0.0551	-0.141**	-0.0787
		(0.0568)	(0.0627)	(0.0788)
$R^2_{i,-}$			-0.00220	-0.000313
			(0.0108)	(0.00197)
$R^2_{i,+}$			0.0217*	0.0122
			(0.0116)	(0.0147)
Competition f.e.	Y	Y	Y	Y
N	1750	2660	3160	4537
R^2	0.385	0.324	0.283	0.232

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the probability of survival as of May, 2014. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 16: Impact of Grant on Firm Exit (IPO or Acquisition)

Dep Var: $Exit_i^{\text{Post}}$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0443***	**0.0556***	**0.0823***	**0.0570****
	(0.0248)	(0.0335)	(0.0434)	(0.0275)
$Exit_i^{\text{Prev}}$	-0.103***	-0.0993***	-0.0970***	-0.0855***
	(0.0389)	(0.0235)	(0.0182)	(0.0134)
VC_i^{Prev}	0.135***	0.000699***	0.000556***	0.000408**
	(0.0428)	(0.000223)	(0.000209)	(0.000184)
$\#SBIR_i^{\text{Prev}}$	0.000741**	0.122***	0.129***	0.127***
	(0.000300)	(0.0286)	(0.0250)	(0.0209)
R_i		-0.00900	-0.0303	-0.00831
		(0.0109)	(0.0254)	(0.00828)
R_i^2			0.00849	0.000828
			(0.00689)	(0.000895)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	4816
R^2	0.412	0.306	0.263	0.212

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the probability of exit. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 17: Impact of Grant on Firm Exit (IPO or Acquisition)

Dep Var: $Exit_i^{\text{Post}}$	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0443***	**0.0760***	**0.141***	**0.0940**
	(0.0248)	(0.0458)	(0.0811)	(0.0615)
$Exit_i^{\text{Prev}}$	-0.103***	-0.100***	-0.0958***	-0.0851***
	(0.0389)	(0.0235)	(0.0179)	(0.0135)
VC_i^{Prev}	0.135***	0.122***	0.129***	0.126***
	(0.0428)	(0.0285)	(0.0250)	(0.0209)
$\#SBIR_i^{\text{Prev}}$	0.000741**	0.000695***	0.000568***	0.000408**
	(0.000300)	(0.000223)	(0.000208)	(0.000184)
$R_{i,-}$		-0.00198	-0.0345	-0.00255
		(0.0115)	(0.0280)	(0.00865)
$R_{i,+}$		-0.0349	-0.0879	-0.0583
		(0.0318)	(0.0784)	(0.0645)
$R_{i,-}^2$			-0.00844	-0.000222
			(0.00590)	(0.000862)
$R_{i,+}^2$			0.0203	0.0103
			(0.0201)	(0.0146)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	4816
R^2	0.412	0.307	0.263	0.212

Note: This table is an RD estimating via OLS the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the probability of exit. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year≥ 1995

Table 18: Impact of Grant on Subsequent Three Year Patenting with no Rank Control (Negative Binomial)

Dep Var: $\#Patent_i^{\text{3 yrs Post}}$	I. BW=1	II. BW=2	III. BW=3	IV. BW=all
$\mathbf{1} \mid R_i > 0$	**1.192*****	**1.342*****	**1.519*****	**2.008*****
	(0.171)	(0.141)	(0.134)	(0.162)
$\#Patent_i^{\text{Prev}}$	0.357***	0.286***	0.313***	0.318***
	(0.0709)	(0.0433)	(0.0392)	(0.0272)
VC_i^{Prev}	1.247***	1.308***	1.194***	1.266***
	(0.244)	(0.173)	(0.165)	(0.192)
$\#SBIR_i^{\text{Prev}}$	0.00945***	0.0109***	0.0105***	0.0109***
	(0.00188)	(0.00179)	(0.00185)	(0.00146)
Topic f.e.	Y	Y	Y	N (year f.e.)
N	1872	2836	3368	5021
Pseudo-R^2	0.218	0.193	0.174	0.111
Log likelihood	-1337.2	-2031.3	-2389.2	-3403.7

Note: This table is an RD estimating via a negative binomial model the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the firm's patent count within three years after grant award. Standard errors robust. *** $p < .01$. Year≥ 1995

Table 19: Impact of Grant on Subsquent Three Year Patenting with Linear and Quadratic Control Functions on Either Side of Cutoff (Negative Binomial)

Dep Var: $\#Patent_i^{\text{3 yrs Post}}$	I. BW=1	II. BW=2	III. BW=3	IV. BW=all
$\mathbf{1} \mid R_i > 0$	**1.192*** **	**0.857*** **	**0.254**	**1.316*** **
	(0.171)	(0.263)	(0.655)	(0.427)
$\#Patent_i^{\text{Prev}}$	0.357***	0.289***	0.314***	0.319***
	(0.0709)	(0.0436)	(0.0386)	(0.0279)
VC_i^{Prev}	1.247***	1.265***	1.130***	1.212***
	(0.244)	(0.175)	(0.166)	(0.197)
$\#SBIR_i^{\text{Prev}}$	0.00945***	0.0108***	0.0102***	0.0107***
	(0.00188)	(0.00176)	(0.00181)	(0.00145)
$R_{i,-}$		0.156	0.558**	0.0153
		(0.112)	(0.261)	(0.0562)
$R_{i,+}$		0.328	0.286	0.459
		(0.224)	(0.468)	(0.322)
$R_{i,-}^2$			0.137***	-0.00161
			(0.0392)	(0.00412)
$R_{i,+}^2$			0.109	-0.0286
			(0.220)	(0.0391)
Topic f.e.	Y	Y	Y	N (year f.e.)
N	1872	2836	3368	5021
Pseudo-R^2	0.218	0.193	0.177	0.112
Log likelihood	-1337.2	-2029.7	-2380.7	-3398.0

Note: This table is an RD estimating via a negative binomial model the impact of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on the firm's patent count within three years after grant award. Standard errors robust. *** $p < .01$. Year$\geq$ 1995

Table 20: Impact of Phase 1 Grant on Patenting within 3 yrs by Firm Age in Years (Negative Binomial)

Dep Var: $\#Patent_i^{\text{3 yrs Post}}$	I.	II.	III.	IV.	V.	VI.
	$Age_i < 3$	$Age_i < 10$	$Age_i < 15$	$Age_i \geq 3$	$Age_i \geq 10$	$Age_i \geq 15$
$\mathbf{1} \mid R_i > 0$	2.371***	1.739***	1.359***	1.503***	1.704***	2.241***
	(0.545)	(0.316)	(0.261)	(0.256)	(0.314)	(0.385)
$\#Patent_i^{\text{Prev}}$	0.471***	0.290***	0.267***	0.324***	0.351***	0.407***
	(0.101)	(0.0472)	(0.0374)	(0.0290)	(0.0303)	(0.0350)
VC_i^{Prev}	2.030***	1.466***	1.196***	0.829***	0.240	0.145
	(0.364)	(0.227)	(0.206)	(0.183)	(0.242)	(0.290)
$\#SBIR_i^{\text{Prev}}$	0.00234	0.0110***	0.00747***	0.0115***	0.0129***	0.0171***
	(0.00651)	(0.00249)	(0.00178)	(0.00155)	(0.00192)	(0.00289)
R_i	-0.218	-0.0280	0.0654	0.110**	0.0992*	-0.00766
	(0.156)	(0.0689)	(0.0544)	(0.0457)	(0.0571)	(0.0702)
R_i^2	0.0245	0.00889	-0.000697	-0.00328	-0.00411	0.00683
	(0.0152)	(0.00595)	(0.00391)	(0.00330)	(0.00387)	(0.00534)
Year f.e.	Y	Y	Y	Y	Y	Y
N	920	2248	2757	4101	2773	2264
Pseudo-R^2	0.150	0.120	0.111	0.113	0.119	0.133
Log Likelihood	-502.7	-1740.6	-2245.7	-2864.6	-1617.7	-1098.0

Note: This table is an RD estimating via a negative binomial model the impact of the grant ($\mathbf{1} \mid R_i > 0$) on the firm's patent count within three years after grant award by firm age, using BW=all. Each column includes only data from firms with the relevant firm age range at application date. I could not estimate difference equations due to non-convergence of the Poisson maximum likelihood. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 21: Selection on Observables - Impact of Grant on Baseline Covariates

Dep Var:	I. VC_i^{Prev}	II.PF_i^{Prev}	III. $Patent_i^{\text{Prev}}$	IV. $Citation_i^{\text{Prev}}$	V. $\#SBIR_i^{\text{Prev}}$
$\mathbf{1} \mid R_i > 0$	**-0.0272**	**-0.0292**	**-1.414***	**1.130**	**-3.504**
	(0.0249)	(0.0283)	(0.851)	(2.532)	(3.711)
R_i	0.0155**	0.0196***	0.509**	0.268	2.202***
	(0.00603)	(0.00726)	(0.212)	(0.332)	(0.805)
R_i^2	-0.000164	-0.000439	-0.0232*	-0.0125	-0.0726
	(0.000313)	(0.000386)	(0.0119)	(0.0161)	(0.0487)
Competition f.e.	Y	Y	Y	Y	Y
N	5021	5021	5021	5021	5021
R^2	0.161	0.156	0.151	0.133	0.231

Dep Var:	VI. $Exit_i^{\text{Prev}}$	VII. MSA_i	VIII. Age_i	IX. $Woman_i$	X. $Minority_i$
$\mathbf{1} \mid R_i > 0$	**0.0178**	**0.0248**	**-1.668**	**-0.0197**	**-0.0335**
	(0.0192)	(0.0401)	(1.364)	(0.0463)	(0.0439)
R_i	-0.00297	-0.000837	0.284	-0.000796	0.000775
	(0.00523)	(0.0115)	(0.242)	(0.0107)	(0.00869)
R_i^2	0.000360	0.000481	-0.0148	-0.0000416	-0.0000647
	(0.000326)	(0.000695)	(0.0136)	(0.000524)	(0.000504)
Competition f.e.	Y	Y	Y	Y	Y
N	5021	5021	3427	1722	1722
R^2	0.146	0.173	0.218	0.426	0.416

Note: This table projects baseline covariates on treatment ($\mathbf{1} \mid R_i > 0$) using BW=all. Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 22: T-tests for difference of means immediately around cutoff

Covariate	N	X_1	X_{-1}	t-statistic	H_1 p-value	H_2 p-value
MSA_i	1872	0.333	0.304	-1.68	**0.243**	**0.122**
Age_i	1272	9.42	10.4	-1.26	**0.208**	**0.896**
$Minority_i$	919	0.0749	0.103	-1.50	**0.134**	**0.933**
$Woman_i$	919	0.070	0.087	-0.962	**0.337**	**0.832**
$Exit_i^{\text{Prev}}$	1872	0.0411	0.0289	1.220	**0.223**	**0.112**
$\#SBIR_i^{\text{Prev}}$	1872	15.2	14.2	0.439	**0.661**	**0.330**
PF_i^{Prev}	1872	0.111	0.103	0.48	**0.630**	**0.315**
VC_i^{Prev}	1872	0.0905	0.0837	0.46	**0.648**	**0.324**
$Patent_i^{\text{Prev}}$	1872	0.475	0.469	0.153	**0.879**	**0.439**
$Citation_i^{\text{Prev}}$	1872	0.483	0.412	1.42	**0.156**	**0.078**

Note: This table tests for continuity of all baseline covariates immediately around the cutoff for the Phase 1 award, comparing centered ranks $R_i = 1$ and $R_i = -1$. First-time winners only; test performed without assuming equal variance. Year$\geq$ 1995

Table 23: Impact of Grant on Number of Subsquent VC Deals

Dep Var: VC_i^{Post}	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.957*****	**1.982*****	**1.846*****	**1.681*****
	(0.283)	(0.591)	(0.687)	(0.379)
VC_i^{Prev}	0.486***	0.481***	0.526***	0.673***
	(0.180)	(0.0998)	(0.0566)	(0.0741)
$\#SBIR_i^{\text{Prev}}$	0.00884***	0.00700***	0.00450***	0.00568***
	(0.00188)	(0.00173)	(0.00104)	(0.00107)
$R_{i,-}$		0.0368	0.0624	0.0603
		(0.265)	(0.289)	(0.0561)
$R_{i,+}$		-1.018**	-1.314	-0.635**
		(0.420)	(0.917)	(0.300)
$R_{i,-}^2$			-0.0279	-0.00127
			(0.0583)	(0.00267)
$R_{i,+}^2$			0.344	0.0767*
			(0.290)	(0.0404)
Competition f.e.	Y	Y	N	N
Topic f.e.	N	N	N	Y
Year f.e.	N	N	Y	N
N	1872	2836	3368	5671

Note: The Poisson maximum likelihood calculations would not converge using competition dummies for some cases, so I use the most granular fixed effects possible (topic or year). Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 24: Impact of Grant on Number of Subsquent VC Deals with no Rank Controls

Dep Var: VC_i^{Post}	I. BW=2	II. BW=3	III. BW=all
$\mathbf{1} \mid R_i > 0$	**0.886*** **	**1.064*** **	**1.219*** **
	(0.238)	(0.158)	(0.170)
VC_i^{Prev}	0.481***	0.531***	0.696***
	(0.0987)	(0.0560)	(0.0746)
$\#SBIR_i^{\text{Prev}}$	0.00705***	0.00462***	0.00578***
	(0.00169)	(0.00105)	(0.00108)
Competition f.e.	Y	N	N
Topic f.e.	N	N	Y
Year f.e.	N	Y	N
N	2836	3368	5671

Note: The Poissson maximum likelihood calculations would not converge using competition dummies for some cases, so I use the most granular fixed effects possible (topic or year). Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 25: Impact of Grant on Number of Subsequent PF Deals

Dependent Variable: PF_i^{Post}	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.975*** **	**2.151*** **	**3.068*** **	**1.300*** **
	(0.244)	(0.433)	(0.695)	(0.366)
PF_i^{Prev}	0.534***	0.484***	0.484***	0.586***
	(0.150)	(0.0854)	(0.0720)	(0.0704)
$\#SBIR_i^{\text{Prev}}$	0.00787***	0.00654***	0.00721***	0.00518***
	(0.00148)	(0.00145)	(0.00133)	(0.00108)
$R_{i,-}$		-0.0526	0.590	0.141**
		(0.206)	(0.386)	(0.0612)
$R_{i,+}$		-1.039***	-3.843***	-0.539
		(0.362)	(0.867)	(0.328)
$R_{i,-}^2$			0.0806	0.00467
			(0.0721)	(0.00293)
$R_{i,+}^2$			1.060***	0.0675
			(0.263)	(0.0452)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3368	5671

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 26: Impact of Grant on Number of Subsquent PF Deals with No Rank Controls

Dependent Variable: PF_i^{Post}	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.947*** **	**1.042*** **	**1.066*** **
	(0.212)	(0.183)	(0.154)
PF_i^{Prev}	0.478***	0.484***	0.589***
	(0.0837)	(0.0716)	(0.0708)
$\#SBIR_i^{\text{Prev}}$	0.00654***	0.00711***	0.00509***
	(0.00141)	(0.00134)	(0.00107)
Competition f.e.	Y	Y	Y
N	2836	3368	5671

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 27: Impact of Grant on Subsquent Early Stage Venture Capital Financing

Dependent Variable: VCE_i^{Post}	I. BW=1	II. BW=2	III. BW=3	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0960*** **	**0.166** **	**0.232*** **	**0.0830**
	(0.0315)	(0.0777)	(0.0888)	(0.0556)
VCE_i^{Prev}	0.260***	0.318***	0.296***	0.307***
	(0.0616)	(0.0422)	(0.0393)	(0.0314)
$\#SBIR_i^{\text{Prev}}$	0.00132***	0.00104***	0.00108***	0.000939***
	(0.000333)	(0.000280)	(0.000257)	(0.000201)
$R_{i,-}$		-0.0100	0.0144	0.0134**
		(0.0198)	(0.0579)	(0.00579)
$R_{i,+}$		-0.0566	-0.226**	-0.00764
		(0.0606)	(0.0888)	(0.0512)
$R_{i,-}^2$			0.00101	0.000307
			(0.0143)	(0.000324)
$R_{i,+}^2$			0.0669***	-0.00189
			(0.0202)	(0.00750)
Competition f.e.	Y	Y	Y	Y
N	1872	2836	3366	5671
R^2	0.475	0.388	0.344	0.254

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 28: Impact of Grant on Subsequent Early Stage Venture Capital Financing with No Rank

Dependent Variable: VCE_i^{Post}			
	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**0.0880*** **	**0.0979*** **	**0.0960*** **
	(0.0251)	(0.0239)	(0.0199)
VCE_i^{Prev}	0.318***	0.298***	0.308***
	(0.0424)	(0.0394)	(0.0314)
$\#SBIR_i^{\text{Prev}}$	0.00104***	0.00107***	0.000959***
	(0.000280)	(0.000259)	(0.000198)
Competition f.e.	Y	Y	Y
N	2836	3368	5671
R^2	0.387	0.339	0.251

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 29: Impact of Grant on Subsequent Financing Logit

Dependent Variable: VC_i^{Post}			
	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**1.351*** **	**1.178*** **	**1.250*** **
	(0.347)	(0.254)	(0.229)
VC_i^{Prev}	2.633***	2.767***	2.545***
	(0.405)	(0.290)	(0.258)
$\#SBIR_i^{\text{Prev}}$	0.0130***	0.00896***	0.00956***
	(0.00277)	(0.00231)	(0.00216)
Competition f.e.	Y	Y	Y
N	700	1250	1614
R^2	0.251	0.241	0.230

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Dependent Variable: PF_i^{Post}			
	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**1.352*** **	**1.263*** **	**1.368*** **
	(0.318)	(0.241)	(0.222)
PF_i^{Prev}	2.712***	2.756***	2.657***
	(0.348)	(0.250)	(0.227)
$\#SBIR_i^{\text{Prev}}$	0.0147***	0.0100***	0.0106***
	(0.00337)	(0.00235)	(0.00224)
Competition f.e.	Y	Y	Y
N	846	1482	1908
R^2	0.249	0.242	0.238

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 30: Impact of Grant on Subsequent Financing Logit with Topic-level Dummies

Dependent Variable: VC_i^{Post}

	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**1.113*** **	**1.044*** **	**1.118*** **
	(0.245)	(0.187)	(0.174)
VC_i^{Prev}	2.359***	2.411***	2.255***
	(0.302)	(0.213)	(0.189)
$\#SBIR_i^{\text{Prev}}$	0.00951***	0.00750***	0.00760***
	(0.00253)	(0.00186)	(0.00174)
Topic f.e.	Y	Y	Y
N	1194	2054	2528
R^2	0.232	0.205	0.193

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Dependent Variable: PF_i^{Post}

	I. BW=1	II. BW=2	V. BW=all
$\mathbf{1} \mid R_i > 0$	**1.045*** **	**1.022*** **	**1.100*** **
	(0.204)	(0.168)	(0.160)
PF_i^{Prev}	2.260***	2.339***	2.310***
	(0.242)	(0.175)	(0.163)
$\#SBIR_i^{\text{Prev}}$	0.00997***	0.00775***	0.00784***
	(0.00271)	(0.00195)	(0.00175)
Topic f.e.	Y	Y	Y
N	1346	2246	2764
R^2	0.214	0.201	0.195

Note: Standard errors robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 31: Estimating Spillovers with the Number of Awards in a Competition

Dependent Variable: VC_i^{Post}				
	Comparing effect on VC, among losers, of competitions with 1 award vs. > 1 award		Comparing effect on VC, among losers, of competitions with ≤ 2 award vs. > 2 awards	
	I.	II.	III.	IV.
($\mathbf{1}$ | # Awards > 1)	**.0017**	**.0081**		
	(.01)	(.011)		
($\mathbf{1}$ | # Awards > 2)			**.014**	**.019**
			(.011)	(.011)
VC_i^{Prev}	.33***	.33***	.33***	.33***
	(.029)	(.027)	(.029)	(.027)
$\#SBIR_i^{\text{Prev}}$	.001***	.00089***	.001***	.00089***
	(.00018)	(.0002)	(.00018)	(.0002)
R_i		.0018		.0018
		(.0033)		(.0033)
R_i^2		-.000037		-.000026
		(.00015)		(.00015)
Year f.e.	Y	Y	Y	Y
N	5042	5042	5042	5042
R^2	.12	.12	.12	.12

Note: This table reports regression estimates of the effect of having multiple awards in the competition for losers, using a bandwidth of all the data. The sample only includes losing firms. I control for rank in columns II and IV, and do not in columns I and III. I expect that negative spillovers will cause the indicators for more winners to have positive coefficients. Standard errors are robust and clustered at the topic-year level. *** $p < .01$. Year≥ 1995

Appendix H: Robustness Tests

Figure 1: Applicant Baseline Covariates by Rank (Phase 1)

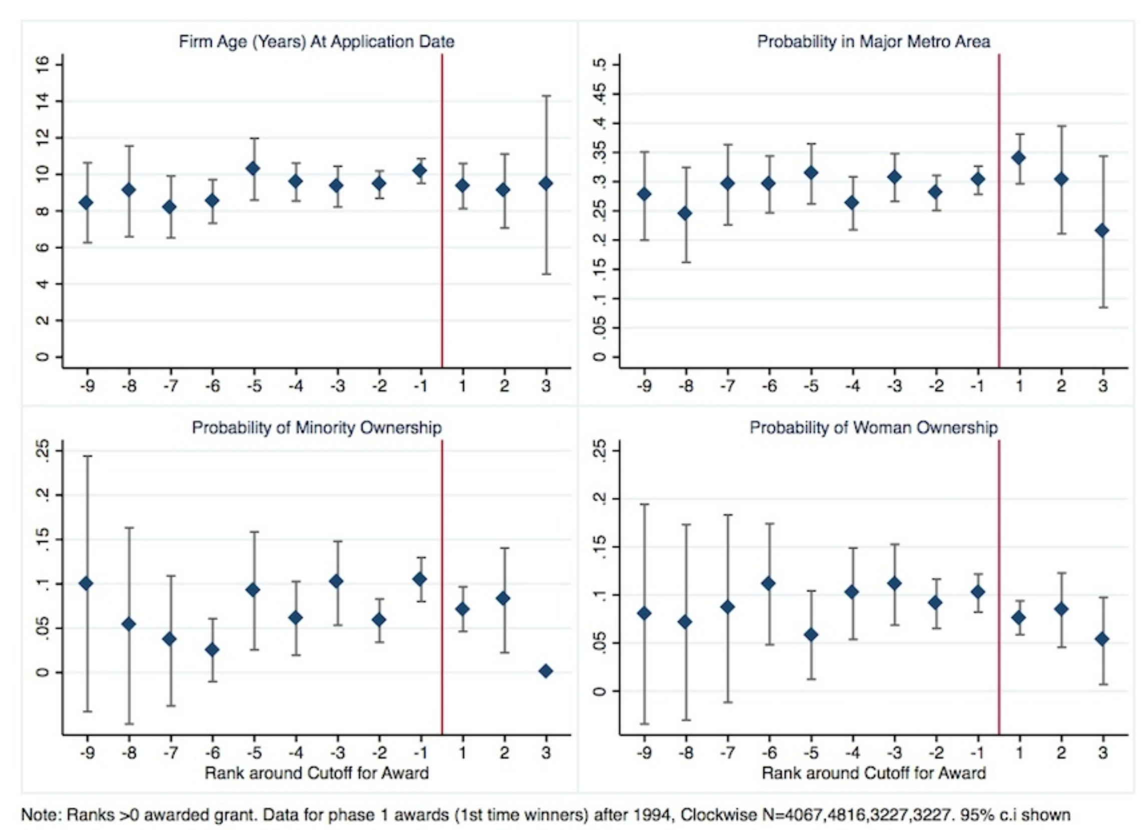


Figure 2: Number of Phase 1 All-Gov't SBIR Awards Before Grant by Rank (Phase 1)

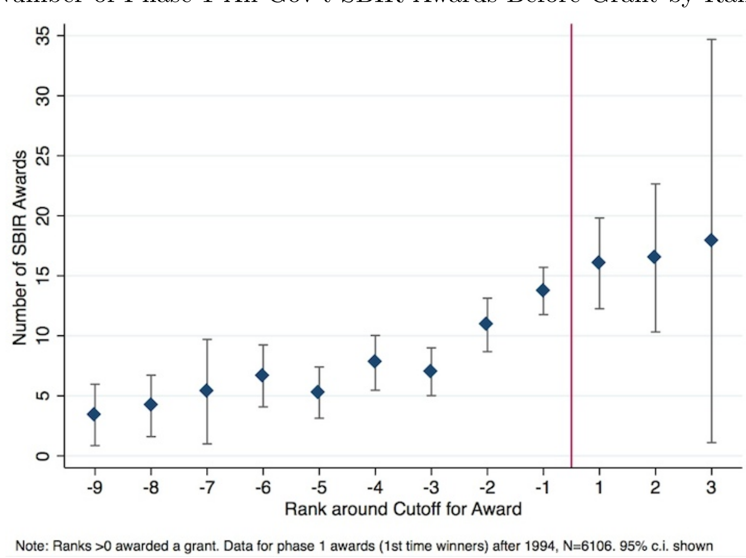


Figure 3:

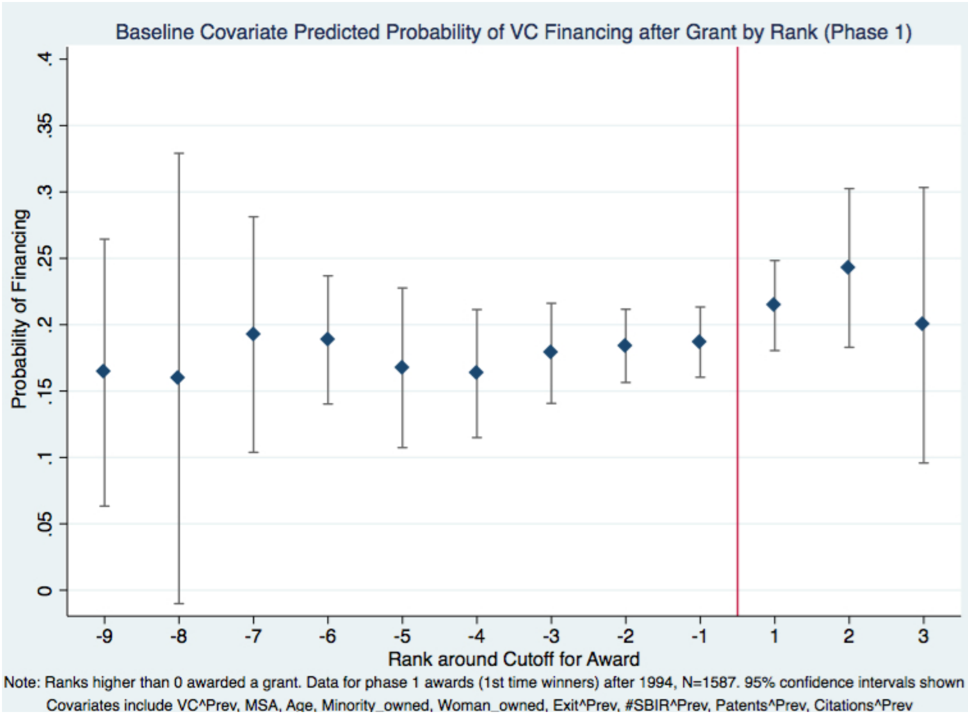


Figure 4:

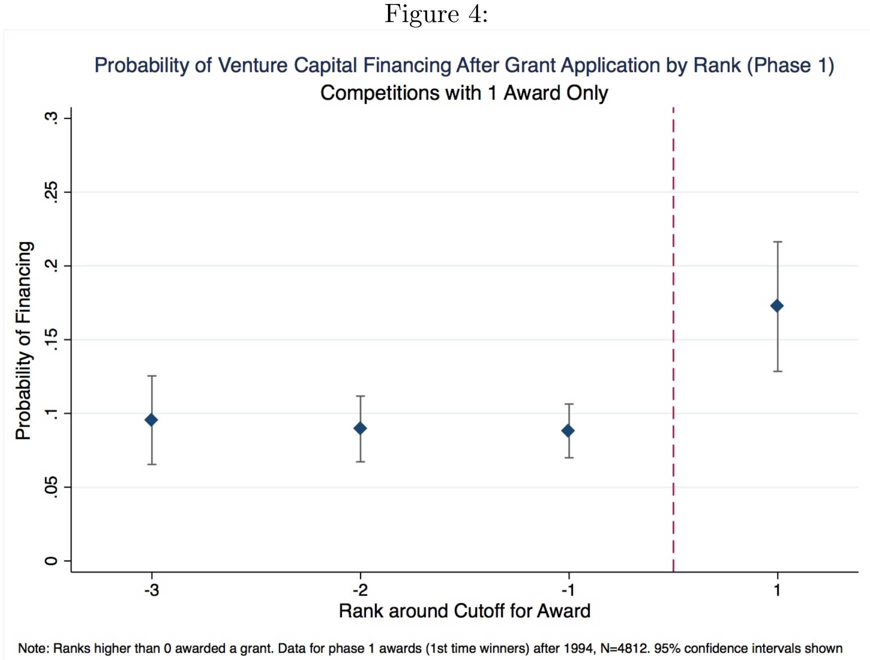


Figure 5:

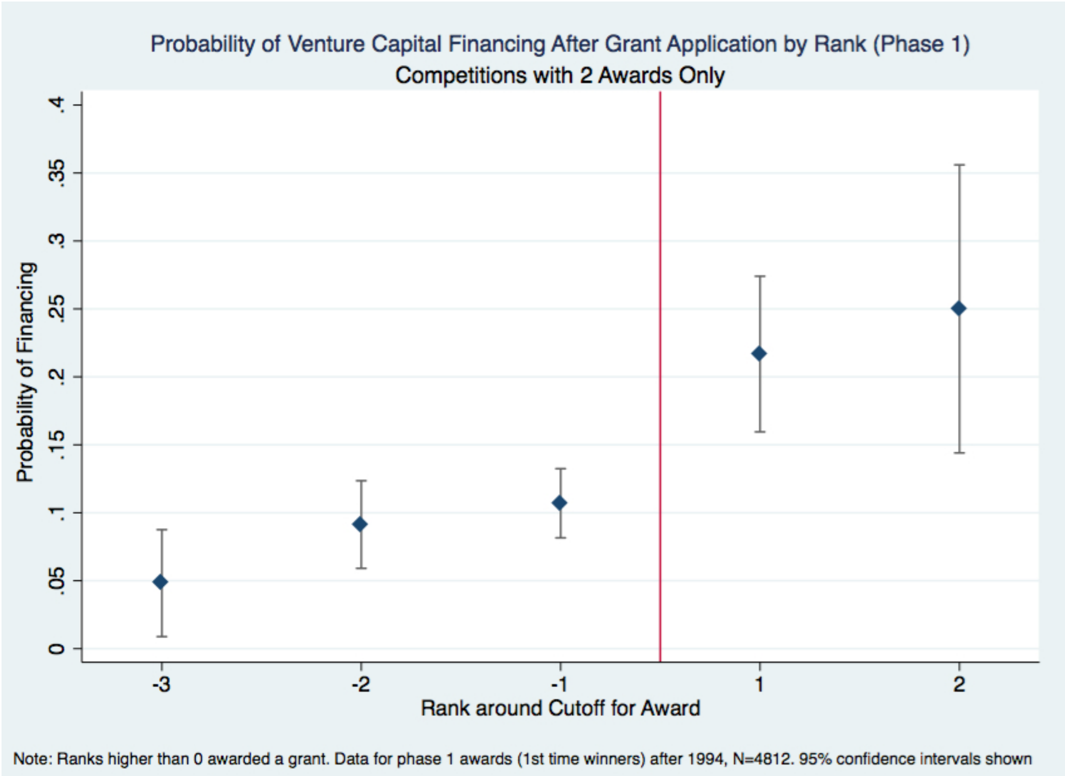


Figure 6:

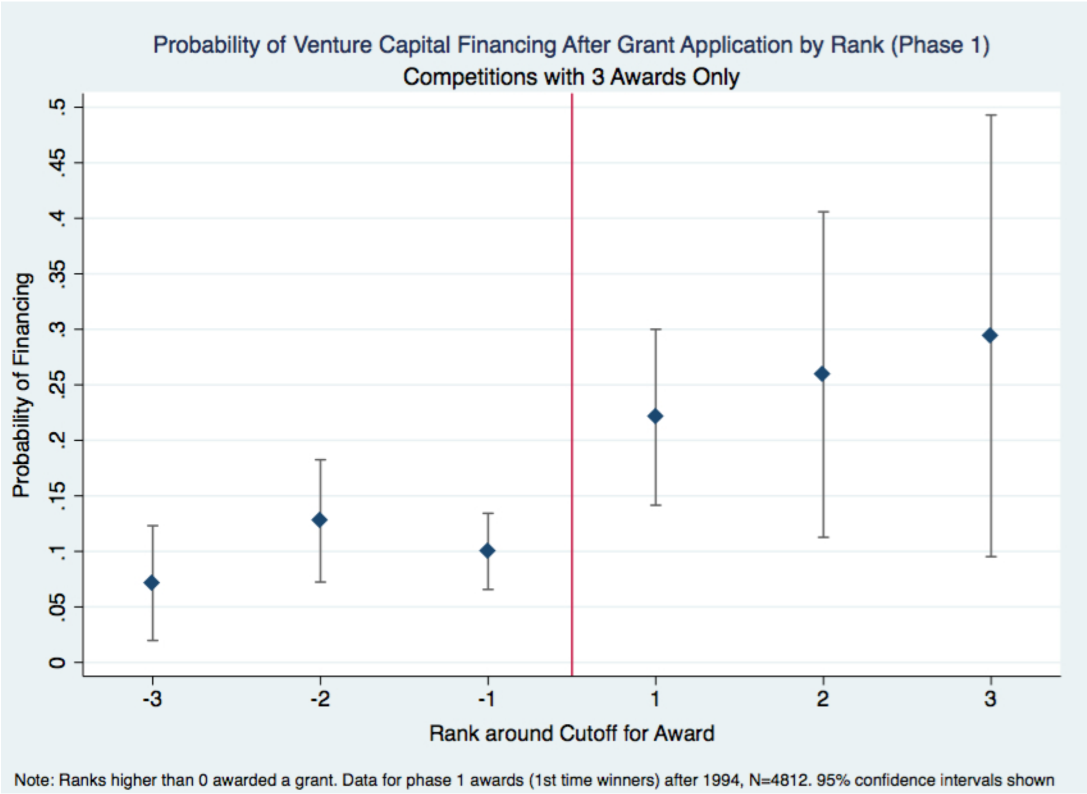


Table 1: Impact of Grant on Subsequent VC by Cutoff Point (by Number of Awards in Competition)

Dependent Variable: VC_i^{Post}					
	Bandwidth=1		Bandwidth=all		
# Awards:	I. 1	III. > 1	IV. 2	VIII. 3	IX. > 3
$\mathbf{1} \mid R_i > 0$	**.11****	**.088****	**.14****	**.18****	**.13**
	(.05)	(.041)	(.054)	(.089)	(.086)
VC_i^{Prev}	.24***	.3***	.33***	.28***	.39***
	(.088)	(.08)	(.054)	(.099)	(.066)
$\#SBIR_i^{\text{Prev}}$	.00089	.0014***	.0013***	.00047	.00042
	(.00067)	(.00037)	(.00034)	(.00063)	(.00081)
R_i			-.012	-.034	.0044
			(.014)	(.027)	(.017)
R_i^2			.0018	.0061***	-.00033
			(.0012)	(.0021)	(.00072)
Comp. f.e.	Y	Y	Y	Y	Y
N	860	1012	1386	720	680
R^2	0.52	0.44	0.30	0.30	0.23

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC, where each column includes only competitions with the designated number of awards. The specifications are variants of the model in Equation 1. The dependent variable $VC^{\text{Post}}{}_i$ is 1 if the company ever received VC after the award decision, and 0 if not. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 2: Unrestricted Regression of Impact on Venture Capital and Private Finance for Goodness of Fit Test

Dep Var:	VC_i^{Post}		PF_i^{Post}	
	I. BW=all	II. BW=3	III. BW=all	IV. BW=3
-11	0.105**		0.158***	
	(0.0499)		(0.0558)	
-10	0.0797***		0.109***	
	(0.0262)		(0.0293)	
-9	0.0360		0.0541*	
	(0.0292)		(0.0326)	
-8	0.0867***		0.116***	
	(0.0234)		(0.0261)	
-7	0.102***		0.111***	
	(0.0166)		(0.0186)	
-6	0.0949***		0.117***	
	(0.0173)		(0.0193)	
-5	0.0904***		0.115***	
	(0.0161)		(0.0180)	
-4	0.0828***		0.109***	
	(0.0138)		(0.0155)	
-3	0.0998***	-	0.125***	-
	(0.0105)		(0.0117)	
-2	0.0989***	0.0998***	0.130***	0.125***
	(0.00824)	(0.0109)	(0.00920)	(0.0121)
-1	0.136**	0.0989***	0.136*	0.130***
	(0.0656)	(0.00859)	(0.0733)	(0.00955)
1	0.207***	0.207***	0.259***	0.259***
	(0.0141)	(0.0147)	(0.0157)	(0.0163)
2	0.232***	0.232***	0.283***	0.283***
	(0.0309)	(0.0322)	(0.0346)	(0.0358)
3	0.237***	0.237***	0.342***	0.342***
	(0.0499)	(0.0520)	(0.0558)	(0.0578)
4	0.182***		0.318***	
	(0.0656)		(0.0733)	
N	5693	3368	5693	3368
R^2	0.118	0.129	0.149	0.162

Note: This table reports "unrestricted regression" estimates of VC and PF projected on centered rank dummies for the Card and Lee (2008) goodness-of-fit test. Standard errors are robust and clustered at the topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 3: Unrestricted Regression of Impact on Revenue, Survival and Exit for Goodness of Fit Test

Dep Var:	$Revenue_i$		$Survival_i$		$Exit_i^{\text{Post}}$	
	I. BW=all	II. BW=3	III. BW=all	IV. BW=3	V. BW=all	VI. BW=3
-11	0.658***		0.892***		0.0263	
	(0.0845)		(0.0792)		(0.0290)	
-10	0.486***		0.822***		0.0362**	
	(0.0443)		(0.0415)		(0.0152)	
-9	0.486***		0.802***		0.00901	
	(0.0494)		(0.0468)		(0.0169)	
-8	0.543***		0.811***		0.0173	
	(0.0396)		(0.0376)		(0.0136)	
-7	0.535***		0.828***		0.0175*	
	(0.0282)		(0.0267)		(0.00965)	
-6	0.566***		0.837***		0.0222**	
	(0.0293)		(0.0278)		(0.0100)	
-5	0.564***		0.799***		0.0274***	
	(0.0273)		(0.0260)		(0.00934)	
-4	0.523***		0.769***		0.0222***	
	(0.0234)		(0.0224)		(0.00802)	
-3	0.532***	-	0.759***	-	0.0302***	-
	(0.0177)		(0.0169)		(0.00608)	
-2	0.533***	0.532***	0.718***	0.759***	0.0344***	0.0302***
	(0.0139)	(0.0181)	(0.0134)	(0.0182)	(0.00478)	(0.00652)
-1	0.409***	0.533***	0.500***	0.718***	0.0455	0.0344***
	(0.111)	(0.0143)	(0.114)	(0.0144)	(0.0381)	(0.00513)
1	0.659***	0.659***	0.827***	0.827***	0.0774***	0.0774***
	(0.0238)	(0.0244)	(0.0227)	(0.0245)	(0.00816)	(0.00876)
2	0.747***	0.747***	0.832***	0.832***	0.0303*	0.0303
	(0.0523)	(0.0535)	(0.0494)	(0.0533)	(0.0179)	(0.0192)
3	0.711***	0.711***	0.811***	0.811***	0.105***	0.105***
	(0.0845)	(0.0864)	(0.0792)	(0.0854)	(0.0290)	(0.0311)
4	0.773***		0.857***		0.136***	
	(0.111)		(0.105)		(0.0381)	
N	5693	3367	5365	3159	5693	3367
R^2	0.507	0.492	0.699	0.644	0.040	0.045

Note: This table reports "unrestricted regression" estimates of revenue, survival and exit projected on centered rank dummies for the Card and Lee (2008) goodness-of-fit test. Standard errors are robust and clustered at the topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 4: Regression of Impact on Venture Capital with Absolute Rank (Non-Centered) Dummies

Dependent Variable: VC_i^{Post}

	I. Rank Dummies Only	II. Award Dummy & Rank Dummies	III. Award Dummy, Controls & Rank Dummies
$\mathbf{1} \mid R_i > 0$		**0.143*** **	**0.139*** **
		(0.0402)	(0.0406)
VC_i^{Prev}			0.323***
			(0.0295)
$\#SBIR_i^{\text{Prev}}$			0.000939***
			(0.000204)
$R_i = 1$	0.0825***	-0.0560	-0.0834*
	(0.0274)	(0.0466)	(0.0472)
$R_i = 2$	0.0237	0.0100	-0.0131
	(0.0188)	(0.0176)	(0.0178)
$R_i = 3$	-0.0154	-0.0123	-0.0289
	(0.0239)	(0.0226)	(0.0217)
$R_i = 4$	-0.0406	-0.0243	-0.0287
	(0.0291)	(0.0283)	(0.0264)
$R_i = 5$	-0.0738**	-0.0505	-0.0568*
	(0.0354)	(0.0344)	(0.0300)
$R_i = 6$	-0.0885**	-0.0595	-0.0541*
	(0.0399)	(0.0375)	(0.0313)
$R_i = 7$	-0.117**	-0.0852*	-0.0769*
	(0.0472)	(0.0450)	(0.0400)
$R_i = 8$	-0.140**	-0.100*	-0.0854
	(0.0568)	(0.0560)	(0.0532)
$R_i = 9$	-0.193***	-0.145**	-0.150***
	(0.0662)	(0.0650)	(0.0555)
$R_i = 10$	-0.139	-0.0949	-0.0679
	(0.101)	(0.0960)	(0.0841)
$R_i = 11$	-0.137	-0.0850	-0.0542
	(0.0976)	(0.0928)	(0.0782)
$R_i = 12$	-0.179***	-0.145**	-0.0791
	(0.0603)	(0.0565)	(0.0480)
$R_i = 13$	-0.0907	-0.0452	0.00922
	(0.244)	(0.234)	(0.229)
$R_i = 14$	0.300	0.345	0.346
	(0.485)	(0.473)	(0.485)
N	5671	5671	5671
R^2	0.176	0.181	0.261

Note: This table reports regression estimates using absolute rank dummies rather than centered/percentile continuous rank variables. Column I projects VC finance on only the rank dummies, and subsequent columns include Phase 1 treatment ($\mathbf{1} \mid R_i > 0$) Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 5: Placebo Test of Grant Impact on All Outcomes (Artificial Cutoff between Ranks 1 and 2)

Dep.Variable:	I. VC_i^{Post}	II. PF_i^{Post}	III.$\#Patent_i^{\text{3 yrs Post}}$	IV. $Revenue_i$	V. $Survival_i$	VI. $Exit_i^{\text{Post}}$
$\mathbf{1} \mid R_{i,P} > 0$	**-.027**	**-.02**	**-.14**	**.0055**	**-.088**	**-.053**
	(.083)	(.088)	(.37)	(.097)	(.087)	(.048)
VC_i^{Prev}	.33***		1.2***	.17***	.1***	.13***
	(.038)		(.17)	(.036)	(.03)	(.028)
PF_i^{Prev}		.36***				
		(.036)				
$\#SBIR_i^{\text{Prev}}$	.001***	.0012***	.0095***	.0017***	.00074***	.00069***
	(.00029)	(.0003)	(.0015)	(.00022)	(.00019)	(.00022)
$\#Patent_i^{\text{Prev}}$			.29***			
			(.041)			
$Exit_i^{\text{Prev}}$						-.1***
						(.023)
$R_{i,P}$	.049***	.058***	.72***	.038*	.027	.02*
	(.015)	(.017)	(.087)	(.021)	(.018)	(.011)
$R_{i,P}^2$	-.028	-.017	-.19**	-.014	-.012	.00062
	(.017)	(.018)	(.078)	(.021)	(.017)	(.012)
Topic f.e.	N	N	Y	N	N	N
Competition f.e.	Y	Y	N	Y	Y	Y
N	2916	2916	2916	2916	2734	2916
R^2	.38	.38		.33	.32	.3
Pseudo-R^2			.19			
Log lik.			-2129			

Note: This table reports regression estimates of the effect of the placebo Phase 1 grant ($\mathbf{1} \mid R_{i,P} > 0$) on all the outcome metrics using a bandwidth of 2. The specifications are variants of the model in Equation 1. The treatment indicator and rank controls are altered so that the award cutoff is between centered ranks 1 and 2, rather than -1 and 1. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 6: Impact of Grant on All Outcomes with Alternative Fixed Effects

Panel A								
Dep. Variable:		VC_i^{Post}		$\#Patent_i^{\text{3 yrs Post}}$			$Revenue_i$	
	I.	II.	III.	IV.	V.	VI.	VII.	VIII.
$\mathbf{1} \mid R_i > 0$	**.11****	**.11*****	**.13*****	**1.2*****	**1.4*****	**.068**	**.069**	**.11****
	(.045)	(.04)	(.04)	(.26)	(.32)	(.05)	(.045)	(.048)
VC_i^{Prev}	.34***	.35***	.36***	1.3***	1.1***	.18***	.19***	.24***
	(.033)	(.03)	(.03)	(.2)	(.24)	(.031)	(.028)	(.029)
$\#SBIR_i^{\text{Prev}}$	.00099***	.00097***	.00094***	.0091***	.0098***	.0017***	.002***	.0018***
	(.00025)	(.00021)	(.00021)	(.0016)	(.0019)	(*.0002*)	(.00019)	(.00019)
R_i	-.005	-.0028	-.0087	.15**	.15*	.017	.018	.0079
	(.016)	(.014)	(.014)	(.074)	(.081)	(.019)	(.017)	(.018)
$\#Patent_i^{\text{Prev}}$				.29***	.31***			
				(.038)	(.041)			
Topic f.e.	Y	N	N	N	N	Y	N	N
Year f.e.	N	Y	N	Y	N	N	Y	N
N	2836	2836	2836	2836	2836	2836	2836	2836
R^2	.24	.14	.13			.18	.095	.058
Pseudo-R^2				.1	.072			
Log lik.				-2255	-2335			

Panel B						
Dep. Variable:		$Survival_i$			$Exit_i^{\text{Post}}$	
	IX.	X.	XI.	XII.	XIII.	XIV.
$\mathbf{1} \mid R_i > 0$	**.075***	**.11*****	**.17*****	**.049***	**.054*****	**.046****
	(.043)	(.037)	(.042)	(.025)	(.021)	(.02)
VC_i^{Prev}	.00079***	.001***	.00089***	.12***	.13***	.12***
	(.00016)	(.00012)	(.00013)	(.024)	(.022)	(.022)
$\#SBIR_i^{\text{Prev}}$	.079***	.077***	.13***	.00062***	.00059***	.00062***
	(.025)	(.023)	(.024)	(.00019)	(.00017)	(.00017)
R_i	-.0045	-.017	-.033**	-.0068	-.0081	-.0051
	(.015)	(.013)	(.015)	(.008)	(.0062)	(.0062)
$Exit_i^{\text{Prev}}$				-.08***	-.083***	-.087***
				(.015)	(.012)	(.012)
Topic f.e.	Y	N	N	Y	N	N
Year f.e.	N	Y	N	N	Y	N
N	2660	2660	2660	2836	2836	2836
R^2	.2	.087	.025	.17	.072	.055

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all outcomes and using bandwidth of 2. The specifications are variants of the model in Equation 1, with alternative fixed effects. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 7: Impact of Grant on All Outcomes with Standard Errors Clustered by Rank

Dep. Variable:	VC_i^{Post}		$\#Patent_i^{\text{3 yrs Post}}$		$Revenue_i$		$Survival_i$		$Exit_i^{\text{Post}}$	
	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
$\mathbf{1} \mid R_i > 0$	**.11*** **	**.072*** **	**2*** **	**1.8*** **	**.12*** **	**.029**	**.043** **	**.024**	**.036*** **	**.052*** **
	(.0093)	(.022)	(.16)	(.24)	(.013)	(.025)	(.018)	(.041)	(.0085)	(.017)
VC_i^{Prev}	.32***	.32***	1.3***	1.2***	.24***	.23***	.1***	.1***	.13***	.14***
	(.032)	(.031)	(.19)	(.2)	(.024)	(.023)	(.011)	(.01)	(.018)	(.018)
$\#SBIR_i^{\text{Prev}}$	.00087***	.00084***	.011***	.011***	.002***	.0019***	.00079***	.00078***	.00039**	.0004**
	(.00025)	(.00025)	(.0015)	(.0015)	(.00014)	(.00014)	(.000073)	(.000069)	(.00018)	(.00018)
$\#Patent_i^{\text{Prev}}$			.32***	.31***						
			(.027)	(.027)						
$Exit_i^{\text{Prev}}$									-.087***	-.087***
									(.0098)	(.0099)
R_i		.0086				.025***		.0041		-.0042
		(.0062)				(.0065)		(.0082)		(.0034)
R_i^2		-.000074				- .00081**		.000048		.000094
		(.00048)				(.0004)		(.00043)		(.00018)
Competition f.e.	Y	Y	N	N	Y	Y	Y	Y	Y	Y
Topic f.e.	N	N	Y	Y	N	N	N	N	N	N
N	5021	5021	5021	5021	5021	5021	4731	4731	5021	5021
R^2	.27	.27			.22	.23	.22	.22	.2	.21
Pseudo-R^2			.11	.11						
Log lik.			-3404	-3401						

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all outcomes and using bandwidth of all. The specifications are variants of the model in Equation 1, where for each outcome there is one model without rank controls and one with them. Standard errors are robust and clustered by rank. *** $p < .01$. Year$\geq$ 1995

Table 8: Impact of Grant on VC with Logit Model

Dependent Variable: $Revenue_i$								
Bandwidth:	1		2		3		All	
	I.	II.	III.	IV.	V.	VI.	VII.	VIII.
$\mathbf{1} \mid R_i > 0$	**1.35*** **	**1.11*** **	**1.18*** **	**1.04*** **	**1.25*** **	**1.12*** **	**1.16*** **	**1.04*** **
	(0.35)	(0.245)	(0.25)	(0.19)	(0.23)	(0.17)	(0.18)	(0.16)
VC_i^{Prev}	2.633***	2.3***	2.76***	2.41***	2.54***	2.25***	2.44***	2.29***
	(0.4)	(0.3)	(0.29)	(0.21)	(0.26)	(0.19)	(0.18)	(0.15)
$\#SBIR_i^{\text{Prev}}$	0.013***	0.0095***	0.009***	0.0075***	0.0096***	0.0076***	0.0075***	0.0073***
	(0.0027)	(0.0025)	(0.0023)	(0.0018)	(0.0021)	(0.0017)	(0.0014)	(0.0013)
Competition f.e.	Y	N	Y	N	Y	N	Y	N
Topic f.e.	N	Y	N	Y	N	Y	N	Y
N	700	1194	1250	2054	1614	2528	3450	4672
Pseudo-R^2	0.25	0.232	0.241	0.21	0.23	0.19	0.21	0.18

Note: This table reports logit regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC. The specifications are variants of the model in Equation 1. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 9: Impact of Grant on Revenue with Logit Model

Dependent Variable: $Revenue_i$								
Bandwidth:	1		2		3		All	
	I.	II.	III.	IV.	V.	VI.	VII.	VIII.
$\mathbf{1} \mid R_i > 0$	**0.66*** **	**0.57*** **	**0.49*** **	**0.53*** **	**0.551*** **	**0.57*** **	**0.61*** **	**0.58*** **
	(0.21)	(0.15)	(0.17)	(0.12)	(0.15)	(0.12)	(0.12)	(0.1)
VC_i^{Prev}	1.41***	1.34***	1.3***	1.1***	1.27***	1.12***	1.47***	1.29***
	(0.33)	(0.23)	(0.223)	(0.172)	(0.19)	(0.15)	(0.14)	(0.12)
$\#SBIR_i^{\text{Prev}}$	0.023***	0.021***	0.023***	0.023***	0.023***	0.024***	0.024***	0.024***
	(0.0052)	(0.0042)	(0.00423)	(0.0036)	(0.0037)	(0.0035)	(0.003)	(0.0023)
Competition f.e.	Y	N	Y	N	Y	N	Y	N
Topic f.e.	N	Y	N	Y	N	Y	N	Y
N	1546	2176	2827	3588	3550	4310	6569	7162
Pseudo-R^2	0.15	0.14	0.15	0.14	0.15	0.134	0.14	0.11

Note: This table reports logit regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC. The specifications are variants of the model in Equation 1. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 10: Impact of Grant on All Outcomes with No Covariates

Dep. Variable:	VC_i^{Post}		$\#Patent_i^{\text{3 yrs Post}}$		$Revenue_i$		$Survival_i$		$Exit_i^{\text{Post}}$	
Bandwidth:	I. 2	II. 3	III. 2	IV. 3	V. 2	VI. 3	VII. 2	VIII. 3	IX. 2	X. 3
$\mathbf{1} \mid R_i > 0$	**.094*** **	**.11*** **	**.99*** **	**1.3*** **	**.094*** **	**.11*** **	**.048***	**.043***	**.034***	**.044*** **
	(.026)	(.025)	(.16)	(.15)	(.031)	(.028)	(.026)	(.024)	(.018)	(.015)
Competition f.e.	Y	Y	N	N	Y	Y	Y	Y	Y	Y
Topic f.e.	N	N	Y	Y	N	N	N	N	N	N
N	2836	3368	2836	3368	2836	3368	2660	3158	2836	3368
R^2	.32	.27			.31	.27	.32	.27	.27	.22
Pseudo-R^2			.13	.11						
Log lik.			-2190	-2563						

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all outcomes. The specifications are variants of the model in Equation 1 with no covariates. Standard errors are robust and clustered at the topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 11: Impact of Grant on All Outcomes with Additional Covariates

Dep. Variable:	VC_i^{Post}		$\#Patent_i^{\text{3 yrs Post}}$		$Revenue_i$		$Survival_i$		$Exit_i^{\text{Post}}$	
Bandwidth:	I. 2	II. 3	III. 2	IV. 3	V. 2	VI. 3	VII. 2	VIII. 3	IX. 2	X. 3
$\mathbf{1} \mid R_i > 0$	**.1*** **	**.11*** **	**1.1*** **	**1.2*** **	**-.0012**	**.0088**	**-.045**	**-.051** **	**.029**	**.033***
	(.033)	(.031)	(.15)	(.14)	(.034)	(.031)	(.028)	(.025)	(.024)	(.02)
VC_i^{Prev}	.32***	.3***	1.3***	1.1***	.059	.063	.025	.018	.11***	.13***
	(.044)	(.042)	(.18)	(.17)	(.045)	(.04)	(.031)	(.029)	(.034)	(.029)
$\#SBIR_i^{\text{Prev}}$	.001***	.0011***	.0095***	.0088***	.00068***	.00084***	.00011	.00021	.00074***	.00058**
	(.00035)	(.00033)	(.0014)	(.0015)	(.00021)	(.00018)	(.0002)	(.00018)	(.00025)	(.00023)
Age_i	-.00063	-.00099	-.0022	-.0004	.0026**	.0026**	.0015**	.0016**	-.00095*	-.0008*
	(.0014)	(.0012)	(.0047)	(.0043)	(.0012)	(.0011)	(.0007)	(.00063)	(.00053)	(.00047)
MSA_i	.014	.035	-.3**	-.2	-.0091	.004	-.017	-.00019	-.016	-.015
	(.028)	(.025)	(.13)	(.12)	(.035)	(.03)	(.026)	(.022)	(.019)	(.015)
$Exit_i^{\text{Prev}}$	.049	.079	-.75**	-.32	.037	.03	.023	-.0057	-.11***	-.12***
	(.076)	(.068)	(.33)	(.37)	(.065)	(.062)	(.05)	(.049)	(.032)	(.025)
$Patent_i^{\text{Prev}}$	-.004*	-.0042*	.19***	.2***	.0083**	.0082***	.0025	.0029	-.0016	-.00068
	(.0021)	(.0022)	(.042)	(.042)	(.0035)	(.0031)	(.0022)	(.0022)	(.0018)	(.0019)
$Citation_i^{\text{Prev}}$	.0014***	.0017***	.011	.022	-.00074	-.0008	-.00042	-.0006	.0014***	.0014***
	(.00032)	(.00035)	(.032)	(.03)	(.0006)	(.00062)	(.00031)	(.00045)	(.00025)	(.00023)
Competition f.e.	Y	Y	N	N	Y	Y	Y	Y	Y	Y
Topic f.e.	N	N	Y	Y	N	N	N	N	N	N
N	1918	2286	1916	2286	1918	2286	1902	2268	1918	2286
R^2	.47	.42			.38	.33	.38	.32	.4	.35
Pseudo-R^2			.21	.19						
Log lik.			-1663	-1970						

Note: This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on all outcomes. The specifications are variants of the model in Equation 1 with no covariates. Standard errors are robust and clustered at the topic-year level. *** $p < .01$.
Year$\geq$ 1995

Table 12: Impact of Grant on Subsequent VC with Alternative Polynomials in Rank

Dependent Variable: VC_i^{Post}	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
$\mathbf{1} \mid R_i > 0$	**0.104*** **	**0.0731*** **	**0.0818*** **	**0.0921*** **	**0.0828** **	**0.101* **	**0.100*** **	**0.0738*** **	**0.114** **	**0.101* **
	(0.0201)	(0.0255)	(0.0221)	(0.0327)	(0.0323)	(0.0525)	(0.0210)	(0.0229)	(0.0512)	(0.0515)
VC_i^{Prev}	0.323***	0.321***	0.321***	0.321***	0.321***	0.321***	0.321***	0.321***	0.323***	0.321***
	(0.0292)	(0.0293)	(0.0292)	(0.0293)	(0.0293)	(0.0293)	(0.0293)	(0.0293)	(0.0292)	(0.0294)
$\#SBIR_i^{\text{Prev}}$	0.000965***	0.000951***	0.000949***	0.000948***	0.000947***	0.000948***	0.000956***	0.000948***	0.000965***	0.000947***
	(0.000202)	(0.000203)	(0.000203)	(0.000203)	(0.000204)	(0.000203)	(0.000202)	(0.000204)	(0.000202)	(0.000204)
R_i		0.00751								
		(0.00495)								
$R_{i,-}$			0.00840*	0.00870*	0.0141**	0.00869*		0.0141**		0.0101
			(0.00503)	(0.00477)	(0.00575)	(0.00480)		(0.00577)		(0.0122)
$R_{i,+}$				-0.00753	-0.00640	-0.0168			-0.0104	-0.0223
				(0.0167)	(0.0162)	(0.0450)			(0.0456)	(0.0464)
$R_{i,-}^2$					0.000403		-0.000390	0.000416		-0.000341
					(0.000301)		(0.000353)	(0.000306)		(0.00216)
$R_{i,+}^2$						0.00154	-0.000744		0.00180	0.00260
						(0.00643)	(0.00235)		(0.00628)	(0.00656)
$R_{i,-}^3$										0
										(.)
$R_{i,+}^3$										0.0000288
										(0.0000746)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5693	5693	5693	5693	5693	5693	5693	5693	5693	5693
R^2	0.256	0.257	0.257	0.257	0.258	0.257	0.257	0.258	0.256	0.258

This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on VC using a bandwidth of all. The specifications are variants of the model in Equation 1. The dependent variable ${VC^{\text{Post}}}_i$ is 1 if the company ever received VC after the award decision, and 0 if not. Specifications vary the rank control. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 13: Impact of Grant on Revenue with Alternative Polynomials in Rank

Dependent Variable: $Revenue_i$	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
$\mathbf{1} \mid R_i > 0$	**0.124*** **	**0.0769*** **	**0.0919*** **	**0.0838** **	**0.0708* **	**0.0933**	**0.111*** **	**0.0813*** **	**0.111* **	**0.107**
	(0.0224)	(0.0296)	(0.0261)	(0.0359)	(0.0385)	(0.0668)	(0.0249)	(0.0280)	(0.0648)	(0.0660)
VC_i^{Prev}	0.245***	0.241***	0.241***	0.241***	0.242***	0.241***	0.242***	0.242***	0.245***	0.241***
	(0.0232)	(0.0232)	(0.0231)	(0.0232)	(0.0232)	(0.0232)	(0.0231)	(0.0232)	(0.0233)	(0.0231)
$\#SBIR_i^{\text{Prev}}$	0.00196***	0.00194***	0.00194***	0.00194***	0.00194***	0.00194***	0.00195***	0.00194***	0.00196***	0.00194***
	(0.000173)	(0.000172)	(0.000172)	(0.000172)	(0.000172)	(0.000172)	(0.000172)	(0.000172)	(0.000173)	(0.000172)
R_i		0.0114**								
		(0.00446)								
$R_{i,-}$			0.0120**	0.0118**	0.0194**	0.0118**		0.0195**		-0.00340
			(0.00477)	(0.00498)	(0.00841)	(0.00501)		(0.00840)		(0.0160)
$R_{i,+}$				0.00587	0.00745	-0.00429			0.00431	-0.00938
				(0.0164)	(0.0169)	(0.0570)			(0.0566)	(0.0578)
$R^2_{i,-}$					0.000565		-0.000524	0.000549		-0.00346
					(0.000462)		(0.000380)	(0.000455)		(0.00224)
$R^2_{i,+}$						0.00169	0.00132		0.00205	0.00253
						(0.00768)	(0.00213)		(0.00780)	(0.00788)
$R^3_{i,-}$										0
										(.)
$R^3_{i,+}$										0.000151**
										(0.0000744)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5693	5693	5693	5693	5693	5693	5693	5693	5693	5693
R^2	0.214	0.216	0.216	0.216	0.216	0.216	0.215	0.216	0.214	0.216

This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on revenue using a bandwidth of all. The specifications are variants of the model in Equation 1. Specifications vary the rank control. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 14: Impact of Grant on Survival with Alternative Polynomials in Rank

Dependent Variable: $Survival_i$	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
$\mathbf{1} \mid R_i > 0$	**0.0510*** **	**0.0427***	**0.0423** **	**0.0783*** **	**0.0837*** **	**0.131** **	**0.0559*** **	**0.0454***	**0.137*** **	**0.136** **
	(0.0187)	(0.0235)	(0.0213)	(0.0300)	(0.0319)	(0.0534)	(0.0211)	(0.0238)	(0.0522)	(0.0539)
VC_i^{Prev}	0.110***	0.109***	0.109***	0.110***	0.109***	0.109***	0.109***	0.109***	0.111***	0.109***
	(0.0183)	(0.0184)	(0.0184)	(0.0183)	(0.0183)	(0.0183)	(0.0183)	(0.0184)	(0.0183)	(0.0183)
$\#SBIR_i^{\text{Prev}}$	0.000856***	0.000853***	0.000850***	0.000846***	0.000846***	0.000846***	0.000849***	0.000851***	0.000854***	0.000846***
	(0.000119)	(0.000120)	(0.000120)	(0.000121)	(0.000121)	(0.000122)	(0.000120)	(0.000120)	(0.000121)	(0.000122)
R_i		0.00195								
		(0.00283)								
$R_{i,-}$			0.00317	0.00421	0.00119	0.00413		0.00104		-0.00340
			(0.00306)	(0.00316)	(0.00771)	(0.00316)		(0.00763)		(0.0154)
$R_{i,+}$				-0.0262*	-0.0269**	-0.0822*			-0.0795*	-0.0795*
				(0.0134)	(0.0133)	(0.0466)			(0.0463)	(0.0473)
$R_{i,-}^2$					-0.000224		-0.000274*	-0.000157		-0.00114
					(0.000394)		(0.000145)	(0.000380)		(0.00214)
$R_{i,+}^2$						0.00926	-0.00291		0.00943	0.00869
						(0.00651)	(0.00205)		(0.00647)	(0.00669)
$R_{i,-}^3$										0
										(.)
$R_{i,+}^3$										0.0000375
										(0.0000730)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5365	5365	5365	5365	5365	5365	5365	5365	5365	5365
R^2	0.218	0.218	0.219	0.219	0.219	0.219	0.219	0.219	0.219	0.219

This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on survival using a bandwidth of all. The specifications are variants of the model in Equation 1. Specifications vary the rank control. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995

Table 15: Impact of Grant on Exit with Alternative Polynomials in Rank

Dependent Variable: $Exit_i^{\text{Post}}$	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
$\mathbf{1} \mid R_i > 0$	**0.0337*****	**0.0415*****	**0.0373*****	**0.0607*****	**0.0561*****	**0.0838****	**0.0415*****	**0.0328****	**0.0827****	**0.0843****
	(0.0123)	(0.0144)	(0.0132)	(0.0201)	(0.0211)	(0.0388)	(0.0137)	(0.0139)	(0.0388)	(0.0395)
$Exit_i^{\text{Prev}}$	-0.0840***	-0.0839***	-0.0839***	-0.0846***	-0.0845***	-0.0843***	-0.0845***	-0.0838***	-0.0843***	-0.0837***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0119)
VC_i^{Prev}	0.129***	0.129***	0.129***	0.130***	0.130***	0.129***	0.130***	0.129***	0.129***	0.129***
	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)
$\#SBIR_i^{\text{Prev}}$	0.000311**	0.000315**	0.000314**	0.000312**	0.000311*	0.000312*	0.000313**	0.000313**	0.000310*	0.000311*
	(0.000157)	(0.000158)	(0.000158)	(0.000158)	(0.000158)	(0.000159)	(0.000158)	(0.000158)	(0.000158)	(0.000159)
R_i		-0.00190								
		(0.00152)								
$R_{i,-}$			-0.00137	-0.000706	0.00197	-0.000732		0.00178		-0.000310
			(0.00165)	(0.00159)	(0.00320)	(0.00163)		(0.00316)		(0.00601)
$R_{i,+}$				-0.0170**	-0.0165**	-0.0419			-0.0425	-0.0450
				(0.00822)	(0.00832)	(0.0321)			(0.0321)	(0.0323)
$R^2_{i,-}$					0.000198		0.0000964	0.000232		-0.000261
					(0.000159)		(0.0000711)	(0.000154)		(0.000858)
$R^2_{i,+}$						0.00414	-0.00187**		0.00412	0.00474
						(0.00419)	(0.000887)		(0.00420)	(0.00426)
$R^3_{i,-}$										0
										(.)
$R^3_{i,+}$										0.0000190
										(0.0000288)
Competition f.e.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5693	5693	5693	5693	5693	5693	5693	5693	5693	5693
R^2	0.180	0.180	0.180	0.181	0.181	0.181	0.181	0.180	0.181	0.182

This table reports regression estimates of the effect of the Phase 1 grant ($\mathbf{1} \mid R_i > 0$) on exit using a bandwidth of all. The specifications are variants of the model in Equation 1. Specifications vary the rank control. Standard errors are robust and clustered at topic-year level. *** $p < .01$. Year$\geq$ 1995