Evaluating Government R&D Grants to Startups: The Case of a Small Open Economy

Annamaria Conti[1,2]

Abstract

Government R&D grants are widespread policy instruments to ease startups' liquidity constraints. These grants generate spillovers that are appropriable by foreign agents. Small open economies are the most concerned and often impose restrictions on the offshoring of government-funded output, increasing foreign investors' opportunity costs. Examining Israeli startups, I find that these restrictions act as screening mechanisms inducing startups to reveal their characteristics. *Ex-ante*, startups with a high probability of being acquired by foreign companies are deterred from applying for grants. *Ex-post*, grant funds positively affect the probability that their recipients experience a successful exit but not the probability that foreign companies acquire them. Finally, grant recipients receive follow-on financing but not foreign venture capital.

1. Introduction

Access to capital is a well-known problem for technology startups, and government R&D grants are commonly used to ease startups' liquidity constraints (Evans and Jovanovic, 1989). The challenge for governments is to ensure that their limited resources are allocated to startups that best conform to their goals. One possibility is to design *ad hoc* screening mechanisms that prompt only certain startup types to apply for government support (Atkinson and Stiglitz, 1976). In this paper, I examine the design of grant incentives for startups with a specific focus on small open economies[3]. In the case of these economies, the problem is that the effects of government interventions are likely to be appropriated by foreign economic agents and diverted from domestic objectives, such as employment and growth. The reason is that startups have an incentive to reach larger markets, often by seeking foreign investors and acquirers. Governments in small open economies are well aware of this problem and many of them have implemented restrictions on the

[1] Annamaria Conti, Scheller College of Business, Georgia Institute of Technology.
E-mail: annamaria.conti@scheller.gatech.edu.

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[3] I consider a small open economy an economy that participates in international trade, but is small enough compared to its trading partners that it cannot affect world prices.

overseas transfer of government-funded projects and their results. These measures increase the opportunity costs for foreign investors by imposing constraints on their decisions regarding the optimal allocation of their investments.

One possible outcome of the aforementioned restrictions is a screening separating equilibrium in which, *ex-ante*, only startups with a low probability of attracting foreign investors and acquirers apply for government support. *Ex-post*, government grants could have a positive impact on the likelihood that their recipients attract external funds and experience a successful exit. However, foreign investment or acquisitions by foreign companies should not be affected, given the grant applicants' characteristics. Because setting an optimal screening mechanism is a difficult task, other outcomes are also possible. For instance, it may be that attracting foreign investors is correlated with the quality of a startup's project, and thus government regulations encourage only those startups with low quality projects to apply.

For the analysis, I use a novel dataset of 1,639 Israeli startups that had an exit event (IPO, acquisition, or having ceased operations) during 1991-2014. This empirical context is suitable for three main reasons. First, Israel is undoubtedly a small open economy. Second, it has the highest number of per-capita startups in the world[4]. Third, the Israeli government has adopted a variety of programs to support its startups, and many of them have been copied by several other small economies[5]. The program that I examine in this paper consists of R&D grants that are offered by the Israeli Office of the Chief Scientist (OCS) at the Ministry of Industry and Trade. The OCS awards grants for R&D projects to Israeli firms, including startups, which are required to match the amount received by the OCS. Once a company obtains a grant, it commits to pay back the initial amount, usually in the form of royalties (Trajtenberg, 2000). This repayment scheme implies that the grant is *de facto* a loan at a low interest rate, conditional on the success of the project[6] (Lach, 2002). As I detail later in this paper, the OCS envisions severe penalties in case grant

[4] "All together now, what entrepreneurial ecosystems need to flourish," The Economist, January 18th, 2014.
[5] See, for instance, Singapore, New Zealand, South Korea, Taiwan, and Australia.
[6] Grant programs in other countries have adopted a similar repayment scheme. See, for instance, the conditional grants provided by the Ontario government in Canada (http://www.mentorworks.ca/blog/government-funding/ontario-small-business-grants-new-investment-projects), or those awarded by the French Banque Publique d'Investissement (http://www.bpifrance.fr), or those assigned by the New Zealand government (http://www.computerworld.co.nz/article/530544/new_govt_grants_startups_come_clawback_provisions).

recipients transfer overseas their manufacturing activities or the know-how generated from the grant funds.

I find that the decision to apply for a grant is an endogenous one. To address the endogeneity of this decision, I use information available prior to a startup's expected first grant application as a source of exogenous variation in a startup's expected probability of being acquired by a foreign company. The reason is that if startups have rational expectations then the error in the forecast of their probability of being acquired by foreign companies is uncorrelated with information available prior to considering applying for government support. The results show that grant applicants have a low expected probability of being acquired by foreign companies. These findings are corroborated by a placebo test that exploits a change in the OCS policy regarding the overseas transfer of government-funded results.

I next assess the impact of government R&D grants on startup applicants' exits and their ability to raise follow-on financing. I distinguish not only between exit outcomes, but also between investors that are more or less likely to be affected by the government restrictions on the localization of the grant results. In the analysis, I address the endogeneity of a startup's grant funds by estimating an instrumental variable regression model. I thus propose the appointment of a new Chief Scientist as a source of exogenous variation in the availability of grant funds. Strikingly, I find that, conditional on having applied for a grant, a 1% increase in grant funds increases the recipient's probability of a successful exit by about 5%. However, the impact of these funds on the probability that a foreign company acquires a startup is insignificant. Consistently, I also find that recipients of government funds attract follow-on financing but not foreign venture capital.

Taken together, my results confirm the conjecture that government regulations on the offshoring of government-funded projects act as a screening separating mechanism that allows governments to finance startups inclined to operate domestically. The *ex-post* effects of government interventions, however, can vary depending on the availability of domestic capital. In the Israeli case, I find evidence that government funds have a positive impact on the startups' ability to attract follow-on financing and, ultimately, achieve a successful exit.

My paper relates to a growing body of literature concerned with the effects of government R&D grants on firm outcomes. Some of these studies have examined the impact of grants on private R&D spending (Wallsten, 2000; Busom, 2000; Lach, 2002; Almus and Czarnitzki, 2003; Gonzalez, 2005). Other studies have focused on firms' outcomes, such as employment (Lerner, 1999; Wallsten, 2000), sales (Lerner, 1999), commercialization of innovations (Audretsch et al., 2002), capacity of attracting complementary sources of financing (Lerner, 1999; Feldman and Kelley, 2006), and survival (Zhao and Ziedonis, 2012). Relative to the cited studies, this paper is the first to examine government R&D grant regulations as screening mechanisms that prompt companies to reveal their characteristics. It is also the first paper to evaluate the impact of grants while distinguishing between startup outcomes that are more or less affected by government regulations. These analyses were made possible by the unique nature of the dataset that I use. None of the aforementioned works have detailed information about startups that applied and did not apply to government R&D grants.

The paper proceeds as follows. Section 2 details the predictions of how government regulations should affect the selection of grant applicants and of how grants should impact the startups' ability to attract follow-on financing and experience successful exits. Section 3 discusses the empirical context. Section 4 describes the dataset. Section 5 analyzes the impact of the Israeli government R&D grant program on the characteristics of its applicants. Section 6 examines the impact of the grants on startups' exits. Section 7 investigates how R&D grants affect follow-on financing. Section 8 concludes.

2. Screening and government R&D grants

Traditionally, government grants for startups have been viewed as a means of easing the liquidity constraints that these companies face (Greenwald et al., 1984; Evans and Jovanovic, 1989; Hall and Lerner, 2005). However, because government resources are scarce and not all startups can be funded, an adverse selection problem exists whereby startups that do not conform to government objectives have no incentive to reveal their private information. Thus, one challenge that governments face is to implement effective screening mechanisms and consequently assign grants to startups that best comply with their goals.

The problem of adverse selection is particularly acute in the case of small open economies. In fact, because of their small market size, startups located in these economies have an incentive to reach foreign markets, often by seeking foreign investors, including acquirers. Thus, the effects of government interventions risk being appropriated by foreign agents and diverted from domestic objectives, such as employment and growth. A number of governments in small open economies have implemented screening mechanisms to ensure that the returns on their grant interventions are kept domestically[7]. These mechanisms typically increase foreign investors' opportunity costs of investing in grant recipients.

Suppose that startups knew the value they could generate from a given grant and the probability with which this value is transferred overseas and that this information is (at least partially) private to the startups. Moreover, assume that these startup characteristics were independent from one another. Then, a government could design an optimal screening mechanism to induce a Perfect Bayesian Separating Equilibrium whereby only those startups that produce a high domestic value apply for grants. Such a mechanism would encompass application costs to separate low- from high-value startups and an *ex-post* redemption fee in case the grant results are transferred overseas. This last fee would separate startups with a high probability to transfer their grant results overseas from those startups with a low probability to do so.

The Israeli R&D Law can be interpreted in light of a screening model, which would lead to the following three empirical predictions. The first is that the pool of grant applicants consists of startups that have a low expected probability of attracting foreign investors. The second prediction is that a government grant increases the value of a startup, improving the odds that the startup will receive follow-on financing and, ultimately, experience a successful exit. The third prediction is that a government grant does not affect the likelihood that a company receives funding from foreign investors or that foreign companies acquire it due to the composition of the applicant pool.

The reality, however, is more complicated, and it is not *a priori* clear whether the above predictions would be borne by the data. A government may not be able to precisely determine the optimal grant application costs or the redemption fee in the case the grant results are transferred overseas. Moreover, even if the government was able to do so, the characteristics of the contracts that a government offers to startup applicants are typically embodied in laws or regulations.

[7] See, for instance, governments in New Zealand, Australia, South Korea, Singapore, and Brazil. Also, in the US, states like Texas, Utah, and Massachusetts have enacted restrictions on the out-of-state transfer of government-funded projects.

Inevitably, a certain amount of inertia exists in the response of government rules to variations in the characteristics of startups and government preferences. Additionally, the grant value a startup generates and the probability that this value is transferred overseas may not be independent events.

Given the difficulty of implementing an optimal screening policy, it is not clear that governments can induce separating equilibria. For instance, redemption fees, to be paid when grant results are transferred overseas, could affect the quality of grant applicants by increasing their opportunity costs of seeking government support. However, if the opportunity costs of applying for government grants are smaller than the ones associated with alternative financing sources, startups with potentially good projects and also a high probability that the related results are transferred overseas could be observed among the grant applicants.

The expectations regarding the impact of R&D grants on startups' exits are also mixed. For instance, if the startups that can generate a large value from their grants are constrained from applying, then these grants should improve neither the probability that the recipients attract follow-on financing nor the probability that they achieve successful exits. Conversely, if redemption fees are not large relative to the costs of alternative investment options, government grant interventions could improve their recipients' likelihood of attracting follow-on financing, including foreign investment, and achieving successful exits, including acquisitions by foreign companies.

3. Empirical context

Since the end of the 1960's, the Israeli government has implemented a number of policies to sustain industrial R&D. For the purpose of this study, I will follow Trajtenberg (2000, 2005) and identify two related milestones. The first is the creation of the OCS, with the scope of subsidizing R&D projects developed by private Israeli firms, in 1968. The second milestone is the passing, in 1985, of the Law for the Encouragement of Industrial R&D (R&D Law). As stated in Trajtenberg (2000), the goal of this law was to "develop science-based, export-oriented industries, which will promote employment and improve the balance of payment." To achieve these goals, the R&D Law encompasses a system of financial incentives, which are managed by the OCS.

Among these incentives, the largest is the grant funding that the OCS disburses to support Israeli firms' R&D activities. Each year the OCS sets a budget for R&D projects to which companies can apply. In doing so, it adopts a "neutrality approach", in the sense that it does not target any specific sector or technology (Trajtenberg, 2000). Once companies have applied for government support, a research committee, chaired by the Chief Scientist, reviews the grant proposals and decides what percentage of each proposal should be financed. In making its selections, the research committee considers the following criteria: i) the level of a proposed product's inventiveness and uniqueness; ii) market needs and the contribution of a given project to the Israeli economy; and iii) the company's ability to carry out a proposed project. Moreover, grant recipients are required to match government funds with alternative financing. Proposals that could bring substantial improvements to existing products or processes typically receive the largest fraction of the proposed R&D grant budget. In general, startups' projects receive a small share of the total OCS budget relative to established companies. For example, during the period 1995-1999, startups were awarded about 20% of the total grant amount (Trajtenberg, 2000).

Once a company receives a grant, it commits to paying back the initial amount, but the annual payback cannot account for more than a small percentage of the company's sales (Trajtenberg, 2000). This repayment scheme implies that, in the case of successful projects, the grant is, in fact, a loan offered by the OCS at a low interest rate, while in the case of unsuccessful projects, the OCS amount is a grant *sensu stricto*.

Because Israel is a small open economy, one of its government's concerns was that the results produced with OCS grants could be appropriated by economic agents outside of Israel if the grant recipients were to transfer overseas their production and know-how. Hence, the R&D Law established severe penalties for this eventuality. For instance, the Law stipulated an increase in the royalty rate by approximately 1% if the company receiving the grant performs overseas manufacturing. The applied royalty rate could be even higher if that manufacturing is performed by another foreign entity. Additionally, the ceiling on total royalties, which is ordinarily 100% of the grant amount, is augmented proportionally to the share of manufacturing activities transferred abroad.

If a company transfers abroad the know-how generated with grant funds, then the company must repay the greater of the following two options: *i*) the amount equal to the sale price of the know-how, multiplied by the fraction of the total grant amount awarded by the OCS to the total amount disbursed for the OCS-funded research project; *ii*) the total grant amount, plus annual interest, minus the royalty paid. This payment scheme becomes more onerous if the grant recipient transfers the know-how as a part of a foreign acquisition.

4. Data

My sample is made of 1,639 Israeli startups for which I assembled detailed information, using data from the Israel Venture Capital Research Center (IVC). IVC specializes in monitoring Israel's high-tech industry and collects extensive information about the population of Israeli startups. From the IVC dataset, I selected all of the Israeli startups that, as of September 2014, had an exit event, either successful or unsuccessful, and for which information is complete.

The distribution of the 1,639 sample startups across sectors is as follows: 295 operated in communications, 295 in the internet sector, 355 in the IT and software sectors, 128 in the hardware sector, 86 in semiconductors, 106 in cleantech, 177 in life science, and 197 in medical devices. As noted in Conti et al. (2013), this distribution reflects Israel’s comparative advantage in information and communication technologies (ICT).

On average, startups had an exit event 6 years from inception. Regarding the exit outcome, 138 startups went public via an IPO, 561 were acquired, and 940 had ceased to operate. Foreign companies, 85% of which were from the US, acquired a total of 430 Israeli startups. The distribution of foreign acquisitions by sector is: 19% in communications, 16% in internet, 36% in IT and software, 4% in hardware, 10% in semiconductors, 1% in cleantech, 5% in life science, and 9% in medical devices.

The average total amount raised, across all rounds, in constant US dollars, is $11 million. The companies with no external funding have all ceased to operate. 45% of the startups had received funds from foreign investors. Of those startups, US investors financed 79%. Moreover, 770 companies had received venture capital. Of those, 628 companies had received funds from Israeli venture capitalists and 450 from foreign venture capitalists. Foreign companies acquired 53% of the startups that were financed by foreign venture capitalists, while the percentage of foreign acquisitions among startups with only domestic venture capital is 25.

The number of startups that had applied for an OCS grant is 561[8]. The majority of applicants (84%) apply for their first grant within three years of inception. The percentage of applicants in the communication sector is 35, in internet is 13, in IT and software is 37, in hardware is 39, in semiconductors is 51, in cleantech is 32, in life sciences is 44, and in medical devices is 41. 25% of the startups located in the Tel Aviv district had applied for government support, while the percentage in the other districts is 42. Conditional on having applied at least once, 31% of the startups were never awarded a grant. The total number of applications observed in my sample is 2,326 and the percentage of awarded grants is 74. This last percentage is very close to the one observed for the entire population of Israeli applicants. In fact, Trajtenberg (2000) reports that the acceptance rate for OCS grants is about 70%. As the statistics indicate, startups with an initial OCS grant tend to apply for additional grants later on. Conditional upon having received at least one grant, the average amount awarded by the OCS to a startup is about 7.4 million of constant shekels, which is approximately $2 million. The median amount, however, is only 2.7 million of constant shekels (approximately $0.74 million), suggesting that the grant distribution is skewed to the right. Regarding the distribution of grants by sector, 18% of the awarded grants are in communications, 4% in internet, 23% in IT and software, 9% in hardware, 10% in semiconductors, 6% in cleantech, 15% in life science, and 15% in medical devices. This distribution is similar to the one observed for the entire population of Israeli firms, including startups[9].

5. Assessing the characteristics of grant applicants

One of the implications ensuing from a government screening mechanism that is aimed at supporting startups with a high propensity for operating domestically is that only startups with a low expected probability of being acquired by foreign companies apply for grants. Here, I test this implication by estimating the following linear probability model:

$$Apply_{it}=\beta_0+E_{it}(Acquired\ by\ Foreign\ Company_{\ it+1})+\boldsymbol{\beta_2 X_{it}}+\beta_3 LocationFE_i+\beta_4 SectorFE_i+\beta_5 InceptionYearFE_i+\boldsymbol{\beta_6 P_{it}}+\boldsymbol{\beta_7\,\Gamma_{it}}+u_{it} \qquad (1)$$

where $Apply_{it}$ is a dummy variable that equals 1 if a startup i had applied for government support. $E_{it}(Acquired\ by\ Foreign\ Company_{\ it+1})$ is proxied with an indicator variable that equals 1 if a startup

[8] I consider all the grant applications from the moment a company was founded to its exit.

[9] Information can be found at http://www.moital.gov.il/CmsTamat/Rsrc/MadaanEnglish/MadaanEnglish.html.

was *actually* acquired by a foreign company in $t+1$. The vector $\boldsymbol{X_{it}}$ includes a number of predetermined startup and founder characteristics. The time-variant characteristics are measured up until the year following the startup's inception. Because the majority of startups applied for an OCS grant during the first and second year after inception, time-varying regressors measured during the aforementioned interval are predetermined. The subscript t thus refers to the period between a startup's foundation and its expected application year. I control for the amount of external investment (in constant US dollars) that a company had received. I also control for whether a startup had obtained any foreign venture capital and for whether it had received domestic venture capital[10].

I control for founders' characteristics, such as whether they had initiated successful startups in the past. I include the founders' count and its squared term. I add an indicator for whether at least one founder was a university professor. I use an indicator that equals 1 if at least one of the founders had a Russian last name or spoke Russian. At the end of the 80's and at the beginning of the 90's, Israel experienced a large inflow of immigrants from the ex-Soviet Union. Many of them were highly educated and had a strong background in science and engineering. Hence, my Soviet dummy measures aspects of the startups founders' technological skill. An indicator of whether a startup or its founders had applied for US patents captures additional technology characteristics. I use a dummy that equals 1 if a startup was founded in an incubator. Startups that receive support from government incubators are subject to similar restrictions regarding the overseas transfer of manufacturing and know-how as recipients of R&D grants. Moreover, incubator startups may deal with more basic technologies than those outside of an incubator.

I include six indicator dummies for the districts in which startups are located. I introduce dummies for the following sectors: communication, information technology and software, internet, semiconductors, hardware, cleantech, life science, and medical devices. Furthermore, I add inception-year fixed effects. $\boldsymbol{P_{it}}$ includes characteristics that are common to startups from the same sector and inception year. I use the amount of US venture capital (in constant US dollars), by sector, to control for the availability of alternative investment sources. The availability of US

[10] This equation specification is dictated by fact that I only have information about the total amount invested in a startup, by round, and about the investors that participated in each round. Unfortunately, I do not have information regarding the amount invested by each investor.

capital is measured during the first and second year following a startup's inception, given that the majority of the startups applied for a grant during this timeframe. I add a dummy for whether the startup operated in the ICT sectors and was founded during the dot.com bubble (1998-1999 period). I include the number of Israeli startups that were acquired by a foreign company and were founded during *i*'s inception year, in *i*'s sector. Finally, $\boldsymbol{\Gamma}_{it}$ includes interactions between the variable just described and the indicators for whether a startup had received foreign venture capital and was located in the Tel Aviv district. Summary statistics are presented in Table 1.

One problem with estimating equation (1) is that, rather than observing the *expected* probability of being acquired by a foreign company, I observe the *actual* probability that this event occurs. However,

$$\text{Acquired by Foreign Company}_{it+1} = E_{it}(\text{Acquired by Foreign Company}_{it+1}) - \varepsilon_{it} \qquad (2)$$

implying that my interest variable is measured with error and, thus, endogenous. To address this problem, I estimate an instrumental variable (IV) regression. In doing so, I note that if startups have rational expectations, meaning that they use all available information in making their decisions, then the error in the forecast of $\text{Acquired by Foreign Company}_{it+1}$ is uncorrelated with information dated at time t and earlier (Gali and Gertler, 1999). Hence, an ideal instrument should be measured in t or earlier.

Although the error in the forecast of $\text{Acquired by Foreign Company}_{it+1}$ is uncorrelated with information at the time of an expected application or earlier, an instrument must address two additional sources of endogeneity. The first arises from the fact that in a Perfect Bayesian Separating Equilibrium the decision to apply for a grant and a startup's exit events are simultaneously determined. The second stems from the difficulty of controlling for all aspects of a startup's technology. Hence, it must be that a candidate instrument only affects the probability that a startup applies for a grant through its expected probability of being acquired by a foreign company.

Based on the above discussion, I propose the following instruments. The first is the number of US venture-backed acquisitions that occurred in the year preceding startup *i*'s inception and in the same sector as the one of *i*. The second and third instruments are interactions between the variable just described and the indicators for whether a startup had received foreign venture capital and for whether it was located in the Tel Aviv district. The reason why I choose these interactions is that descriptive statistics reveal that having received foreign venture capital and being located in Tel Aviv are strongly correlated with acquisitions by foreign companies. Thus, it is likely that the effect of the number of US venture-backed acquisitions on the startups' expectations vary with the characteristics just mentioned. Hence, I estimate the following first-stage regression:

$$\text{Acquired by Foreign Company}_{it+1} = \phi_0 + \phi_1 \mathbf{Z_{it}} + \phi_2 \mathbf{X}_{it} + \phi_3 LocationFE_i + \phi_4 SectorFE_i + \phi_5 InceptionYearFE_i + \phi_6 \mathbf{P_{it}} + \phi_7 \mathbf{\Gamma_{it}} + \nu_{it} \quad (3)$$

where $\mathbf{Z_{it}}$ is the instrument vector.

Conditional on the covariates in (3), the chosen instruments plausibly satisfy the exclusion restrictions. Indeed, equation (3) includes a detailed set of measures that are meant to capture over time changes in the characteristics of startups belonging to a given sector. Among others, it encompasses the count of startups that were acquired by foreign companies and had started in *i*'s inception year and sector. Moreover, it contains interactions between this last measure and the indicators for whether a startup had received foreign venture capital and was located in Tel Aviv. Upon controlling for these aspects, the instruments should capture the expected availability of US potential acquirers that is exogenous to a startup's decision to apply for a grant in *t*.

As a robustness check, I limit the analysis to startups that had experienced a successful exit, thus examining a more homogenous sample. Third, I interact my sector dummies with an indicator for whether a startup was founded in the 1990s or in the 2000s. These interactions capture sector-specific variations in the startup characteristics within a time frame of approximately 10 years. Fourth, I re-estimate the IV model, including interactions between inception year dummies and an indicator for whether a startup operated in the ITC sector, area in which Israel enjoys a comparative advantage. Finally, I implement a placebo test that exploits an amendment to the Israeli R&D Law that was enacted in 2005. Regression results results are presented in Tables 2, 3, A1, and 4.

In columns I to III of Table 2, I report the baseline results. Standard errors are clustered around sector and inception year. Column I contains the OLS results. *Ceteris paribus*, the coefficient of the dummy for being acquired by a foreign company is negative and statistically significant. I observe additional interesting correlations. For instance, founders who had initiated successful ventures in the past are more likely to apply for OCS grants than other founders. To the extent that having founded successful ventures in the past correlates positively with the quality of a current project, this finding suggests that application costs may screen out startups with expected low quality projects. Founders are required to obtain additional funds that match the grant amount, and startups with low quality projects may find it difficult to secure these funds. Having obtained foreign venture capital has a negative impact on the probability of applying, the correlation being strongest when a startup is operates during a period characterized by a large number of acquisitions by foreign companies. Conversely, having received domestic venture capital and having applied for patents has a positive effect. Companies operating in the life science sector, which is my base outcome, are more likely to apply than startups in the other sectors.

Column II contains the first-stage results. An F-test on the joint significance of the instruments' coefficients rejects the null hypothesis that they are jointly equal to zero with a test statistic of 14. As expected, the coefficient of the number of US acquisitions prior to a startup's inception is positive. Moreover, the interactions between the number of US venture-backed acquisitions and the indicators for whether a startup had obtained foreign venture capital and was located in Tel Aviv are all positive. These results suggest that the impact of the number of US venture-backed acquisitions on $E_{it}(\textit{Acquired by Foreign Company}_{it+1})$ is largest for those startups that face the largest risk of being acquired by foreign companies. I highlight some results of interest regarding the controls. Specifically, there is a positive correlation between the amount of external investment that the startups had received and their expected probability of being acquired by a foreign company. Conversely, being founded in an incubator and having at least one university professor as a founder are negatively correlated with the startups' expected probability of being acquired by a foreign company. In column III, I report the IV estimates. To test for the endogeneity of $\textit{Acquired by Foreign Company}_{it+1}$ I use a Hausman specification test, which rejects the null hypothesis that the specified regressor is exogenous with a p-value of 0.04. Moreover, a Sargan-Hansen test of overidentifying restrictions fails to reject the joint null hypothesis that the instruments are uncorrelated with the error term and that the excluded instruments are correctly omitted from equation (1). The p-value value is 0.72. Having addressed the endogeneity of my interest variable, its coefficient remains significant at the 5% confidence level and its magnitude increases to 0.38.

In columns IV to VI of Table 2, I report the OLS and IV results, having restricted the sample to startups that had experienced a successful exit. The results are similar to the ones presented in columns I to III. The results of the F-tests on the excluded instruments, the Hausman and the Sargan-Hansen tests lead to similar conclusions as the ones reached for the entire sample. Regarding, my interest variable, its coefficient is negative and statistically significant at the 5% confidence level. The coefficient's magnitude suggests that startups that were acquired by foreign companies are 30% less likely to apply for an OCS grant. Regardless of the sample definition, I observe that the IV estimates are larger in magnitude than the corresponding OLS ones. This result is consistent with the fact that my interest variable is measured with error and measurement error biases the OLS estimates towards zero[11].

<Insert Table 2 about here>

Additional robustness checks

In Table 3, I estimate the IV model including an interaction between the sector dummies and a dummy that equals 1 if a startup was founded after 1999. For the sake of brevity I only report the results for the interest coefficients. In Appendix A, I estimate the models in Table 2, interacting inception-year fixed effects with an indicator for ICT startups. As shown, the results are similar to those presented in Table 2.

<Insert Table 3 about here>

As a further check, I implement a placebo test that exploits a variation in the Israeli R&D policy that occurred between 2005 and 2006. Initially, any overseas transfer of know-how had to be approved on a case-by-case basis by the OCS. This rule created a great deal of uncertainty as regards to the possibility that startups could bring overseas the results of government-funded know-how. In March 2005, policy makers modified the Israeli R&D Law fearing that companies would be deterred from applying for grants and that grant recipients could find it difficult to attract foreign investment[12]. The amendment became effective as of January 2006. As described in Section 2, it now allows the transfer of know-how generated from R&D grants under the condition

[11] An additional reason is simultaneity bias.
[12] It is unlike that this policy change was triggered by over time variations in the startups' characteristics, given that startups receive only 20% of the OCS funds.

that a redemption fee is paid. This amendment is considered to have substantially lowered startups' opportunity costs of applying for R&D grants, by introducing clear rules regulating the overseas transfer of government-funded know-how. Thus, one possible consequence of modifying the R&D Law is that, following 2005, the proportion of startup applicants increases and even those startups with the highest opportunity costs for applying take advantage of the rule change. The startups with the highest opportunity costs are the ones with a high expected probability of being acquired by foreign companies.

In column I of Table 4, I explore the effects of the policy change. I estimate the probability of applying for a first grant as a function of an indicator for that takes the value of 0 if a startup's first expected grant application occurred before 2006 and 1 if it occurred starting from 2006. In the case of grant applicants, I use the actual year of a first grant application. For the non-applicants, I consider the year following inception as the period in which a startup is at risk of applying. I denote the so constructed indicator as *Applied after amendment to R&D Law*. I restrict the sample to startups that were founded during 2002-2007. In this way, I exclude the possibility that startups may have applied for government support because of the economic recessions that occurred in 2001, 2002, and 2009. Moreover, I restrict the sample to startups with a successful exit to limit the problem of confounding factors that may be correlated with a startup's quality. In column I, I present the baseline results. I use the same set of controls as in equation (1), except for the interactions in $\boldsymbol{\Gamma}_{\boldsymbol{it}}$[13]. In column II, I interact the *Applied after amendment to R&D Law* indicator with a dummy for whether the startup had received foreign venture capital. The reason for considering this interaction is that I observe a strong positive correlation between the probability that a startup is acquired by a foreign company and having obtained foreign venture capital. In column I, the coefficient of *Applied after amendment to R&D Law* is positive and significant, while the coefficient for having received foreign venture capital is negative. The coefficient for the interaction between *Applied after amendment to R&D Law* and having obtained foreign venture capital is positive. A test of equality of coefficients rejects the null hypothesis that the coefficient of the interest interaction and the one for having received foreign venture capital are the same with a p-value of 0.04. In column III, I interact the *Applied after amendment to R&D Law* indicator with a dummy for whether a startup was located in the Tel Aviv district. Again, the reason is that

[13] The reason why I exclude the interaction terms is because they are highly correlated with the probability that a startup attracts foreign venture capital and it is located in Tel Aviv.

startups located in Tel Aviv face a high risk of being acquired by foreign companies relative to startups located in other districts. The results are very similar to the ones presented in column II. In line with the prior results, these findings suggest that startups with the highest opportunity costs for applying increased their applications, following a reduction in their costs.

<Insert Table 4 about here>

6. Impact of government grants on startups' exit events

Here, I investigate the impact of government R&D grants on Israeli startups' exits. I showed earlier that the applicant pool is made of startups with a low expected probability of being acquired by foreign companies. Thus, the R&D grants should not affect the probability that their recipients experience an acquisition by a foreign company. However, they could positively affect the probability that the recipients experience either IPOs or acquisitions by domestic companies. I thus begin by estimating the impact of R&D grants on the probability that the startups achieve a successful exit. I then distinguish among exit types. In my estimations, I restrict the sample to the grant applicant pool. I initially estimate the following linear probability regression model:

$$\begin{aligned} \mathit{Successful\ exit}_{it+1} = {} & \gamma_0 + \gamma_1 \mathit{Grant\ funds}_{it} + \boldsymbol{\gamma_2 X_{it}} + \gamma_3 \mathit{LocationFE}_i + \gamma_4 \mathit{SectorFE}_i + \gamma_5 \mathit{InceptionYear\ FE}_i \\ & + \gamma_6 \mathit{ICT\ company\ founded\ during\ dot.com\ bubble}_i + \gamma_7 \mathit{RecessionWhenApply}_i + \gamma_8 \mathit{VC\ Availability}_i \\ & + \varpi_{it} \end{aligned} \quad (4)$$

where *Successful exit*$_{it+1}$ is a dummy variable indicating whether a startup i experienced a successful exit in $t+1$ (either through an acquisition or an IPO). *Grant funds*$_{it}$, my interest variable, is the total amount of OCS grant funds that a startup had received from inception to its exit event. It is measured as the natural logarithm (plus 0.01) of 10,000 constant Israeli shekels. I use a logarithmic scale because the grant amount distribution is highly skewed. The subscript t refers to the period preceding an exit event. The vector $\mathbf{X_{it}}$ contains a similar set of variables as the one that I used for equation (1). The time-varying covariates are measured from a startup's inception to the year of its first grant request. I thus include the amount of external investment (in constant US dollars) that a company had received. I control for whether a startup had received any foreign venture capital and for whether it had received funding from domestic venture capitalists. This time, I also include an indicator variable for whether a startup had experienced positive sales prior to applying for OCS support[14]. I add a count of the number of years elapsed from inception to the first grant request. I also add a dummy for whether a startup had obtained Binational Industrial Research and Development (BIRD) grants, up until the year following the first OCS grant application. I use a dummy for whether the startup founders had initiated successful ventures in the past. I also include the founders' count and its squared term. I add an indicator for whether at least one founder was a university professor and another indicator that equals 1 if at least one of the founders had a Russian last name or spoke Russian. I control for the technology aspects of a startup with a dummy that equals 1 if a startup or its founders had applied for US patents and with an indicator for whether a startup was founded in an incubator. I use dummies for the geographical districts in which the startups had been located. I control for the sectors in which the startups had operated. I also include inception-year fixed effects. I add a dummy for whether the startup operated in ICT and was founded during the dot.com bubble. I use an indicator that equals 1 if at least one startup's grant application occurred during a recession. Upon inspection of the Israeli GDP, I consider the following recession years: 2001, 2002, and 2009. Finally, I add the average amount of domestic venture capital available to a startup from its inception to its exit. Summary statistics are presented in Table 5.

<Insert Table 5 about here>

Estimating equation (4) using OLS leads to biased results since the grant amount that a startup applicant receives is endogenous. The reason is twofold. First, in a Perfect Bayesian Equilibrium, a startup's exit and the grant amount it receives are simultaneously determined. Second, despite the fact that my data is rich in observed characteristics of startups that allow me to compare companies as similar as possible, I may still have omitted characteristics that are correlated with both the grant amount that a startup receives and its exit. I address the endogeneity of $\textit{Grant funds}_{it}$ by estimating an IV model. As a source of exogenous variation for the grant amounts allocated to my sample startups, I propose the appointment of the Chief Scientist of the Israeli Ministry of Industry, Trade, and Labor. The Chief Scientist is nominated by the Minister of Industry, Trade, and Labor, but the government must approve the nomination. There is no specific duration for the Chief Scientist's mandate, though the appointment of a new Chief Scientist

[14] I did not include this variable in equation (1) because very few startups experienced positive sales during inception of in the year following inception.

typically follows the formation of a new government. One of the roles of the Chief Scientists, once they begin their mandate, is to secure budget increases for their office. As I show in Figure 1, the year in which new Chief Scientists are appointed are typically characterized by large budget spikes. There is only one recent exception, which occurred in conjunction with the retirement of Doctor Hoper and the appointment of Avi Hasson[15]. However, this is not surprising. Avi Hasson became Chief Scientist in 2011, following the Great Recession of 2009. As Figure 1 shows, the Israeli government adopted a countercyclical policy during this recession and increased the availability of funds for R&D grants. Hence, it would have been very difficult for the new Chief Scientist to secure a larger budget than the one allocated in 2009 and 2010, and, indeed, if I compare the 2011 budget with the pre-recession one, in 2008, I observe that it is 4% higher. From 2002-2010, just one officer held the position of Chief Scientist. Hence, to introduce exogenous variation in my data for this period, I flag 2006 as if a new Chief Scientist was appointed during that year. The reason why I do so is because 2006 marks the beginning of a new government, following the 2003-2005 Netanyahu government during which the Chief Scientist's budget was drastically cut (Cohen et al., 2010).

<Insert Figure 1 about here>

I construct my instrument as an indicator variable that equals 1 if at least one of a startup's grant applications occurred during the year in which a new Chief Scientist was appointed. For this instrument to be valid, it must be correlated with the probability that a startup experiences a successful exit only via the OCS grants that the startup receives. One related concern is that the spike I observe in 2002 may be not so much due to the nomination of a new Chief Scientist, but rather represents a response to the 2001-2002 recession. The recession, in turn, may have affected startups' capacity of securing funds and innovating. I address this concern with my control for whether at least one of a startup's grant applications occurred during an economic downturn. After I add this control, the percentage of compliers is 25%. Another related concern is that the spikes that I observe in 1992 and in 2000 may stem from the high economic growth that Israel experienced in these years, which could be correlated with the OCS budget and with a startup's exit type. I address this concern with the measure for the availability of domestic venture capital from a

[15] This is the only case in which the appointment of a Chief Scientist does not follow the formation of new government. Rather it follows the retirement of the previous Chief Scientist.

startup's inception to its exit. Conditional on these controls, the instrument should capture plausibly exogenous variations in the OCS budget. I estimate the following first-stage regression:

$$\textit{Grant funds}_{it} = \alpha_0 + \alpha_1 \textit{Apply during Chief Scientist's appointment year}_{it} + \boldsymbol{\alpha_2 X_{it}} + \alpha_3 \textit{LocationFE}_i + \alpha_4 \textit{SectorFE}_i + \alpha_5 \textit{InceptionYearFE}_i + \alpha_6 \textit{ICT company founded during dot.com bubble}_i + \alpha_7 \textit{RecessionWhenApply}_i + \alpha_8 \textit{VC Availability}_i + \eta_{it} \quad (5)$$

The results are presented in Table 6. I cluster standard errors around companies that were founded during the same year and operated in the same sector. Column I shows the OLS results, column II displays the first-stage results, and column III presents the IV results. The OLS estimates indicate that a 1% rise in the grant funds awarded to a startup increases its probability of experiencing a successful exit by about 1.4%. I also observe that applicants that were founded in an incubator, were financed by domestic venture capital, or were located in the periphery have a lower probability of experiencing a successful exit. Conversely, having received large amounts from external investors is positively correlated with either an IPO or an acquisition. While the correlations I show are interesting, I cannot attribute causality to the OLS results on the effects of the government grants. I thus turn to the IV model.

The first-stage regression results show that my instrument has a strong positive effect on the grant amount that a startup receives. The F-statistic on the significance of the instrument's coefficient is 45. Having applied at least once in the year in which a new Chief Scientist was appointed increases the total amount received from the OCS by about 331,000 Israeli shekels (approximately $89,000), which corresponds to about 30% of the median grant amount. As expected, startups that applied at least once in a recession obtain larger grants, whereas ICT startups that were founded during the dot.com bubble receive fewer funds. Consistent with the idea that the OCS budget may be larger in periods of high economic growth, I observe that when there is a large availability of domestic capital startups tend to receive conspicuous grants. Startups located in peripheral districts and those founded by successful serial entrepreneurs receive larger government support. The same is true for startups that had received domestic venture capital. This last result is in line with the OCS policy that requires that government funds must be matched with funds from external investors. Companies that had received foreign venture capital received smaller amounts. This finding is consistent with the Israeli government objective of keeping the results of government-funded projects domestically. Finally, the longer the amount of time elapsed from foundation to the first grant request, the smaller the amount awarded by the OCS, suggesting that the OCS may favor early ventures. The IV results in column III show that the impact of the OCS grant amount on the probability that a startup experiences a successful exit is highly significant. A 1% increase in the grant amount increases the successful exit probability by 4.7%. In Appendix B, I estimate equations (4) and (5) replacing the interest variable with an indicator that equals 1 if a startup had received any funds. I estimate a linear regression with endogenous treatment effect. I find that grant recipients are 36% more likely to experience a successful exit. The coefficient of the dummy is significant at the 5% confidence level. The F-statistic on the significance of the instrument's coefficient is 27.

<Insert Table 6 about here>

Discussion of the IV estimates

While the variations in the OCS budget that I capture with the *Apply during Chief Scientist's appointment year* instrument are not the response to overtime changes in the startups' characteristics, it is still possible that grant examiners' acceptance criteria vary with the government budget size. One concern is that when there is a budget expansion, the OCS funds infra-marginal projects that could have been financed with non-government investment sources. I explore this possibility in the following. I restrict the sample to startups that had obtained some government support. I consider four proxies for whether startups with infra-marginal projects receive OCS funding. I then assess whether there exists a positive correlation between these proxies and the *Apply during Chief Scientist's appointment year* instrument. The four proxies are: i) the number of years elapsed between inception and the first grant request, ii) the amount of external financing that a startup had received during the period antecedent to the first grant request, iii) a dummy for whether a company had experienced positive sales prior to a first grant request, and iv) an indicator for whether a startup had applied for patents. The rationale for using these proxies is that startups in their early stages or that deal with more embryonic technologies are likely to face larger costs to secure non-government funding than the other startups. In the regressions, I control for the founders' count, whether they had initiated successful ventures in the past, and whether at least one of them was a professor or had Russian origins. I also include the dummy for whether startups were founded in an incubator. I include the dummy for whether a startup had at least one grant application during a recession and the one for whether an ICT startup was founded during the dot.com bubble. I also control for the availability of domestic capital. Inception-year and sector fixed effects are included. The results are in Table 7.

When the dependent variable is the number of years elapsed from inception to the first grant request, I use a Poisson specification with robust standard errors, given that this variable can take only positive and integer values. In the other cases, I estimate OLS models and cluster standard errors around sector and foundation year. I find that having applied for government support during the year in which a new Chief Scientist was appointed is significantly and negatively correlated with the time elapsed before applying for a first grant (column I), having obtained large external investment (column II), having experienced positive sales (column III), and having applied for patents (column IV). Contrary to what suggested above, these results indicate that when there are budget expansions the proportion of startups with more uncertain projects increases. These findings could also explain why I observe that the IV estimates are higher than the corresponding OLS estimates[16]. In fact, the IV estimates can be interpreted as a Local Average Treatment Effect to the extent that the compliers are those startups with the highest returns in their grant funds (Imbens and Angrist, 1994).

<Insert Table 7 about here>

Robustness checks

In Table 8, I implement a number of robustness checks. First, one important omitted variable in equation (4) is a company's R&D expenditure. Unfortunately, this information is not available. However, for 474 startups I was able to collect their R&D budget request at the time of their first grant application. I introduce the natural logarithm of this variable in equations (4) and (5) and present the results in columns I and II. As shown, the impact of the grant amount on a startup's probability to experience a successful exit continues to be highly significant. Startups apply for and receive multiple grants. It is possible that some startups secure repeated support from the government not because they are liquidity constrained but because they produce knowledge or goods that are strategic for a domestic economy. To address this concern, in columns III and IV, I exclude from the sample those companies that are in the last quartile for their number of applications. Similarly, in columns V and VI, I exclude from the sample those companies that are

[16] Another important reason for obtaining higher IV estimates is simultaneity bias.

in the last quartile for their grant amount received. Finally, in columns VII and VIII, I remove from the sample 19 startups that had applied for more than two grants, but had never obtained one. These startups may be fundamentally different from the other grant applicants. Regardless of the sample specification, my interest coefficients remain statistically significant at conventional levels and their magnitude is very similar to the VI estimates in Table 6.

<Insert Table 8 about here>

Distinguishing between exit outcomes

Because the applicant pool is composed of startups with a low expected probability of being acquired by foreign companies, I expect the impact of the R&D grants on this exit outcome to be insignificant. I verify this conjecture in Tables 9 and 10.

Table 9 presents the results of a multinomial logit model in which the dependent variable is an indicator that equals 0 if a startup had ceased operations as of September 2014, 1 if it was acquired by a foreign company, and 2 if it had experienced a successful exit other than an acquisition by a foreign company. The interest variable is the grant amount that a startup had received. Because grant funds are endogenous, in Table 10 I estimate IV models for the probability that a startup is acquired by a foreign company relative to having ceased operations (columns I and II). I also estimate models for the probability that a startup experiences a successful exit, other than being acquired by a foreign company, relative to having ceased operations (columns III and IV). Finally, I estimate models for the probability that a startup is acquired by a foreign company relative to other successful exits (columns V and VI)[17]. The set of controls that I employ in Tables 9 and 10 is very similar to the one in Table 6. However, this time, because the bilateral comparisons between exit events use a smaller sample size than the one in the previous tables, I substitute inception-year fixed effects with dummies for whether the startups were founded during the same two-year time interval. I thus cluster standard errors around sector and inception-time.

[17] The multinomial logit and the IV models would be correctly specified if the odds associated with each startup's exit event were to comply with the Independence of Irrelevant Alternative property. To verify that this property is satisfied I implemented a Hausman test of the hypothesis that the parameter estimates obtained on a subset of alternatives do not significantly differ from those obtained with the full set of alternatives. In all instances, I could not reject the null hypothesis that the coefficients are the same with p-values greater than 0.6.

In line with my expectations, I observe that the impact of grant funds on the probability that a startup is acquired by a foreign company relative to having ceased operations is not significant. Moreover, in line with my finding that startup applicants have a low *ex-ante* probability of being acquired by foreign companies, I do not observe that R&D grants induce their recipients to switch from one exit type to another because of the restrictions on the overseas transfer of government-funded output.

<Insert Tables 9 and 10 about here>

7. Impact of government grants on startups' follow-on financing

I now analyze the impact of government R&D grants on follow-on financing. I also examine whether grant recipients attract foreign venture capital. Because restrictions on the overseas transfer of government-funded output increase the opportunity costs of foreign acquirers, it is likely that they also increase the opportunity costs of foreign venture capitalists. Interviews with startup founders and investors revealed that one of the roles of foreign venture capitalists is to connect startups with foreign markets and potential acquirers. I estimate the following equations:

$$\begin{aligned}&\textit{Follow-on Financing}_{it+1}=\zeta_0+\zeta_1\textit{Grant funds}_{it}+\boldsymbol{\zeta_2 X_{it}}+\zeta_3\textit{LocationFE}_i+\zeta_4\textit{SectorFE}_i+\\&\zeta_5\textit{InceptionYearFE}_i+\zeta_6\textit{ICT company founded during dot.com bubble}_{it}+\zeta_7\textit{RecessionWhenApply}_{it}\\&+\zeta_8\textit{VC Availability}_i+\varkappa_{it} \qquad (6)\end{aligned}$$

$$\begin{aligned}&\textit{Received foreign venture capital}_{it+1}=\theta_0+\theta_1\textit{Grant funds}_{it}+\boldsymbol{\theta_2 X_{it}}+\theta_3\textit{LocationFE}_i+\theta_4\textit{SectorFE}_i+\\&\theta_5\textit{InceptionYearFE}_i+\theta_6\textit{ICT company founded during dot.com bubble}_{it}+\theta_7\textit{RecessionWhenApply}_{it}\\&+\theta_8\textit{VC Availability}_i+\varrho_{it} \qquad (7)\end{aligned}$$

In equation (6), I define the dependent variable as a dummy that equals 1 if a startup received an annual amount of follow-on financing after the first grant request that is above the sector median. The annual amount is defined by the total follow-on financing (in constant million USD) that a startup had received, divided by the number of years elapsed between the startup's first grant request and its exit (plus 1). I prefer to consider this outcome rather than the amount of investment a startup had obtained in the year following the first grant request because the majority of the grant recipients continued to receive OCS funds after their first award. Hence, it makes more sense, in this case, to examine the impact of the total amount of government funds that a startup had obtained on the total follow-on investment that the startup received after its first grant request. Because startups differ considerably with respect to the time interval between a first grant request and an exit, I use this interval to normalize their follow-on financing. The distribution of the constructed variable is very skewed. The median value is 0.15 million constant USD, whereas the mean is $1 million, and the difference between the mean and the median remains substantial across sectors. For this reason, I redefine my outcome as a dummy that takes the value of 1 if a startup had received an amount of follow-on financing above the sector median. The vector $\mathbf{X}_{\mathbf{it}}$ encompasses the same regressors as in equation (4).

In equation (7), the dependent variable is a dummy that equals 1 if a startup had attracted foreign venture capital. This specification is dictated by the fact that, unfortunately, I do not have information about the amount invested by each investor. I only have information about the total amount that startups secure in each round and the list of investors that participate in these rounds. Because there is large variation in the number of years elapsed between a startup's first grant request and its exit, I include this number in the vector $\mathbf{X}_{\mathbf{it}}$. The remaining regressors in $\mathbf{X}_{\mathbf{it}}$ are the same as the ones I listed in equations (4) and (6).

Given that the total amount of government grant funds that the startups had obtained is endogenous, I estimate IV models. As before, I instrument *Grant funds* with an indicator for whether at least one of the startup's grant applications occurred during the year in which a new Chief Scientist was appointed. The results are presented in Table 11. I cluster standard errors around the startup's sector and inception year. I do not present the first stage results because they are identical to the ones displayed in Table 6. The OLS estimates point to a significant, positive correlation between the amount of grant funds and the probability of receiving follow-on financing above the sector median. Once I instrument the startups' grant funds, I continue to find that the associated coefficient is highly significant. Specifically, a 1% increase in these funds triggers a 4.7% increment in follow-on financing. This outcome is consistent with the fact that grant recipients are required to match government funds with those from external investors. In columns III and IV of Table 11, I examine the impact of grant funds on startups' ability to attract follow-on venture capital. This time, I find that both the OLS and the IV estimates are not statistically different from zero. In Appendix B, I estimate equations (6) and (7) replacing the interest variable with an indicator that equals 1 if a startup had received any funds. I estimate a linear regression with endogenous treatment effect. While the impact of having received grant funds on the probability of obtaining follow-on financing is positive and significant, the effect on the probability of attracting foreign venture capital is not significantly different from zero.

Overall, my results are consistent with the findings in the previous section. Government R&D grants have a positive impact on the ability of startups to attract follow-on financing and ultimately achieve a successful exit. However, restrictions on the offshoring of government-funded projects appear to have an effect on the typology of grant applicants, indirectly impacting the recipients' ability to attract foreign investors and acquirers.

<Insert Table 11 about here>

Robustness checks

The results that I presented in Table 11 hold when I introduce a startup's R&D budget request relative to its first grant application, when I remove from the sample startups in the last quartile for their number of applications, and when I remove startups in the last quartile for their grant amount received. Moreover, the results do not change when I exclude those startups that had applied for more than two grants but had never obtained one. The results of these robustness checks are displayed in Table 12. Finally, in Appendix C, I show that the impact of government funds is insignificant even when I consider as an outcome a startup's follow-on financing by any foreign investor rather than by just foreign venture capitalists.

<Insert Table 12 about here>

8. Concluding remarks

This paper examines the role of government R&D grant regulations as screening mechanisms that induce technology startups to reveal their characteristics. For this purpose, I focus on small open economies with restrictions in place on the extent to which government-funded projects and their results can be offshored. These restrictions raise the opportunity costs of non-domestic investors and could prevent them from investing in grant recipients.

Analyzing a large sample of Israeli startups, I find that the decision to apply for government R&D grants is an endogenous one, and the related grant program only attracts startups with a low expected probability of being acquired by foreign companies. Moreover, I find that, conditional on a grant application, grants increase their recipients' likelihood of experiencing a successful exit and attracting follow-on financing. However, they do not significantly affect those startups' probability of being acquired by a foreign company and attracting follow-on foreign venture capital. These findings are derived from estimating IV models that account for the endogeneity of the grant application decision and of the grant impact on the startups' outcomes.

My results show the importance of assessing the impact of R&D grant regulations on the characteristics of the grant applicants. Grant rules affect the opportunity costs of potential applicants and encourage only the ones with relatively low opportunity costs to eventually apply for government support. The characteristics of the applicants ultimately affect the impact of the grant funds on their recipients.

In the specific case of small open economies, my findings uncover important aspects of the government interventions in domestic startups. Establishing incentives to keep the results of government-funded projects domestically is a subject of discussion in several small open economies. While countries like New Zealand have strengthened their initial restrictions, others like Brazil debate about whether such restrictions may act as a barrier to foreign direct investment. Israel hosts a well-established ecosystem of technology startups and a developed network of domestic investors. Hence, in a certain measure, it is possible for the Israeli government to support startups with good quality projects and a high propensity for executing them domestically. In other small open economies, however, it may be very difficult to separate the two startups' characteristics. Thus, restrictions similar to the ones imposed by the Israeli government may have an overall negative impact on the quality of startup applicants and reduce the probability that grant recipients attract follow-on financing and experience successful exits.

This paper only scratches the surface of the impact of grants on technology startups. Two related directions for extension are immediately clear. First, I measure startups' private returns with the amount of follow-on financing that the companies receive and with their likelihood of achieving successful exits. While these are, indeed, important outcomes for technology startups, other aspects such as employment and R&D investment could have been examined. Second, I do not consider the social returns and, thus, the welfare implications of the government R&D grant programs. A welfare analysis would have demanded an investigation of the spillovers that the government-funded projects generate for the rest of the economy. Moreover, it would have been important to measure the opportunity costs of devoting public resources to technology startups, as opposed to other economic agents and uses. While these are fundamental steps to assess the validity of R&D policies, they are a topic for future research.

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Appendix A: Robustness checks for the probability of applying for government R&D grants

<Insert Table A1 about here>

Appendix B: Regression results having changed the interest regressor into an indicator for whether a startup applicant had received grant funds

In Table B1, I re-estimate the models in equations 4-7 having replaced the amount of grant funds that a startup received with an indicator that equals 1 if a startup had obtained government support. Because the treatment is a binary variable, I estimate a linear regression with endogenous treatment effects (Wooldridge, 2010). I consider the following three outcomes: having experienced a successful exit (column II), having obtained an annual amount of follow-on financing above the sector median (column III), and having received foreign venture capital (column IV). I instrument the binary treatment with the dummy for whether at least one grant application occurred during the appointment of a new Chief Scientists. I present two-step estimates and bootstrap standard errors with 500 replications. As shown in column I, the coefficient of the instrument is highly-significant. In line with prior findings, having received grant funds has a positive impact on the probability that a startup experiences a successful exit and that it receives follow-on financing above the sector median. Moreover, the treatment effect on the probability of receiving foreign venture capital is insignificantly different from zero.

<Insert Table B1 about here>

Appendix C: Results for the probability of attracting follow-on foreign investment (including but not limited to foreign venture capital)

<Insert Table C1 about here>

Figure 1: OCS Budget (Annual growth)

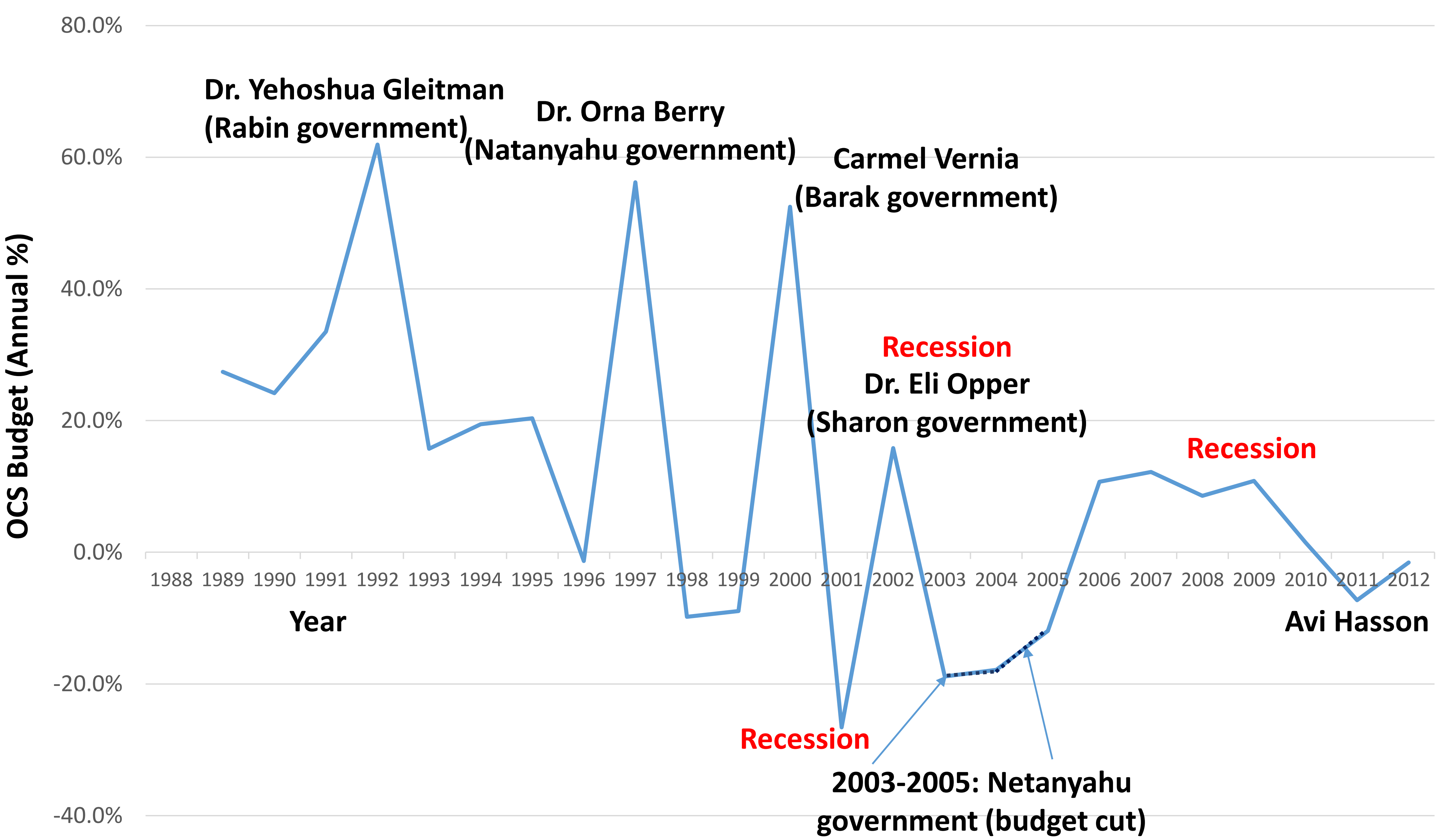

Table 1: Descriptive statistics

	Applied for government grants (N. 561)		Never applied for government grants (N. 1070)	
	Mean	**SD**	**Mean**	**SD**
Acquired by a foreign company	0.25	0.43	0.27	0.44
Amount from external investors (million constant USD)	2.64	6.46	2.5	8.28
Received foreign venture capital	0.11	0.31	0.14	0.35
Received domestic venture capital	0.34	0.47	0.26	0.44
Founded successful startups in the past	0.22	0.41	0.16	0.37
Founders' count	2.06	1.07	2.09	1.11
Professor founder	0.11	0.31	0.08	0.28
Soviet founder	0.11	0.31	0.1	0.3
Applied for US patent	0.47	0.5	0.28	0.45
Founded in an incubator	0.25	0.43	0.23	0.42
North	0.12	0.32	0.08	0.28
Haifa	0.09	0.29	0.09	0.28
Center	0.35	0.48	0.2	0.4
South	0.05	0.21	0.04	0.2
Jerusalem	0.07	0.25	0.08	0.27
Tel Aviv	0.33	0.47	0.51	0.5
Communications	0.19	0.39	0.18	0.38
Internet	0.07	0.25	0.24	0.43
IT and software	0.23	0.42	0.21	0.41
Seminconductors	0.08	0.27	0.04	0.19
Hardware	0.09	0.29	0.07	0.25
Cleantech	0.06	0.24	0.09	0.29
Life science	0.14	0.35	0.07	0.26
Medical devices	0.14	0.35	0.11	0.31
Availability of foreign VC at time of expected application (million constant USD)	4023.79	4966.45	4192.96	5533.48
ICT startups founded during dot.com bubble	0.08	0.27	0.10	0.30
N startups acquired by foreign companies and founded in the same year and sector as startup *i*	4.45	5.64	4.84	5.48
Number of US acquisitions prior to a startup's inception, by sector	40.29	60.9	70.40	80.48

Note: Time-varying covariates are measured up until the year following a startup's inception.

Table 2: Regression results for the probability of applying for government R&D grant:

	(1)	(2)	(3)	(4)	(5)	(6)
	Entire sample			Sample of startups with a successful exit		
	OLS	First-stage	IV	OLS	First-stage	IV
Acquired by a foreign company	-0.0762**		-0.3826**	-0.1319***		-0.2953**
	(0.0299)		(0.1685)	(0.0386)		(0.1502)
Amount from external investors (natural log + 1)	0.0070	0.0166**	0.0124*	-0.0017	-0.0091	-0.0026
	(0.0062)	(0.0066)	(0.0072)	(0.0103)	(0.0096)	(0.0100)
Received foreign venture capital	-0.0237	-0.0507	0.0384	-0.0415	0.1361	-0.0083
	(0.0450)	(0.1161)	(0.0638)	(0.0563)	(0.1354)	(0.0678)
Received domestic venture capital	0.0641**	-0.0060	0.0603*	0.0417	0.0590	0.0514
	(0.0297)	(0.0258)	(0.0321)	(0.0486)	(0.0417)	(0.0483)
Founded successful startups in the past	0.0882***	0.0322	0.0981***	0.0795*	-0.0346	0.0725*
	(0.0303)	(0.0325)	(0.0303)	(0.0444)	(0.0468)	(0.0435)
Founders' count	0.0647*	0.1073***	0.0947***	0.0667	0.0578	0.0755
	(0.0336)	(0.0393)	(0.0363)	(0.0576)	(0.0593)	(0.0578)
Founders' count ^ 2	-0.0119**	-0.0119*	-0.0149**	-0.0139	-0.0078	-0.0150
	(0.0056)	(0.0071)	(0.0059)	(0.0096)	(0.0094)	(0.0095)
Professor founder	-0.0389	-0.0580**	-0.0567	-0.0222	-0.0164	-0.0266
	(0.0399)	(0.0282)	(0.0405)	(0.0705)	(0.0653)	(0.0677)
Soviet founder	0.0549	0.0469	0.0680*	0.1684**	0.1337**	0.1866***
	(0.0379)	(0.0302)	(0.0388)	(0.0655)	(0.0671)	(0.0670)
Applied for US patent	0.0775***	0.1230***	0.1161***	0.0384	0.0266	0.0444
	(0.0296)	(0.0323)	(0.0374)	(0.0410)	(0.0435)	(0.0400)
Founded in an incubator	-0.0159	-0.0807***	-0.0417	0.1517**	0.0416	0.1562**
	(0.0387)	(0.0285)	(0.0399)	(0.0665)	(0.0665)	(0.0664)
Availability of foreign VC at time of expected application (natural log)	-0.0322	0.0197	-0.0279	-0.0729	-0.0061	-0.0779*
	(0.0261)	(0.0239)	(0.0260)	(0.0443)	(0.0428)	(0.0421)
ICT company founded during dot.com bubble	-0.0246	-0.0170	-0.0392	0.0234	-0.0481	0.0158
	(0.0632)	(0.0651)	(0.0603)	(0.0916)	(0.1059)	(0.0902)
N startups acquired by foreign companies and founded in the same year	-0.0025	0.0009	-0.0024	-0.0011	0.0019	-0.0002
and sector as startup *i*	(0.0029)	(0.0038)	(0.0032)	(0.0046)	(0.0059)	(0.0047)
N startups acquired by foreign companies and founded in the same year	-0.0084*	0.0012	-0.0082*	-0.0092**	-0.0024	-0.0101**
and sector as startup *i* * Received foreign venture capital	(0.0043)	(0.0061)	(0.0049)	(0.0045)	(0.0085)	(0.0049)
N startups acquired by foreign companies and founded in the same year	-0.0178***	-0.0101	-0.0144***	-0.0167***	-0.0079*	-0.0156***
and sector as startup *i* * Located in Tel Aviv	(0.0036)	(0.0074)	(0.0035)	(0.0040)	(0.0043)	(0.0036)
Constant	0.4809**	-0.0403	0.4744**	0.7891**	0.0695	0.8219***
	(0.1974)	(0.1954)	(0.1926)	(0.3030)	(0.3005)	(0.2899)
Number of US acquisitions prior to a startup's inception, by sector		0.0771***			0.2419***	
(natural log)		(0.0269)			(0.0411)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0656**			0.0108	
Received foreign venture capital		(0.0286)			(0.0317)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0722***			0.0520***	
* Located in Tel Aviv		(0.0175)			(0.0182)	
Sector FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓	✓
Observations	1639	1639	1639	699	699	699
F-stat of Instruments		13.49			13.35	
Sargan-Hansen test of overidentifying restrictions		0.64			1.05	
R-squared	0.17	0.24		0.19	0.23	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Columns I to III present the results for the probability of applying for a government grant, using the entire sample. Column I presents the OLS results. Column II presents the first-stage results for the probability of being acquired by a foreign company. Column III presents the IV estimates. Columns IV to VI present the results for the probability of applying for a government grant, using the sample of startups with a successful exit. Column IV presents the OLS results, Column V shows the first-stage results for the probability of being acquired by a foreign company, and Column VI displays the IV estimates.

Table 3: Regression results for the probability of applying for government R&D grants - Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
		Entire sample		Sample of startups with a successful exit		
	OLS	First-stage	IV	OLS	First-stage	IV
Acquired by a foreign company	-0.0775**		-0.2953**	-0.1302***		-0.5174**
	(0.0298)		(0.1502)	(0.0405)		(0.2357)
Number of US acquisitions prior to a startup's inception, by sector		0.2419***			0.1381**	
(natural log)		(0.0411)			(0.0550)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0108			0.0126	
Received foreign venture capital		(0.0317)			(0.0324)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0520***			0.0548***	
* Located in Tel Aviv		(0.0182)			(0.0184)	
Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓	✓
Sector FE x 2000's DUMMY	✓	✓	✓	✓	✓	✓
Observations	1,639	1,639	1,639	699	699	699
F-stat of Instruments		12.04			5.51	
Sargan-Hansen test of overidentifying restrictions		1.93			0.55	
R-squared	0.17	0.23		0.21	0.25	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Relative to the results in Table 2, I include interaction terms between the sector dummies and an indicator that equals 1 if a startup was founded after 1999. Columns I to III present the results for the probability of applying for a government grant, using the entire sample. Columns IV to VI present the results for the probability of applying for a government grant, using the sample of startups with a successful exit.

Table 4: Regression results for the probability of applying for a first grant - Exploiting an amendment to the Israeli R&D Law

	(1)	(2)	(3)
Applied after amendment to R&D Law	0.4160***	0.3903**	0.3329**
	(0.1429)	(0.1471)	(0.1589)
Applied after amendment to R&D Law * Received foreign venture capital		0.1618	
		(0.1022)	
Applied after amendment to R&D Law * Located in Tel Aviv			0.1987
			(0.1356)
Received foreign venture capital	-0.1460**	-0.2391**	-0.1425**
	(0.0619)	(0.0901)	(0.0663)
Tel Aviv	-0.1864**	-0.1823**	-0.2966**
	(0.0785)	(0.0790)	(0.1183)
Controls	✓	✓	✓
Sector FE	✓	✓	✓
Region FE	✓	✓	✓
Inception-year FE	✓	✓	✓
Observations	199	199	199
R-squared	0.27	0.27	0.28

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. The regressor of interest is an indicator that takes the value of 1 if a startup's expected first application year follows the year in which the amendment to the Israeli R&D Law was enacted. I only consider startups that were founded between 2002 and 2007. Moreover, I only examine startups that had experienced a successful exit.

Table 5: Descriptive statistics for the sample of grant applicants

	Applied and received grant funds (N. 389)		**Applied and did not receive grant funds (N.172)**	
	Mean	**SD**	**Mean**	**SD**
Experienced successful exit	0.52	0.50	0.41	0.49
Acquired by foreign company	0.25	0.43	0.23	0.42
Average annual amount from external investors after first grant request (=1 if above sector median)	0.56	0.50	0.35	0.48
Elapsed time from first grant request to exit	6.59	4.40	3.97	3.40
Received foreign venture capital after first grant request	0.26	0.44	0.15	0.36
Grant funds (10,000 constant Israeli shekels)	738.93	1423.62	0.00	0.00
Amount from external investors (million constant USD), before and during first grant request	3.76	9.83	6.10	18.64
Received foreign venture capital, before and during first grant request	0.10	0.30	0.19	0.39
Received domestic venture capital, before and during first grant request	0.36	0.48	0.33	0.47
Received BIRD grant, before and during first grant request	0.04	0.19	0.02	0.15
Had positive sales by the time of first grant request	0.04	0.20	0.12	0.33
Elapsed time from inception to first grant request	1.42	1.94	2.55	2.32
Founded successful startups in the past	0.23	0.42	0.18	0.39
Founders' count	2.09	1.08	1.99	1.06
Professor founder	0.11	0.31	0.11	0.31
Soviet founder	0.10	0.30	0.13	0.33
Applied for US patent	0.28	0.45	0.29	0.46
Founded in an incubator	0.25	0.43	0.24	0.43
North	0.12	0.33	0.11	0.31
Haifa	0.10	0.30	0.07	0.26
Center	0.35	0.48	0.34	0.48
South	0.05	0.21	0.05	0.21
Jerusalem	0.07	0.25	0.06	0.25
Tel Aviv	0.31	0.46	0.37	0.48
Communications	0.19	0.39	0.19	0.39
Internet	0.04	0.19	0.14	0.35
IT and software	0.23	0.42	0.23	0.42
Seminconductors	0.10	0.29	0.04	0.20
Hardware	0.09	0.29	0.08	0.27
Cleantech	0.06	0.24	0.06	0.23
Life science	0.15	0.35	0.12	0.33
Medical devices	0.15	0.35	0.14	0.35
ICT company founded during dot.com bubble	0.05	0.22	0.14	0.35
RecessionWhenApply	0.54	0.50	0.37	0.48
VC Availability	0.28	0.14	0.26	0.12
Apply during Chief Scientist's appointment year	0.74	0.44	0.37	0.48

Note: Time-varying covariates are measured from inception to the year of first grant request.

Table 6: Regression results for having experienced a successful exit

	(1) OLS	(2) First-stage	(3) IV
Grant funds (natural log + 0.01)	0.0143***		0.0475***
	(0.0049)		(0.0167)
Amount from external investors (natural log + 0.01)	0.0170	-0.0021	0.0181
	(0.0126)	(0.1157)	(0.0128)
Received foreign venture capital, before and during first grant request	0.1065	-0.9326	0.1347**
	(0.0651)	(0.6523)	(0.0676)
Received domestic venture capital, before and during first grant request	-0.1078**	1.0677**	-0.1440**
	(0.0531)	(0.5045)	(0.0619)
Received BIRD grant, before and during first grant request	0.0697	0.8971	0.0644
	(0.1073)	(0.9858)	(0.1145)
Had positive sales by the time of first grant request	0.1694*	-0.3784	0.1886**
	(0.0944)	(0.9106)	(0.0946)
Elapsed time from inception to first grant request (natural log + 1)	0.0054	-1.7165***	0.0712
	(0.0391)	(0.3372)	(0.0569)
Founded successful startups in the past	0.1068*	1.0406**	0.0802
	(0.0567)	(0.4807)	(0.0609)
Founders' count	0.2314***	0.4564	0.2100***
	(0.0732)	(0.5750)	(0.0692)
Founders' count ^ 2	-0.0286**	-0.0377	-0.0263**
	(0.0128)	(0.1031)	(0.0120)
Professor founder	-0.0796	-0.8939	-0.0550
	(0.0745)	(0.6833)	(0.0767)
Soviet founder	0.1053*	-0.7183	0.1278*
	(0.0610)	(0.6341)	(0.0690)
Applied for US patent	-0.0295	0.6671	-0.0503
	(0.0527)	(0.5076)	(0.0539)
Founded in an incubator	-0.1292**	-0.6432	-0.1111**
	(0.0548)	(0.4837)	(0.0545)
ICT company founded during dot.com bubble	0.1175	-2.3566**	0.2117**
	(0.0901)	(1.0302)	(0.1079)
RecessionWhenApply	0.0741	1.4766***	0.0016
	(0.0476)	(0.4039)	(0.0569)
VC Availability (natural log)	0.0470	0.9683***	0.0130
	(0.0530)	(0.3368)	(0.0494)
Constant	0.4681***	3.0881**	0.2774
	(0.1678)	(1.2363)	(0.1923)
Apply during Chief Scientist's appointment year		3.1574***	
		(0.4514)	
Sector FE	✓	✓	✓
Region FE	✓	✓	✓
Inception-year FE	✓	✓	✓
Observations	561	561	561
F-stat of Instrument		45.27	
R-squared	0.22	0.35	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Column I presents the OLS results. The dependent variable is a dummy that equals 1 if a grant applicant had experienced a successful exit. Column II presents the first-stage results for the grant amount that the applicant had received prior to an exit. Column III presents the IV estimates.

Table 7: Exploratory results for the typology of grant applicants in the year in which a new Chief Scientist is appointed

	(1)	(2)	(3)	(4)
	Elapsed time from inception to first grant request	Amount from external investors (natural log + 0.01)	Had positive sales by the time of first grant request	Had applied for patents by the time of first grant request
Apply during Chief Scientist's appointment year (Instrument)	-0.4093***	-0.6265*	-0.0508**	-0.0804
	(0.1573)	(0.3206)	(0.0246)	(0.0548)
RecessionWhenApply	0.1077	1.1505***	-0.0262	0.1812***
	(0.1633)	(0.2792)	(0.0250)	(0.0521)
Controls	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓
Observations	389	389	389	389
R-squared	0.09	0.33	0.10	0.19

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. I restrict the sample to grant recipients. Column I presents the Poisson estimates for the number of years elapsed from a startup's inception to its first grant request. Column II presents the OLS estimates for the amount of external investment that a startup had received during the period antecedent to the first grant request. Column III presents the linear probability estimates for the likelihood of having experienced positive sales prior to the first grant request. Column IV presents the linear probability estimates for the likelihood that a startup had applied for patents prior to the first grant request. I control for the founders' count, whether they had initiated successful ventures in the past, and whether at least one of them was a professor or had Soviet origins. I also include dummies for whether startups were founded in an incubator, for whether they had at least one grant application during a recession, and for whether they are ICT companies founded during the dot.com bubble. Finally, I control for the availability of domestic venture capital.

Table 8: Regression results for having experienced a successful exit - Robustness checks

	(1) First-stage	(2) IV	(3) First-stage	(4) IV	(5) First-stage	(6) IV	(7) First-stage	(8) IV
Apply during Chief Scientist's appointment year	3.3998***		2.2829***		2.4102***		3.1454***	
	(0.4915)		(0.4982)		(0.5000)		(0.4565)	
Grant funds (natural log + 0.01)		0.0399**		0.0551**		0.0418*		0.0463***
		(0.0170)		(0.0256)		(0.0216)		(0.0168)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	474	474	404	404	422	422	547	547
F-stat of Instrument	42.92		19.74		23.62		43.22	
R-squared	0.39		0.21		0.31		0.36	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Columns I and II present the first-stage and IV results for the probability of a successful exit, having introduced as control a startup's R&D budget request for the first grant. This information is only available for 474 applicants. Columns III and IV present the first-stage and IV results for the probability of a successful exit, having removed those companies that are in the last quartile for their number of applications. Results in columns V and VI are obtained by removing those companies that are in the last quartile for their grant amount received. Results in columns VII and VIII are obtained by removing those startups that had applied for more than two grants but had never received one. In all regressions I use the same controls as in Table 6.

Table 9: Multinomial logit results for the startups' exit events

	(1)	(2)	(3)
	Having ceased operations (N=287)	Being acquired by a foreign company (N=138)	Other successful exit (N=136)
Grant funds (natural log + 0.01)	BASE OUTCOME	0.0460	0.1063***
		(0.0283)	(0.0297)
Controls	✓		
Sector FE	✓		
Region FE	✓		
Inception-time FE	✓		
Observations	561		
R-squared	0.21		

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception time. In columns I to III the dependent variable takes the value of 0 if a startup had ceased to operate as of September 2014, the value of 1 if the startup was acquired by a foreign company, and the value of 2 if the startup had experienced a successful exit other than being acquired by a foreign company. I use the same controls as in Table 6.

Table 10: Regression results for the startups' exit events

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of being acquired by a foreign company relative to having ceased operations		Probability of other successful exits relative to having ceased operations		Probability of being acquired by a foreign company relative to other successful exits	
	First-stage	IV	First-stage	IV	First-stage	IV
Apply during Chief Scientist's appointment year	2.9286***		2.9939***		3.6148***	
	(0.5300)		(0.5149)		(0.7197)	
Grant funds (natural log + 0.01)		0.0267		0.0548***		-0.0036
		(0.0169)		(0.0185)		(0.0189)
Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Inception-time FE	✓	✓	✓	✓	✓	✓
Observations	425	425	423	423	274	274
F-stat of Instrument	25.97		37.45		25.29	
R-squared	0.35		0.34		0.41	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception time. Columns I and II present the first-stage and IV estimates for the probability that a startup was acquired by a foreign company, relative to having ceased operations as of September 2014. Columns III and IV present the first-stage and IV estimates for the probability that a startup had a successful exit, other than being acquired by a foreign company, relative to having ceased operations. Columns V and VI present the first-stage and IV estimates for the probability that a startup was acquired by a foreign company relative to having experienced another successful exit. I use the same controls as in Table 6.

Table 11: Regression results for having received follow-on financing and for having obtained foreign venture capital

	(1)	(2)	(3)	(4)
	Dependent variable=1 if average annual investment following first grant request>sector median		Dependent variable=1 if a startup had received foreign venture capital after the first grant request	
	OLS	IV	OLS	IV
Grant funds (natural log + 0.01)	0.0147***	0.0474***	0.0064	0.0133
	(0.0051)	(0.0145)	(0.0046)	(0.0113)
Amount from external investors (natural log + 0.01)	-0.0113	-0.0102	0.0020	0.0020
	(0.0117)	(0.0123)	(0.0098)	(0.0095)
Received foreign venture capital, before and during first grant request	0.1300*	0.1577**	0.2615***	0.2677***
	(0.0715)	(0.0730)	(0.0603)	(0.0586)
Received domestic venture capital, before and during first grant request	0.0482	0.0125	-0.0082	-0.0149
	(0.0519)	(0.0523)	(0.0459)	(0.0433)
Received BIRD grant, before and during first grant request	-0.2224**	-0.2272**	-0.0890	-0.0904
	(0.0916)	(0.0885)	(0.0739)	(0.0681)
Had positive sales by the time of first grant request	-0.2061**	-0.1872**	-0.1461**	-0.1480**
	(0.0834)	(0.0888)	(0.0655)	(0.0637)
Elapsed time from inception to first grant request	-0.1552***	-0.0901*	-0.0759**	-0.0657*
	(0.0393)	(0.0482)	(0.0329)	(0.0363)
Elapsed time from first grant request to exit (natural log + 0.01)			0.0198**	0.0157
			(0.0087)	(0.0102)
Founded successful startups in the past	0.0943*	0.0683	-0.0079	-0.0137
	(0.0521)	(0.0535)	(0.0500)	(0.0488)
Founders' count	0.0715	0.0504	0.1636***	0.1598***
	(0.0773)	(0.0736)	(0.0538)	(0.0505)
Fouders' count ^ 2	-0.0115	-0.0092	-0.0249***	-0.0245***
	(0.0140)	(0.0130)	(0.0091)	(0.0085)
Professor founder	0.0847	0.1088*	-0.0371	-0.0309
	(0.0626)	(0.0588)	(0.0589)	(0.0559)
Soviet founder	-0.0360	-0.0137	0.0143	0.0181
	(0.0581)	(0.0596)	(0.0453)	(0.0443)
Applied for US patent	-0.0144	-0.0347	-0.0231	-0.0266
	(0.0551)	(0.0541)	(0.0424)	(0.0416)
Founded in an incubator	-0.1841***	-0.1662***	-0.0876**	-0.0838**
	(0.0522)	(0.0552)	(0.0427)	(0.0404)
ICT company founded during dot.com bubble	0.1131	0.2063**	0.0850	0.1033
	(0.0801)	(0.0889)	(0.0861)	(0.0868)
RecessionWhenApply	0.1233**	0.0521	0.0993**	0.0843*
	(0.0493)	(0.0518)	(0.0417)	(0.0449)
VC Availability (natural log)	0.2206***	0.1872***	0.1461***	0.1449***
	(0.0426)	(0.0452)	(0.0338)	(0.0319)
Constant	0.8995***	0.7114***	0.2051*	0.1821
	(0.1314)	(0.1555)	(0.1088)	(0.1111)
Sector FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Inception-time FE	✓	✓	✓	✓
Observations	561	561	561	561
R-squared	0.29		0.27	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Column I presents the OLS results for the probability of receiving annual follow-on investment above the sector median, after the first grant request. Column II presents the IV estimates. Column III presents the OLS results for the probability of receiving foreign venture capital, after the first grant request. Column IV presents the IV estimates. First-stage results are in Table 6 - Column II. As before, the instrument that I use is a dummy that equals 1 if a startup had at least one grant application during the year in which a new Chief Scientist was appointed. I use the same regressors as in Table 6. However, for the probability of receiving foreign venture capital, I also add a count for the number of years elapsed from the first startup's grant request to its exit.

Table 12: Regression results for having received follow-on financing and for having obtained foreign venture capital - Robustness checks

	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
	Dependent variable=1 if average annual investment following first grant request>sector median				Dependent variable=1 if a startup had received foreign venture capital after the first grant request			
	IV	IV	IV	IV	IV	IV	IV	IV
Grant funds (natural log + 0.01)	0.0497***	0.0469**	0.0428**	0.0445***	0.0125	0.0162	-0.0023	0.0113
	(0.0141)	(0.0216)	(0.0199)	(0.0148)	(0.0120)	(0.0151)	(0.0140)	(0.0109)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	474	404	422	547	474	404	422	547

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Columns I to V present the IV regression results for the probability of receiving annual follow-on investment above the sector median. In column I, I include as a control a startup's R&D budget request. In column II, I exclude those startupsthat are in the last quartile for their number of applications. In column III, I remove those companies that are in the last quartile for their grant amount received. In column IV, I eliminate from the sample those startups that had applied for more than two grants but had never obtained one. Columns VI to IX present the IV regression results for the probability of receiving foreign venture capital, after the first grant request. I replicate the models in columns I to IV. I use the same instrument and controls as in Table 11.

Table A1: Regression results for the probability of applying for government R&D grants - Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
		Entire sample			Sample of startups with a successful exit	
	OLS	First-stage	IV	OLS	First-stage	IV
Acquired by a foreign company	-0.0717**		-0.4456**	-0.1242***		-0.4557**
	(0.0301)		(0.1885)	(0.0419)		(0.2176)
Number of US acquisitions prior to a startup's inception, by sector		0.0637			0.2131***	
(natural log)		(0.0495)			(0.0688)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0658**			0.0006	
Received foreign venture capital		(0.0294)			(0.0334)	
Number of US acquisitions prior to a startup's inception, by sector *		0.0710***			0.0558***	
* Located in Tel Aviv		(0.0177)			(0.0191)	
Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓	✓
Inception-year FE x ICT DUMMY	✓	✓	✓	✓	✓	✓
Observations	1,639	1,639	1,639	699	699	699
F-stat of Instruments		11.25			5.89	
Sargan-Hansen test of overidentifying restrictions		1.79			0.59	
R-squared	0.18	0.25		0.20	0.27	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are clustered around sector and inception year. Relative to the results in Table 2, I include interaction terms between inception-year dummies and an indicator that equals 1 if a company operates in the ICT sectors. Columns I to III present the results for the probability of applying for a government grant, using the entire sample. Columns IV to VI present the results for the probability of applying for a government grant, using the sample of startups with a successful exit.

Table B1: Regression results for having experienced a successful exit, having obtained a grant amount above the sector mean, and having received foreign venture capital (linear regression with endogenous treatment effects - two-step estimates)

	(1)	(2)	(3)	(4)
	Having received grant funds	Having experienced a successful exit	Having received an average annual investment following first grant request>sector median	Having received foreign venture capital after the first grant request
	First-Stage	IV	IV	IV
Apply during Chief Scientist's appointment year	0.914***			
	(0.1769)			
Having received grant funds		0.3580**	0.3753***	0.0588
		(0.1473)	(0.1401)	(0.1215)
Controls	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Inception-time FE	✓	✓	✓	✓
Observations	561	561	561	561

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. They are bootstrapped with 500 replications. I use the same controls as in equations 4-7. The instrument in the first-stage regression is a dummy that equals 1 if a startup had applied at least once during the Chief Scientist's appointment year.

Table C1: Regression results for having obtained follow-on foreign investment

	(1)	(2)	(3)	(4)	(5)
Dependent variable=1 if a startup had received foreign investment after the first grant request	Baseline results	Introducing the control on the startups' R&D budget requests	Eliminating startups in the last quartile for their number of applications	Eliminating startups in the last quartile for their grant amount received	Eliminating those startups that had applied for more than two grants but had never obtained one
	IV	IV	IV	IV	IV
Grant funds (natural log + 0.01)	0.0141	0.0187	-0.2011	0.0064	0.0104
	(0.0143)	(0.0145)	(0.1251)	(0.0179)	(0.0146)
Controls	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Inception-year FE	✓	✓	✓	✓	✓
Observations	561	474	404	422	547

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are in parentheses. The dependent variable is a dummy that equals one if a startup had received foreign investment after the first grant request. I use the controls listed in equation 7. The first-stage results are presented in Table 11. The instrument in the first-stage regressions is a dummy that equals 1 if a startup had applied at least once during the Chief Scientist's appointment year.