APPROXIMATING EXOGENOUS VARIATION IN R&D: EVIDENCE FROM THE KENTUCKY AND NORTH CAROLINA SBIR STATE MATCH PROGRAMS

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Abstract—This paper exploits policy discontinuities at U.S. state borders to examine the effect of R&D investments on innovative projects. We examine the Small Business Innovation Research (SBIR) State Match program, which offers noncompetitive grants to federally awarded SBIR Phase I projects that are eligible to compete for Phase II. Results from SBIR activity (2002–2010) indicate heterogeneous treatment effects. Notably, the positive differential effects are moderated by firms within the science and health fields and with less previous SBIR success. The State Match effectively stabilized Phase II trends in contrast to neighboring states that experienced greater declines from the concurrent recession.

I. Introduction

THERE is an active debate about how best to use public funds to promote innovation (e.g., Griliches & Mairesse, 1998; Hall, 2002; Salter & Martin, 2001; Blume-Kohout, Kumar, & Sood, 2015). While the theoretical rationale for government investment in innovation is well established (Schumpeter, 1934), empirical results have been inconsistent, suggesting the need for new methods and research design (Einiö, 2014). Experimental designs that would randomly assign research resources to treatment or control groups are not politically feasible. Moreover, much of the scholarship on public R&D funding has focused at the level of the firm; this particularly holds for the literature examining the extent to which government funding crowds out private investment. Once again, this research has mixed results (e.g., Lanahan, Graddy-Reed, & Feldman, 2016; David, Hall, & Toole, 2000; García-Quevedo, 2004; Diamond, 1999). This is in no small part because government funding is typically allocated for projects, while analysis focuses on firms. A more salient approach for understanding the effect of public funding on innovation would be to narrow the scope of analysis to measure the impact of government investment in advancing the progress of innovative ideas or projects.

In addition, research on government investment typically examines national policies and programs (e.g., Payne, 2001; Feller, 2007). Even as the literature recognizes that processes of economic growth are more regionally grounded (Audretsch & Feldman, 2004) and that states actively conduct policy experiments (Feldman & Lanahan, 2014), few studies consider subnational policy initiatives and evaluate their impact on innovation, entrepreneurship, technological change, and economic development. And despite the active involvement of a range of actors in federalist systems and an international emphasis on policies at the cluster or city-industry level (Andersson et al., 2004), only recently have scholars begun to direct attention toward understanding the impact of subnational R&D investments and the ways in which multilevel programs interact (Zhao & Ziedonis, 2017; Czarnitski & Lopes-Bento, 2012; Lanahan & Feldman, 2015). Policymakers around the world struggle to develop programs to stimulate and increase the efficiency of the innovation process with both an incomplete understanding of the potential for multilevel coordination between different levels of government and a lack of empirical evidence on investment outcomes.

To address these shortcomings, this paper exploits policy discontinuities at U.S. state borders to examine the effect of public funding on innovative projects. The Small Business Innovation Research (SBIR) State Match programs provide a useful context to examine this variation by offering a noncompetitive match to successful federal SBIR Phase I projects that are then eligible to compete for the larger SBIR Phase II award. This paper draws on SBIR activity from two states with the State Match—Kentucky and North Carolina—and four contiguous states without—Arkansas, Missouri, South Carolina, and Virginia. The two treated states adopted the State Match in 2006 (Kentucky) and 2005 (North Carolina). Importantly, the dollar amount of the matches varies, allowing for differential and marginal examinations. Moreover, within the context of the federal SBIR program, between-state comparisons are feasible given that the population of Phase I recipients demonstrated a minimum quality as determined a priori by the competitive federal SBIR proposal review. This offers a research

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design that treats the noncompetitive State Match as an exogenous increase to R&D investment, while also allowing an examination of the impact on projects rather than firms.

With a focus on the SBIR multilevel policy context, this paper contributes to our developing understanding of government investment in innovation in three ways. First, by taking a closer look at funding at the project level, it enables a more direct and precise evaluation of the effectiveness of government investment in supporting innovative activity. Second, by examining the role of the State Match in complementing the federal SBIR program, it represents one pioneering effort to comprehend the innovation policy mix as comprising multiple layers of overlapping policies (Flanagan, Uyarra, & Laranja, 2011). Finally, this paper presents a creative research design for assessing both the differential and marginal impact of public funding. Given that the federal program is agnostic regarding the firm's geographic location, the SBIR policy mix provides a case that allows for the approximation of exogenous variation in funding.

The results point to a heterogeneous treatment effect. In contrast to projects without the State Match, the results indicate that additional funding improved the competitiveness of Phase I recipients competing for the Phase II awards among projects with a directed focus in the basic sciences and with less previous success with the SBIR program. The differential effect for National Science Foundation (NSF)–funded projects is a 29.4% increase, and the differential effect for Department of Health and Human Services (HHS)–funded projects for firms with less previous SBIR success ranges from a 24.7% to 24.8% increase. Results from a comparison of means test indicate that these firms with less SBIR experience are smaller and younger than the average recipient. Results from the marginal analysis also found positive effects of the state program, with marginal effects ranging from 2.9% to 3.8%. These results indicate that funding is worth more when invested in projects from firms with less experience with the federal SBIR program. While the results are positive, the State Match activity overlapped with the recent economic recession; this aligned with an overall decline in the probability of transition to Phase II not only for the United States but also for the contiguous region of interest. Thus, the State Match effectively stabilized Phase II trends in contrast to neighboring states that experienced greater declines.

The results have implications for firms and policymakers. Regarding the former, this suggests that smaller and younger firms are able to more effectively leverage the additional funding to gain a competitive advantage. As for the latter, policymakers may want to tailor the distribution of the awards based on the focus of the research project and experience of the firm.

This article is organized as follows. Section II provides the policy context, drawing attention to the utility of considering the multilevel innovation policy mix. Section III presents the research design. Section IV discusses the methods. Section V reviews the results. Section VI offers a discussion and considers alternative outcomes. Section VII concludes.

II. Multilevel Innovation Policy Mix

The U.S. SBIR program offers a context to examine the multilevel innovation policy mix and to empirically assess the relationship between public investment and innovation.[1] The program is one of the most studied and widely emulated public R&D programs in the world (e.g., Keller & Block, 2013; Link & Scott, 2012; Wessner, 2008; Toole & Czarnitski, 2007; Audretsch, Link, & Scott, 2002; Tibbetts, 2001; Wallsten, 2000; Lerner, 1999). However, knowledge of the program is incomplete due to a lack of consideration of complementary U.S. state programs.

As of 2013, 45 of the 50 U.S. states had established formal programs designed to complement the federal SBIR program (Lanahan & Feldman, 2015). These programs range from state outreach programs (42 states) to state match programs (17 states).[2] The most resource-intensive program, referred to in this paper as the State Match, offers a noncompetitive match to SBIR Phase I recipients competing for the larger Phase II awards.

While the federal SBIR program aims to enhance private sector R&D and stimulate technological innovation (Link & Scott, 2010), the State Match attempts to leverage the federal SBIR program to increase the public resources and commercial activity within a state's jurisdiction. These programs are similar in structure; however, the size of the matches varies not only across states but also between years. For example, New York's NYSTAR[3] and Kentucky's SBIR/STTR Matching Funds programs offer a dollar-for-dollar match; the Kansas Bioscience Authority provides a 50% match; the Connecticut Innovation Program also provides a 50% match but requires a third-party match; and the One North Carolina Small Business program offers awards ranging from 20% to 70% match (Lanahan & Feldman, 2015).

The level of state SBIR policy activity alone suggests that subnational innovation policies are widespread. Preliminary research on the State Match, in particular, has focused on understanding the antecedent factors associated with state adoption (Lanahan & Feldman, 2015). While the structure of the match programs aligns, adoption of the program is not random; states are more likely to adopt the program when their economic performance lags that of other states.[4] This pattern also holds for a range of state university science and technology policy programs (Feldman & Lanahan, 2014); these adoptions are positively associated

[1] See appendix A, section A.1, for an overview of the program.
[2] State outreach programs provide information or assistance to lower the application costs.
[3] The NYSTAR program was active from 1984 to 1991. When active the program matched 1:1.
[4] See appendix A, section A.2, for a greater discussion of Kentucky and North Carolina's policies and context.

with the state's own internal political and economic climate, in addition to external pressures from neighboring jurisdictions. In short, this evidence suggests that states are responsive to their local conditions.

Additional research examining the outcomes of a broader set of subnational policies indicates that state policies have the capacity to bolster local economic conditions. Zhao and Ziedonis (2017) examine Michigan's innovation subsidy programs on the performance of entrepreneurial firms and find evidence that the state award benefits commercial viability. Czarnitski and Lopes-Bento (2012) focus on a portfolio of multilevel R&D policies in Belgium, finding evidence of a complementary treatment effect. While these studies offer a foundational assessment of subnational programs, we lack complete information on scale and impact. We attribute this to the decentralization and programmatic fragmentation of state policies.

Not only is it useful to examine the role of subnational policy efforts on innovation on its own accord, this level of policy activity offers a useful theoretical framework and empirical context for understanding the relationship between public R&D and innovation more broadly. Following the logic of Supreme Court Justice Brandeis's *laboratories of democracy*, which espouses policy experimentation within a federalist framework, U.S. state governments have flexibility to experiment to create conditions conducive to economic development and prosperity. Fiscal federalism dictates that different levels of government have certain obligations, with each U.S. state responsible for promoting economic growth while also exerting influence over private institutions within their borders.[5] States also have great latitude in designing new initiatives that may be particularly suited to local circumstances. This experimentation is an underappreciated yet important aspect of the innovation policy mix.

The nature of noncompetitive state match programs offers a useful empirical context to examine adjustments of public investment. Politics restricts researchers from setting up experiments that randomly assign resources to discern the effect of public funding on innovation (Burtless, 1995). However, noncompetitive state match programs placed within the context of a federal program offer a close approximation to random assignment with a compelling counterfactual.

A. *SBIR Policy Context: Examining the Impact of R&D Investment on Innovation*

This paper turns to the task of examining the effect of the State Match. First, we review the structure of the federal SBIR program and the intended role played by the State Match. The match most immediately rewards Phase I projects to encourage progress toward securing the larger Phase II award. Federal SBIR Phase I awards are competitive funds for firms to demonstrate proof-of-concept of the scientific, technical, and commercial potential for a project in relation to the federal agency's objectives. Competitive follow-on federal Phase II awards are available to develop the project into a commercially viable product, process, or service. Phase I awards typically do not exceed $150,000 for six months of research support, while Phase II awards are roughly $1 million for two years of support.[6] The average time between awards, however, is slightly more than one year for the 42% of Phase I projects that successfully receive Phase II awards.[7] This program places even the most promising projects in a "valley of death" between proof-of-concept and development (Auerswald & Branscomb, 2003). The State Match is designed to support these projects during this critical interim period.

This paper examines the impact of state matching funds on the probability of projects securing a Phase II award. While Phase I recipients are not required to compete for the Phase II award, we assume that Phase I recipients compete for the Phase II award given that these projects are at a nascent stage of the innovative process, making it difficult to attract private funding.[8] In addition, the size of the award is notably larger, and the success rates are more favorable.[9] Additionally, this clear and quantifiable project-level outcome variable offers a more immediate measure of progress toward commercialization, lessening concerns of potential confounding factors that are common when measuring R&D investment outcomes over longer time horizons (Salter & Martin, 2001; Jaffe, 2008). While states often mention longer-term firm-level benefits such as increased employment and performance, these objectives are predicated on making more immediate progress as signaled by the receipt of a Phase II award.

This paper narrows the scope of analysis to the project level, tracing the path of funds for projects: from Phase I award to State Match (if eligible) to Phase II award (if successful). Efforts were made to include federal SBIR application activity as well; however, only state-level statistics are available.[10] The federal SBIR program is highly competitive and administered without regard to the geographic distribution of recipients. Critical to this paper's research design is the fact that only small businesses that secure a Phase I award are eligible to compete for the larger Phase II award: all eligible competitive projects have demonstrated a minimum level of competency. This addresses primary concerns about selection of the sample.

[5] J. Madison, "Powers and Continuing Advantages of the States," in B. F. Wright, ed., *The Federalist Papers* (New York: MetroBooks, 2002), pp. 324–329.

[6] HHS offers larger awards: $500,000 (Phase I) and $3,000,000 (Phase II).

[7] Derived from sbir.gov. The average time lapse between a Phase I and a Phase II award is 1.2 years.

[8] The One NC Small Business Survey found that roughly 75% of Phase I recipients intended to apply for the Phase II.

[9] Phase I and II success rates are approximately 15% and 40%, respectively (Wessner, 2008).

[10] We spoke with program officers at the SBA, NSF, HHS and DOD regarding SBIR application activity. Comprehensive project-level application data are unavailable for the analysis.

III. Research Design

This study focuses on the effect of the State Match for North Carolina and Kentucky. North Carolina passed legislation in 2005, and Kentucky passed the legislation in 2006. Importantly, these two states were selected for this analysis given that the size of the match varies for Phase I recipients. The Kentucky SBIR/STTR Matching Funds Program provides a dollar-for-dollar state match for Phase I projects.[11] North Carolina's One NC Small Business Program began with $100,000 matches in 2006; however, due to state budgetary restrictions, the size of the match decreased to $30,000 in 2010. This variation allows for both differential and marginal analysis. It is worth noting that state administrative records of matches are not available for all states with the program, so a comprehensive assessment of all State Match programs is not feasible. Section A.2 in appendix A provides more contextual detail for the two respective match programs.

This paper examines the population of SBIR projects in a contiguous region with Phase I projects for firms located in Kentucky and North Carolina comprising the treated region. We then selected the population of Phase I projects in Arkansas, Missouri, South Carolina, and Virginia as controls. This approach mirrors a growing line of scholarship that exploits policy discontinuities at state borders (Card & Krueger, 1992; Lee & Lemieuxa, 2010; Dube, Lester, & Reich, 2010). While Tennessee and Indiana share the longest geographical borders with Kentucky, they are not defensible control regions because Tennessee far surpasses the rest of the region in terms of SBIR activity and Indiana has its own State Match.[12] We exclude the northern region of Virginia, which is part of the Washington, DC, greater metropolitan area and recipient of a disproportionate number of SBIR awards. These contiguous states share similar state-level economic development characteristics (Sallee et al., 2011), making them strong candidates for the control group.

A. *Stratifications*

In setting up the design for this analysis, we account for the decentralized structure of the SBIR program and patterns in the distribution of federal SBIR awards by stratifying two ways: by the funding federal mission agency and by the firms' innovative research capacity. Regarding the former, the Small Business Administration (SBA) coordinates the SBIR program, but eleven federal mission agencies are involved in administering the review of proposals and allocation of funds. While the basic aim of the program is consistent across the agencies, there are operational differences between the agencies (Wessner, 2008). For example, DOD tends to fund contracts and reviews proposals internally, whereas NSF and HHS award grants and administer external peer review processes. In addition, there is a vast range of research fields funded across the SBIR program, including health, science, engineering, transportation, energy, education, security, and aeronautics. Section B.1 in appendix B offers additional discussion of the research focus for the region of interest. Prospective firms must select the appropriate agency depending on the topic of the proposal. This selection process serves as a useful proxy for the specialization of the project, which offers an operational measure for stratifying the sample. Compared to national trends, it is worth noting that there is a higher concentration of activity funded by the science-based mission agencies—HHS and NSF—for the six-state region of interest (refer to table A.1 in appendix A).

The second stratification technique refers to the distribution of Phase I awards by firm. All firms competing for federal SBIR funds must be more than 50% U.S. owned and have fewer than 500 employees.[13] Yet there remains variation in terms of research capacity among eligible firms. Notably, the distribution of awards over time indicates that certain firms have secured a disproportionate number of awards. In fact, the program has been criticized for the continued support of "mills"—firms that seem to receive an inordinate number of awards owing to a special relationship with a government agency or a particular skill in grant writing (Lerner, 1999). In this analysis, three firms account for 18% of the SBIR activity,[14] while 67% of the firms secured three or fewer Phase I awards.[15] We stratify by prior SBIR Phase I activity—specifically the number of prior Phase I awards—to account for this variation in the firm's research capacity.[16]

B. *Identification*

The validity of this design is predicated on specific concerns: (a) identifying a region with a sample of treated and control Phase I projects that are comparable except for exposure to the treatment of receiving state matching funds, (b) ensuring administration of the State Match is noncompetitive, and (c) illustrating that firms do not alter activity—most notably relocation.

Identification: Independence. We assess the strength of this design with a means comparison test for a series of firm-level characteristics: woman owned, HUBZone (historically underutilized business zones), minority owned, year established, employment, and count of prior SBIR

[11] Kentucky's program also provides funds for Phase II recipients. We did not consider this, however.

[12] Indiana's State Match program is the 21Fund.

[13] Additional criteria apply for HHS applicants (https://www.sbir.gov/about/about-sbir).

[14] Luna Innovations, Nanosonic Inc., and Barron Associates.

[15] SBIR activity for 800 firms is included in the sample. Three hundred sixty-six firms secured only one Phase I award, 138 firms secured two, and 64 firms secured three Phase I awards.

[16] We utilize three stratifications: excluding firms with more than five, three, and one prior Phase I awards. We considered stratifying by other firm characteristics, including firm age and number of employees, but we argue that this lagged SBIR performance is the strongest innovation measure.

Phase I activity. We also include a regional measure of the total number of SBIR Phase I awards (CBSA level). Table B.2 in Appendix B reports the means for the treated and control population of firms with SBIR Phase I projects for the full sample of six states. We stratify the data by funding agency and prior Phase I success. We report for the full program in addition to the science-based mission agencies (HHS and NSF) given the concentration of activity in this region for these agencies.

Results from a series of *t*-tests on the full sample indicate that the populations of small businesses in the treated and control groups are comparable for some measures—woman owned, HUBZone, and minority owned; however, they differ for others—firm age, employment, SBIR Phase I awards (CBSA level), and prior Phase I awards. Specifically, the treated firms are younger, smaller, and located in geographic proximity to firms with higher rates of Phase I success. However, when we stratify the results by mission agency and prior Phase I success, the variation lessens (appendix B, Table B.2: row B, columns II and III). Regarding firm age, the treated group's relatively younger age would likely bias the policy effect toward 0 given that these firms have less experience at securing external funding (Kortum & Lerner, 2000). Regarding the regional SBIR measure, firms in the treated region tend to be in geographies with greater demonstrated capacity of securing SBIR awards, so they may benefit from spillover effects (Audretsch & Feldman, 2004). This may introduce bias into the design, so it is necessary to include these measures as controls in the empirical analysis.

Identification: Administration of State Match. The noncompetitive structure of the State Match is a useful feature for the empirical design; this lessens concerns about selection bias of match recipients made by North Carolina and Kentucky. Eligibility for the additional state funding is contingent on receipt of the Phase I award and location of the firm; however, intention to apply for the Phase II award also applies. Both states rely on the federal SBIR Phase I merit-based competition to identify the eligible population. In addition, given that the match is a ratio of the Phase I award, the match amount is determined a priori by the federal program. Theoretically, this allows for a strong research design; however, implementation of the program is subject to the availability of limited funds and administration constraints (Pressman & Wildavsky, 1984).

To examine the extent of selection bias introduced by the implementation of the State Match, we compared the means for the same list of characteristics as reported in table B.2 for the set of eligible firms that either received the match or did not.[17] Row A, column I in table B.3 (appendix B) presents the results from the comparison of means for the full sample of treated and untreated eligible firms. On average, firms with fewer employees and less prior success with the SBIR program received the State Match, suggesting that the treated group was in a less favorable position to compete for R&D funding than the eligible yet untreated group.

To better understand the state administrative differences, we also stratify by state for the full sample (row A, columns II and III in table B.3). For North Carolina, prior SBIR success is no longer statistically different, yet slightly smaller firms tend to receive the match. For Kentucky, the two eligible groups differ based on prior SBIR activity—where those with less prior success or in geographies with less SBIR success tend to receive the State Match. This evidence suggests that the administration of the match program is not as truly noncompetitive as intended. Upon further analysis, however, we find that the differences are driven by a handful of firm outliers (see row B, table B.3). Under this stratification, the two samples are comparable. It appears as though a few outlying firms ("mills") were driving the mean differences for the full sample. This offers evidence that the program awards noncompetitive matches.

Identification: Firm behavior. Given the opportunity for additional nondilutive funding, theoretically the State Match may serve as an incentive for firms to relocate to North Carolina or Kentucky. Kentucky's program, in fact, explicitly invites firms to relocate to the state.[18] Despite this, however, we suspect the match award is not large enough to offset the costs incurred with relocation. To analyze this behavior, we examined relocation patterns across state borders by drawing on geographic data available from the National Establishment Time Series (NETS) and SBIR databases.

Drawing on firm-level geographic data from NETS, there is evidence of relatively little relocation across state borders. Twelve firms (1.5%) moved into North Carolina or Kentucky; 10 firms (1.43%) moved out of North Carolina or Kentucky, and 23 firms (3%) moved either into or out of the four control states. In terms of timing, relocation into the treated states occurred, on average, in 2003—before either North Carolina or Kentucky adopted the program.[19] We compared these trends to moving patterns derived from SBIR data as a robustness check and found similar evidence.[20] Within the time frame, it does not appear as though firms relocated in response to the match incentives. It is worth noting that we examine the State Match right after inception. As the results of the program are realized and publicized, firm behavior may change accordingly.

[17] We posit the following for a nonmatch: (a) insufficient funding; (b) a firm may receive multiple Phase I awards in a given year (exceeding one match per year limit); (c) the firm may be unaware of the State Match; or (d) the firm may opt not to apply for the larger Phase II funding.

[18] http://ksef.kstc.com/index.php?option=com_content&view=article&id=113&Itemid=205.

[19] Contrary to our expectations, the timing of the move from the treated states occurred, on average, in 2006. The timing of the move from control states occurred, on average, in 2004.

[20] When looking at discrepancies between state addresses with these data, 2.5% moved either into or out of the treated states, and another 2.5% relocated among the control states.

IV. Methods

This paper first considers the SBIR activity for all Phase I recipients from the treated and control states by employing a difference-in-difference (DD) research design. A DD approach serves as one of the more robust interrupted times-series designs because it employs a pre- and post-policy comparison group design (Murray & Stern, 2007; Furman & Stern, 2011). Equation (1) is a project-level model estimating the effect of the State Match on Phase II success rates:

$$\Pr(Phase\,II_i) = \beta_0 + \delta_0 Post_t + \beta_1 Treat_i + \delta_1 Post_t \times Treat_i + \beta_k Controls + \varepsilon_i. \tag{1}$$

Phase II_i is the binary outcome variable of interest, and i denotes the SBIR Phase I project. The intercept, β_0, is the average value of the Phase II success rates for states without the policy; $Post_t$ is coded 1 for years the treated state has the program and 0 otherwise. SBIR Phase I projects in 2006 were dropped to ensure a clear cutoff between the pre- and postperiods. The four-year periods from 2002 to 2005 and 2007 to 2010 denote the pre- and postperiods, respectively. The parameter δ_0 captures the change in all Phase II success rates over the specified time frame, and t denotes the year. The coefficient for $Treat_i$, β_1, measures the state effect not due to the policy. $Treat_i$ equals unity for projects from firms located in those states that ever had the policy (North Carolina and Kentucky), and 0 otherwise. The parameter of interest is the interaction term $Post_t \times Treat_i$; δ_1 measures the change in Phase II success rates due to the State Match.

The set of firm-level measures in addition to the regional measure reported in table C.2 (appendix C) are included as controls. Drawing from section IIIB on independence, the results from the comparison means tests of firm-level characteristics between the treated and control regions note some discrepancies between the groups. SBIR firms in the treated states, on average, are younger and smaller; however, the firms are located in geographies with greater SBIR activity, both features that may bias the results. Considerable research has found that innovative capacity is contingent on firm characteristics that include firm age and size (e.g., Fort et al., 2013; Haltiwanger, Jarmin, & Miranda, 2013; Cohen & Klepper, 1996; Sorensen & Stuart, 2000; Stuart, Hoang, & Hybels, 1999). We include measures of age and employment to account for firm maturity and capacity. Moreover, we include a measure of the concentration of Phase I awards in the immediate geography to account for potential regional spillovers (Audretsch & Feldman, 1996, 2004; Griliches, 1998). Spatial benefits that range from increased levels of supply, proximity, pooling of demands for specialized labor, reduced transportation costs, and knowledge spillovers explain why certain localities demonstrate heightened levels of innovative output and economic success. Finally, while the SBIR program purports that award decisions are based solely on scientific and technical merit and commercial promise, it is notable that Congress specified "increased participation among women and minorities" as one of the program's official objectives (Wessner, 2008). Thus, we include measures of firm diversity.

Equation (2) presents a project-level model estimating the marginal impact of the size of the State Match on securing the Phase II award. This model narrows the sample to State Match recipients:

$$\Pr(Phase\,II_i) = \beta_0 + \beta_1 State\,Match\,Size_i + \beta_k Controls + \varepsilon_i. \tag{2}$$

Phase II_i is the binary outcome variable of interest, and i denotes the SBIR Phase I project. The policy variable of interest, *State Match* $Size_i$, is a continuous, deflated measure indicating the size of the public award. The same set of controls used for the differential analysis is included.

A. Data

The data are structured at the SBIR Phase I project level. This paper considers activity for the population of SBIR Phase I recipients located in a contiguous region: Arkansas, Kentucky, Missouri, North Carolina, South Carolina, and Virginia (excluding Northern Virginia).[21] To control for potential fluctuations in the federal SBIR program, the time frame is limited to the most recent federal SBIR reauthorization window: 2002 to 2010. Detailed project-level federal SBIR activity was drawn from the SBA's publicly accessible central repository of SBIR awards. Where applicable, data on the state match award and subsequent Phase II award are matched to the Phase I project. The SBIR program does not link Phase I and Phase II activity with a unique identifier, so we matched both sources of follow-on funding based on a number of project characteristics, including project title, principal investigator, firm name, award date, SBIR agency, and abstract. We also drew from Dun & Bradstreet (D&B) to identify the DUNS ID for the sample of firms to then match to NETS for additional firm-level characteristics. Appendix C provides more detail on the match procedure, data set, and sources.

The Kentucky Science and Technology Corporation provided comprehensive project level award data for Kentucky's State Match. Although the state legislation was passed in 2006, the funding was not made available until 2007. Awards ranged from \$70,000 to \$150,000, averaging \$99,000. North Carolina's Department of Commerce provided comprehensive project-level data for the One North Carolina Small Business Program. The first match awards were made in 2006. Awards ranged from \$30,000 to \$100,000, with an average of \$74,000.

For both the differential and marginal models, we use the binary indicator, *Phase II*, as the dependent variable; this

[21] Source: http://www.novaregion.org/index.aspx?nid=233.

Table 1.—Descriptive Statistics of Indicators for Empirical Models

Variable Label	Mean	SD	Minimum	Maximum
Phase II	0.455	0.498	0	1
Preperiod (2002–2005)	0.479	0.499	0	1
Postperiod (2007–2010)	0.442	0.497	0	1
DD analysis: Policy variable				
Post	0.527	0.499	0	1
Treat	0.316	0.465	0	1
State Match	0.166	0.372	0	1
Marginal analysis: Policy variable				
State Match size (in $10,000s)	7.208	2.369	2.636	13.459
Controls				
Woman owned	0.071	0.256	0	1
HUBZone	0.023	0.149	0	1
Minority owned	0.039	0.194	0	1
SBIR Phase I activity (CBSA)	20.276	11.692	0	44
Year Established	1,996.48	9.295	1,817	2011
Employment	22.185	30.789	1	400

Unless otherwise noted, the number of observations is 2,422 with pre- and postperiods having 1,030 and 1,147 observations, respectively. *Year Established* and *Employment* are 2,346 and 2,036, respectively. The policy variables for the differential analysis exclude 2006, so the number of observations is 2,177. The marginal analysis considers SBIR-related activity only for the sample of Phase I projects that received the state match award (224 total).

indicates that a project advanced. We consider how the state policy increases the likelihood of securing an award rather than the size of the Phase II award given that the SBA sets the size of the Phase II award a priori through federal authorizations. Table 1 provides the descriptive statistics for the full sample of project-level activity under consideration.

On average, the probability of securing a Phase II award is 46%. However, the success rate was higher in the preperiod (48%) compared to the postperiod (44%). This indicates a net decrease in Phase II award activity for the contiguous region. Table A.2 in appendix A details the match rate by state in both periods and reports similar downward trends by state.[22] It is important to note that while the State Match was established prior to the great recession, the policy activity, extending from 2007 to 2010, overlaps with this macroeconomic event that spanned December 2007 to June 2009. Evidence from U.S. SBIR award activity indicates a drop of roughly 13.1 percentage points in Phase II activity in 2007 in contrast to average trends from 2002 to 2006.[23] It was only in 2010 that the national SBIR activity recovered by exceeding the prerecession trends.

Turning to the firm-level characteristics, among the 800 firms in the sample roughly, 12% of the firms are woman owned, minority owned, or located in a HUBZone. The average founding year is 1996, making the average firm 9.7 years old. The average number of employees is 22, and the average number of Phase I awards in the local geography is 20. Appendix B, section B.1, provides additional detail on the industrial distribution. Notably, the majority of firms (58.2%) fall in the professional, scientific, and technical services classification. Within this broad classification, the majority classify as scientific R&D services (28%). Another quarter of the sample classifies within manufacturing.

V. Results

For all models, we cluster the standard errors at the firm level to address issues of autocorrelation given that firms are not precluded from securing multiple SBIR awards. We stratify the data two ways to account for variation in the population: (a) by federal mission agency and (b) by firm research capacity. We derived the latter by considering the number of prior Phase I awards dating back to 2000.[24]

A. DD Results

Table 2 presents the empirical results for the DD model for the sample of Phase I projects for the entire region of interest. We report only those results where we find a statistically significant effect for the State Match.[25] Model 1 in table 2 reports the linear probability model (LPM) estimates for equation (1) for the full sample of NSF Phase I projects; the result for the policy variable is positive and weakly significant. We find evidence that in contrast to projects in states without the match, the State Match increases the probability of securing a Phase II award by 29.4%. In models 2 to 4, the sample is stratified by mission agency and by prior Phase I activity. Model 2 reports the results for HHS participants from firms with five or fewer prior Phase I awards; the result is positive and statistically significant, estimating a differential increase of 24.8%. Model 3 reports for HHS participants with a more restricted sample: three or fewer prior awards; the result is positive and weakly significant (24.7%). Model 4 reports for the full sample of NSF participants with one or no prior Phase I award; the result is positive and statistically significant.

While these effects are positive, it is important to contextualize the results. The coefficient for *Post* is robust, negative, and similar in magnitude to the State Match estimate.

[22] South Carolina is the exception; however, this accounts for only 6.5% of the total project-year sample.

[23] Derived from SBIR Phase II award data from 2002 to 2010. (https://www.sbir.gov/.)

[24] This refers to the cumulative number of Phase I projects up through the prior calendar year. We pulled SBIR activity starting in 2000 to capture prior activity and address censoring.

[25] Results for the full set of stratifications are available on request.

Table 2.—Differential Model: Impact of SBIR State Match on Likelihood of Receiving Phase II Grant, Equation (1)

Variables	(1) Phase II	(2) Phase II	(3) Phase II	(4) Phase II
Post	−0.291***	−0.275***	−0.280***	−0.488***
	(0.074)	(0.083)	(0.097)	(0.161)
Treat	−0.137	−0.100	−0.112	−0.258
	(0.125)	(0.081)	(0.093)	(0.172)
State Match	0.294*	0.248**	0.247*	0.536**
	(0.152)	(0.112)	(0.128)	(0.223)
Woman owned	0.017	0.017	−0.017	−0.177
	(0.116)	(0.084)	(0.103)	(0.203)
HUBZone	0.079	0.209	0.185	−0.067
	(0.242)	(0.145)	(0.153)	(0.226)
Minority owned	0.620***	0.099	0.127	0.691***
	(0.083)	(0.114)	(0.112)	(0.175)
SBIR Phase I activity (CBSA)	0.006*	0.001	0.001	0.008**
	(0.003)	(0.003)	(0.003)	(0.004)
Year established	0.008	−0.002	−0.002	0.019
	(0.007)	(0.003)	(0.004)	(0.016)
Employment	−0.000	−0.001	−0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.004)
Constant	−15.756	4.787	4.317	−36.831
	(13.662)	(6.878)	(7.069)	(31.137)
Observations	162	311	263	88
R^2	0.098	0.048	0.047	0.159
Sample	NSF full	HHS 5 prior	HHS 3 prior	NSF 1 prior

Regression type: OLS LPM; key explanatory variable: SBIR State Match (binary); dependent variable: receipt of SBIR Phase II grant conditional on having won Phase I grant. Data include the population of Phase I activity for the entire region (Kentucky, Arkansas, Missouri, North Carolina, South Carolina, and Virginia (excluding northern Virginia) from 2002 to 2010. Phase I activity for 2006 was dropped from the analysis, allowing for a clear cutoff between the pre- and postpolicy period. Standard errors are in parentheses and are clustered at the firm level (*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$). Model 1 includes the full sample of NSF Phase I recipients. Models 2 and 3 report the coefficients for HHS Phase I projects for firms with five or fewer prior Phase I awards and three or fewer prior Phase I awards, respectively. Model 4 reports the coefficients for NSF Phase I projects for firms with one or no prior Phase I awards. Complete case analysis is used.

The results from a year-by-year trend of Phase II award activity for the treated and control groups illustrate a downward trend; however, the former is flatter, which yields the positive effect (refer to table A.2). This indicates that the State Match effectively stabilized Phase II trends during the recession in contrast to neighboring states that experienced greater declines.

B. *Marginal Results*

In assessing the marginal effect, we include only projects that received a state match (2006–2010) and estimate the effect of increasing the match in \$10,000 increments. Table 3 presents the LPM estimates for equation (2). Model 1 reports the LPM coefficients for the full sample of projects with a State Match award to serve as a baseline. The same stratification techniques used for the DD model are used for this analysis. The State Match is positive and statistically significant when the sample is stratified by prior Phase I activity—specifically from nine or fewer to three or fewer prior Phase I awards (the marginal effects ranged from 2.9% to 3.8%). We report results for nine, five, and three or fewer to demonstrate the trend. We do not find a statistically significant effect when stratifying by mission agency; however, this is likely due to the small sample size. Figure D.1 in appendix D presents the plots of the adjusted predictions with confidence intervals.

Table 3.—Marginal Model: Impact of SBIR State Match Size on Likelihood of Receiving Phase II, Equation (2)

Variables	(1) Phase II	(2) Phase II	(3) Phase II	(4) Phase II
State Match Size, adjusted (in \$10,000)	0.016	0.029*	0.038**	0.032*
	(0.016)	(0.017)	(0.018)	(0.019)
Woman owned	−0.010	−0.166	−0.166	−0.175
	(0.142)	(0.109)	(0.110)	(0.119)
HUBZone	0.077	0.083	0.110	0.366
	(0.178)	(0.176)	(0.173)	(0.223)
Minority owned	−0.295**	−0.331***	−0.331***	−0.265**
	(0.128)	(0.115)	(0.113)	(0.131)
SBIR Phase I activity (CBSA)	0.000	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Year established	0.001	−0.003	−0.003	−0.003
	(0.007)	(0.009)	(0.009)	(0.009)
Employment	0.001	−0.000	−0.000	0.002
	(0.003)	(0.003)	(0.004)	(0.003)
Constant	−2.504	5.331	7.194	6.541
	(14.457)	(17.378)	(17.901)	(18.840)
Observations	182	163	152	136
R^2	0.018	0.041	0.055	0.058
Sample	Full	Nine prior	Five Prior	Three prior

Regression type: OLS LPM. Key explanatory variable: SBIR State Match grant size (continuous). Dependent variable: receipt of SBIR Phase II grant conditional on having won Phase I grant and having received the State Match. Data include the population of Phase I activity for the projects that received a State Match award. Standard errors are in parentheses and are clustered at the firm level (*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$). Model 1 includes the full sample of Phase I projects that received a State Match (baseline). Models 2 to 4 stratify the sample by the level of the firm's prior Phase I awards: nine or fewer, five or fewer, and three or fewer, respectively. Complete case analysis is used.

C. *Robustness Checks*

As robustness checks, we also ran logit models for the differential[26] and marginal analyses.[27] Paying particular attention to the coefficient for the policy variable, tables D.1 and D.2 (appendix D, section D.1) report the marginal effects for the State Match for both sets of estimations, respectively. The results for the differential model from table D.1 indicate that the coefficients are robust across all models. Moreover, we compared the average marginal effect for the State Match estimated from the logit models to the State Match coefficient for the OLS LPM models. The average difference in the marginal effects for the differential analysis between the two estimation procedures for models 1 to 3 was less than 3 percentage points. For the marginal analysis, the coefficients presented in table D.2 for the State Match size are robust, and the difference in marginal effects is negligible. In addition, out-of-range predictions are not a concern for this model (refer to tables D.1 and D.2, row D).

[26] Equation (3) is a project-level model. X includes the vector of controls listed in table C.2 and the policy variables listed for the differential analysis, equation (1):

$$\frac{\partial prob(y|x)}{\partial x_j} = \hat{\beta}_j f\left(X\hat{\beta}\right). \tag{3}$$

[27] Equation (4) is a project-level model. X includes the vector of controls listed in table C.2, and the policy variable listed for the marginal analysis, equation (2). *State Match Size* is adjusted:

$$\frac{\partial prob(y|x)}{\partial x_j} = \hat{\beta}_j f\left(X\hat{\beta}\right). \tag{4}$$

Given that the treatment effect is derived from a state policy, we also ran the DD model, equation (1) using the wild cluster bootstrap procedure (Cameron, Gelbach, & Miller, 2008). This is presented in row E of table D.1. This approach estimates more conservative standard errors when the number of clusters in a sample is relatively small. The direction of the coefficient is consistent with the main findings across the stratifications; however, the statistical significance is not fully robust. Hence, we interpret these results with caution given that we are estimating the model with six state clusters. Results from Cameron et al.'s (2008) Monte Carlo estimations indicate that this method performs well with as few as six clusters.

As added robustness checks, we also estimated the effect using a triple difference (DDD) method (Davidoff, Blumberg, & Nichols, 2008) and propensity score matching (PSM) procedures (Morgan & Winship, 2014).[28] For the DDD, we ran two sets of models: (a) interacting the policy effect with an additional binary variable indicating previous SBIR Phase I activity of the firm and then stratifying by mission agency and (b) interacting the policy effect with an additional binary variable indicating the mission agency and then stratifying by previous Phase I activity. The results are robust and reflect the findings from the DD model. For the PSM procedure, we drew on the set of firm-level covariates listed in table 1 and ran the model using a variety of matching procedures; this included common nearest neighbor, LLR, and kernel matching techniques. The average treatment effects on the treated for the State Match are consistent with the results from the primary model but not robustly efficient. This is likely due to the size of the control group and nonexhaustive set of observables for the set of private firms.

D. Sensitivity Analysis

As noted, data for this analysis were gathered from the central repository of SBIR awards, the two state agencies with the State Match, and NETS. Appendix C details the match procedure. The former two sources are public and comprehensive; however, NETS is less complete. While it is rich in firm-level detail, approximately 15% of the sample was missing. Complete case analysis was used to estimate equations (1) and (2) reported in tables 2 and 3, respectively. As sensitivity measures, we reran the differential and marginal models employing three additional estimation procedures to address issues of missing data: dummy variable adjustment, mean imputation, and a simplified, underspecified model. Section D.2 in appendix D presents the imputation techniques, and table D.3 reports the descriptive statistics for the procedures.

The results for the coefficients on the State Match for the differential and marginal analyses are presented in tables D.4 and D.5 in appendix D, respectively. The direction and significance of the results are robust across all models. It is worth noting, however, that the size of the coefficients for the State Match is slightly larger for the differential analysis (equation [1]). This suggests that the complete case analysis technique may overestimate the size of the effect.

E. Additional Results

We report the results where we find a statistically significant effect; however, we ran the models with additional stratifications, including DOD SBIR activity. Although DOD projects account for a larger portion of the SBIR activity compared to NSF and HHS, the results are not robust. They are noisy with both positive and negative beta coefficients; however, the absolute value does not exceed the size of the marginal effect for the statistically significant results. Given the nature by which the DOD SBIR program operates—by awarding contracts and internally reviewing proposals—we are hesitant to draw comparisons with NSF and HHS stratifications.

The results for the binary indicator—minority owned—are relatively large and statistically significant. However, the direction of the coefficients flips for the differential and marginal analyses. We attribute these results to noise given the limited variation (3.9%).

F. Cohort Study

We also consider the North Carolina region and Kentucky region separately in case the variation in the size of the match between the two programs has an important effect. The full results are presented in appendix D, section D.3. The population of Phase I projects located in North Carolina, South Carolina, and Virginia (excluding northern Virginia) comprise the North Carolina–based study. We included Phase I projects in 2006, coding them in the post-period. The effect of the match is statistically significant and positive among the subsample of projects with less research capacity (refer to tables D.7 to D.10). Moreover, this effect holds for HHS projects with less prior experience.

The population of Phase I projects located in Kentucky, Arkansas, and Missouri comprise the former region. We included Phase I projects in 2006, coding them in the prepolicy period. While the coefficients were consistently positive, they were not statistically different from 0 for the primary model. The small sample size is likely a concern for this cohort. It is worth noting, however, that there is a positive and significant effect for NSF projects with limited prior SBIR experience when running the simplified, underspecified model (refer to tables D.6 and D.11).

VI. Discussion

This paper traces SBIR activity for the population of Phase I projects within a contiguous region to assess both the differential and marginal effects of the State Match. The

[28] The results for DDD and PSM are available from the authors on request.

results show that the State Match is somewhat effective in advancing innovative ideas toward development and commercialization. The effect of the State Match on securing a larger Phase II award varies according to funding agency and prior Phase I success. Results from the differential analysis indicate that the State Match has an overall effect for projects competing in the NSF program. These results align with earlier work that employed a more comprehensive, albeit state-level, assessment of the State Match (Lanahan, 2016). With a national average success rate of 21.2% for the NSF Phase II applicants, a back-of-the-envelope calculation suggests that the State Match increases the success rate to 27.4%. While this does not account for the size of the match, the results indicate that the State Match increases the chances of securing an additional $1 million by roughly 6.2 percentage points. When the sample is stratified by research capacity, results indicate that the program is effective specifically for HHS and NSF Phase I recipients. In other words, the matching funds differentially benefit science-based projects whose firms have less prior success with the SBIR program. We might explain this finding by considering differences in research practices and financial demands across industries (Gagnon & Lexchin, 2008; Graham et al., 2010). The State Match is sufficient to assist science- and health-based projects to competitively differentiate, but insufficient for projects in more downstream, applied fields. Moreover, when considering the greater context, the total effect for states with the match was effectively constant across the time frame of interest. Although the State Match was established before the recent economic recession, the policy activity lessened the economic consequences. Contiguous states without the match experienced greater declines.

When considering the marginal effect of the program, we find evidence that the size of the match affects the probability of securing a Phase II award, though the results show that the state Match Size affects only projects with less research capacity. It appears as though more funding is worth more when invested in projects from firms with less success with the SBIR program. This is not surprising if we understand prior SBIR activity as a proxy for firms' funding reserves: firms with greater levels of prior SBIR success likely have a larger research budget, while firms with less success in the program likely have fewer resources. If we then consider the State Match award as a proportion of the firms' overall research budgets, it would constitute a larger proportion of the research budgets for firms with less prior SBIR experience and a smaller proportion for those with greater prior SBIR experience. For the former, the award would offer more slack resources, theoretically enabling greater flexibility for developing the project. As for the latter, the award would increase a firm's overall research budget by a smaller proportional amount and would thus be less likely to yield a differential effect.

In sum, these findings indicate that the impact of an additional dollar is not consistent across the entire population of projects, and rather varies by research focus and capacity. While we are hesitant to interpret the lack of a policy effect for the entire sample, it is striking to note how the program's effect seems to be limited in specific ways. The nature of innovative research requires substantial investment. The lack of a consistent effect across all of the various stratifications indicates that the size of the State Match is not enough for many of the projects to differentiate themselves as they progress toward the development stage.

While State Match programs are designed to support early-stage innovation, identifying the precise mechanisms by which they contribute presents an added challenge. Assuming that Phase I recipients move on to compete for the Phase II award, the state funds may advance a project by enabling improvements in technical or scientific aspects, or the funds may simply enable improvements in the principal investigator's grant-writing skills. Both of these would improve the competitiveness of a Phase II proposal, but the former more directly meets the objectives of the program: advancing early-stage innovation.

As one effort to understand this mechanism, we examined the time lag from Phase I to Phase II for the projects that received the State Match in contrast to the set of control projects awarded at the same time. If the State Match is used to aid in the technical aspects of the projects (in contrast to merely improving the PI's grant writing), we suspect that the additional funds may be used to increase the incubation period of the project before competing for the larger Phase II funding. The results from a comparison of means test indicate that treated projects that move on to secure the Phase II take longer than those without the State Match: 1.53 years compared to 1.36 years, respectively. This offers preliminary evidence to suggest that the funds are used to extend the initial phase to increase the follow-on proposal's competitiveness.

In another effort, we drew on the results of a survey of the North Carolina State Match recipients. In 2012, John Hardin, executive director for the North Carolina Board of Science, Technology and Innovation, administered the survey to the population of NC SBIR State Match recipients to gauge the efficacy of the program's administration and impact of the funds (82% response rate). Hardin, Lanahan, and Brun (2015) detail the results of the survey and found that flexibility of the program offered a competitive advantage. Specifically, in contrast to the federal SBIR program, these funds could cover legal fees related to intellectual property. Taken together, these results indicate that the funds aided in technical aspects at this early yet critical stage.

A. Other Considerations

The State Match can be understood as both an attempt to help local firms secure the larger Phase II awards and a direct investment in the state's innovative capacity. The Phase II award serves as the most immediate intended outcome and is at the project level. Nevertheless, state governments establish the State Match with specific economic outcomes in mind, notably jobs as manifested by increased employment. This is also tied to firm survival. Research finds such dual advantages associated with investments in innovation (Hsu & Ziedonis, 2013), so it is worth considering these alternative outcomes at the firm level.

We considered two different outcome measures: employment change and firm survival (appendix D, section D.4). Drawing on NETS employment data, we estimated employment change based on annual firm employment for the years associated with receiving the Phase I and II awards (section D.4.1). We ran the models with *Employment Change* as the outcome, applying the same methods we used for the Phase II outcome. The results were not robust for this outcome measure. We are hesitant to conclude that the State Match has no effect on employment change. Instead, we attribute this finding to the quality of the available employment data. The NETS database relies on self-reported data, updated every three years. These data are useful as a proxy for firm size; however, this presents empirical problems when computing employment change over time, especially over one or two calendar years.

Second, we considered firm survival as an outcome. Numerous respondents to the 2012 North Carolina firm survey indicated that the State Match funds ensured firm survival during the tenuous early stages of research when financing is scarce. To substantiate this observation, we relied on the completeness of D&B and NETS data to estimate firm survival (appendix D, section D.4.2). We estimate firm survival in two ways: if the SBIR Phase I firm recipient was successfully matched to D&B or NETS. Table D.12 provides firm-level descriptive statistics of these proxies and offers preliminary evidence to suggest that the State Match improves the rates of firm survival. The measures of firm survival in the treated region in the postperiod exceed the other measures of the postperiod and control region, respectively. In addition, results from a series of comparison of means between the pre- and postperiods and between the treated and control regions support this claim.[29] The effect between the pre- and postperiods was most pronounced with a positive difference of 15.2 percentage points. Estimating the effect of the State Match on firm survival by drawing on firm-level data to estimate equation (1), however, did not yield robust results. These results suggest that the postperiod, which coincides with the recession, is in fact driving the effect. We interpret these results with caution. The null results may be indicative of measurement error. While it is plausible that the State Match is insufficient to ensure firm survival, we do not conclude this and suggest that this is a topic for further research.

[29] The difference in means between the pre- and postperiod is statistically different from 0 with a mean difference of 0.152 (p-value < 0.000). The difference in means between the treated and control regions is weakly significant with a mean difference of 0.042 (p-value $= 0.0553$).

The range of potential outcomes extends to include follow-on funding and innovative outputs. The scholarship on innovative outputs finds compelling evidence that more resources increase patent activity (e.g., Furman, Porter, & Stern, 2002); thus we anticipate similar results for these projects over a longer time horizon. We have less understanding, however, of the relationship between state funding and follow-on venture capital activity. While previous studies have debated whether public funding crowds in or crowds out private funding (e.g., Blume-Kohout et al., 2009; Payne & Siow, 2003; Payne, 2001; David et al., 2000; Diamond, 1999), this literature overlooks the more complex portfolio of funding sources that differentiate public financing. Future research could study whether additional public funding complements or substitutes private financing. While examining longer-term firm outcomes is warranted, this comes with less empirical precision. Focusing on Phase II funding as the outcome allows for a direct, project level analysis.

VII. Conclusions and Policy Recommendations

The federal SBIR program aims to foster innovation by investing in small businesses that demonstrate innovative commercial potential. This program has received considerable attention in both the policy and scholarly communities. Much less attention, however, has been paid to the growing role played by complementary state policies. By examining the State Match, this paper advances the scholarship on R&D by moving beyond the common focus from federal policy toward an appreciation of the innovation policy mix (Lanahan & Feldman, 2015).

The contributions of this paper are compelling on two accounts. First, by considering the state policy within the framework of the federal SBIR program, we are able to set up a research design to assess the marginal effect of external public funding on innovative activity; in short, we rely on the noncompetitive nature of the State Match to approximate exogenous variation in the level of funding for innovative projects. If innovation is a crucial source for economic growth, we should want to identify and advocate the institutions and reward structures that are most efficient at creating new technology and scientific knowledge (Diamond, 1999). By assessing the efficacy of an existing reward structure at the level of the individual project—rather than the firm—this paper's research design provides a model for future analysis.

Second, this analysis finds that that the value of state dollars varies across types of projects. Specifically, the state dollar is effective in assisting firms with less prior SBIR success that carry out projects within the broad fields of science and health. This is likely due to differences in the financial demands of research across different industries and in the proportion of the firms' overall research budgets relative to the State Match award. These results offer compelling policy implications: rather than providing an equal amount of state matching funds, states ought to consider allocating funds more strategically. Moreover, building on Brandeis's laboratories of democracy framework, the State Match can be viewed as a policy experiment approximating a marginal increase in the SBIR Phase I award. Given that the effect varies according to broad research field, federal policymakers might consider revamping the SBIR program to take into account the differing financial demands across research focus.

This paper examines the multilevel innovation policy mix by considering the role of the State Match within the framework of the federal SBIR program. SBIR application activity would extend and complement this analysis; however, these data are difficult to obtain. While this paper assumes that Phase I recipients move on to compete for the larger Phase II funding, the path to commercialization for small firm early-stage projects is likely more varied. Howell (2017) draws on the population of DOE SBIR award and application activity and finds that Phase I funding is critical for nonfederal follow-on funding—notably more so than the Phase II award. This suggests that the Phase I award is more valuable to the firm by offering funds for proof-of-concept; however, the entrepreneurs' revealed preferences to the larger Phase II funding indicates surprisingly low benefits in moving toward commercialization. Taken together, Howell's work and this analysis suggest that there is likely a more complicated relationship between public R&D, innovation, and commercialization. Access to the full set of SBIR applications, in addition to State Match award data, would offer more complete information regarding firm behavioral responses to multilevel public R&D efforts.

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