Entrepreneurial Public Funding Choices*

Katja Kisseleva
Frankfurt School of Finance & Management

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Abstract

Governments deploy grants, loans, and public venture capital, yet empirical evidence rarely evaluates them as an interacting system. Using Norwegian population-level administrative records that track approved and rejected applicants, together with survey evidence, this paper shows sorting across public funding instruments at entry and further segmentation through instrument-specific screening. Application behavior shifts dynamically around approval and rejection decisions. The resulting sequences form a ladder, with broad-access grants as the on-ramp. However, an instrumental-variable design exploiting residualized region–year variation in grant approval rates shows that the apparent grant gateway largely reflects selection and learning: marginal grant approvals do not meaningfully increase subsequent participation in equity programs, while a delayed gateway into loans, which is administered by the same allocator, is economically large but imprecise at five-year horizon. Ultimately, public funding programs operate primarily through targeting complementarity—supporting different types and stages of firms—rather than gateway complementarity within the entrepreneurial ecosystem.

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1 Introduction

Policymakers worldwide use public funding to correct private investment distortions in entrepreneurship (e.g., Lerner, 2009; Bai, Bernstein, Dev, and Lerner, 2021). They face a portfolio problem by offering entrepreneurs a variety of funding tools. Grants address early-stage liquidity needs (e.g., Howell, 2017). Loans reach firms with credible repayment capacity but insufficient collateral (Brown and Earle, 2017). Equity through government venture capital (GVC) targets high-growth ventures requiring strategic support (Brander, Du, and Hellmann, 2015). These instruments are deployed simultaneously, yet most empirical work evaluates one instrument at a time. This single-program lens misses a central feature of policy design: founders choose where to apply, programs screen on different dimensions, and early interactions and decisions may reshape what happens next. This paper studies the entrepreneurial public funding portfolio as such a system.

The challenge is that navigating the public funding system involves three linked, endogenous stages: (1) entry into a program-specific applicant pool, (2) program-specific screening conditional on application, and (3) subsequent application behavior after approvals and rejections. Firms self-select into programs based on their characteristics, programs screen on correlated dimensions, and post-decision behavior reflects what was learned. Any observed sequence of public funding could therefore reflect either a causal gateway—early approval propels firms forward— or selection and learning, where high-quality firms both win early programs and pursue later ones. To tackle these linked stages jointly, this paper uses Norwegian population-level administrative records that track applications and decisions across the main simultaneously implemented instruments of public support: (i) government grants, (ii) government loans, and (iii) equity via financial intermediaries—specifically, a government-owned VC (GVCo) and government-supported seed VCs (GVCs).[1] I comple-

[1] Appendix A provides details on the institutional background.

ment these records with a large-scale survey that elicits entrepreneurs' motives and perceived frictions for applying to each public funding program.

The paper makes two core contributions. First, it characterizes endogenous entry, instrument-specific screening, and cross-program dynamics in a multi-program public funding ecosystem. Specifically, it shows that segmentation arises at entry and is amplified by instrument-specific screening. In the data, pre-application firm fundamentals strongly predict first-program choice. Firms that enter via grants and loans exhibit greater liquidity needs and weaker internal funding capacity, while equity entrants show stronger capitalization and organizational build-out (paid-in equity, employment, and assets), consistent with investor-readiness requirements. These entry patterns align with survey responses: grant and loan applicants emphasize near-term financing needs, whereas equity approaches are more often motivated by scaling ambitions and are constrained by perceived fit and information frictions. The entry segmentation result is stark: predicted first-program propensities based on pre-entry observables map monotonically into realized entry choices, and overlap in predicted propensities is low across the direct programs (grants/loans) and the government equity segment.

Program screening then adds a second, instrument-specific layer of segmentation. Conditional on applying, direct programs approve a large share of applicants but tilt toward implementability and liquidity among the applicant pool. Equity programs are far more selective and load more heavily on investor readiness than on contemporaneous profitability. As a result, the approved portfolio across programs does not draw from, or select within, a common applicant population.

Navigation is equally structured: application behavior re-optimizes around decisions, with grant experiences especially predictive of later engagement elsewhere and equity rejections disproportionately shifting firms toward broad-access instruments—consistent with

learning about program fit and fixed costs of entry being paid upon application rather than approval. Together, these patterns make the public funding ecosystem look like a ladder, with broad-access grants as the on-ramp.

Second, this paper addresses whether the observed ladder reflects a causal gateway complementarity. Grant approval could causally propel marginal firms into later programs by relaxing constraints, certifying quality, or reducing the cost of navigating additional bureaucracy. Alternatively, the ladder could reflect targeting complementarity: grants, loans, and equity serve distinct regions of the firm-state space, and higher-type firms happen to traverse the full system—not because early programs cause later participation, but because they were always the kind of firm that would. Distinguishing these mechanisms requires identifying what grant approval does for a marginal applicant, stripped of the selection that makes approved firms systematically different from rejected ones.

To isolate quasi-exogenous variation in grant approval that is plausibly orthogonal to latent applicant quality, I instrument a firms grant approval with a residualized leave-one-out region–year grant acceptance rate among grant applicants. The raw acceptance rate captures local screening tightness but can also reflect applicant composition. I therefore purge it of the component predictable from predetermined applicant-pool composition (lagged applicant characteristics and prior public-program histories that proxy for latent quality under monotone selection, Chodorow-Reich, Nenov, Santos, and Simsek (2024)) and absorb a rich set of fixed effects, in the spirit of purified supply shifters (Barrot, Martin, Sauvagnat, and Vallee, 2024). The resulting shifter compares region–years with observably similar applicant pools (and thus similar implied latent quality distributions) but different ease of approval, moving marginal applicants from rejection to approval and delivering a LATE for firms near the grant approval threshold. I then estimate how this induced grant approval affects subsequent applications to, and approvals in, loans and equity programs over one-, three-, and

five-year horizons.

The OLS patterns are strongly ladder-shaped: grant recipients are substantially more likely to apply to, and receive, later loans and equity. In contrast, the large positive OLS relationships largely disappear once grant approval is instrumented: point estimates are close to zero and confidence intervals are wide, so the data primarily rule out large gateway effects. That implies that for marginal applicants, grant approval does not meaningfully increase subsequent participation in the selective equity programs. This null for equity is consistent with three channels: real input effects can strengthen firms' outside options and reduce the incremental value of further public funding; informational and administrative costs are often paid upon applying rather than upon approval, limiting the learning shock from being approved; and broad-access grants, with high approval rates, likely carry a thin certification signal for selective equity screens.

In contrast, while there is little effect at short horizons, at the five-year horizon, the 2SLS point estimates for grant-to-loan application and approval are economically large—a grant-to-loan application effect of 18.6 percentage points, i.e. about 19 additional loan applications per 100 marginal grant approvals, implies a substantially delayed take-up response—but imprecisely estimated, so the loan gateway should be interpreted as suggestive. This result is plausible within the same direct allocator, where evaluators, information sets, and screening criteria overlap more closely, making internal certification and updating more likely.

These findings reframe how public funding portfolios can be interpreted. First, the recipient pool of broad-access entry instruments—such as grants—matters: it is disproportionately composed of high-type firms that are more likely to engage with multiple programs over time, so repeated participation and cross-program stacking can concentrate public resources on a subset of firms rather than reflecting broad-based progression through the system. Second, the apparent complementarities across instruments primarily reflect differ-

ences in the firm populations each instrument reaches, indicating that the portfolios aggregate coverage—spanning heterogeneous firm types, constraints, and stages—plays a central role in addressing diverse financing needs.

This paper connects to the extensive literature on the effectiveness of entrepreneurship policies on real outcomes. Closest in spirit to the public funding programs emphasized here, Howell (2017) estimates the causal effect of SBIR R&D grants on innovation and financing outcomes using a regression discontinuity design (RDD) based on application rankings, highlighting real input channels alongside limited certification. On the debt side, Brown and Earle (2017) estimate the effect of SBA loans on firm outcomes using institutional features of the program for identification. Evidence on government VC is comparatively harder to interpret causally, but existing work documents systematic differences across funding modes; for example, Brander, Du, and Hellmann (2015) show that firms funded jointly by private and government VCs outperform those funded by government VCs alone.[2]

In contrast to the single-instrument focus of much of this literature, this paper characterizes how the public funding portfolio allocates capital in equilibrium and tests whether the resulting sequences reflect causal gateways or selection. This positions the paper within the scarce literature on the interplay of entrepreneurship policies. Hellmann and Thiele (2019) provide the closest theoretical foundation, evaluating several policy designs and concluding

[2]Further studies find positive effects of programs providing funds to entrepreneurs directly (e.g., Jones and Williams, 1998; Lerner, 1999; Azoulay, Graff Zivin, Li, and Sampat, 2018; Zhao and Ziedonis, 2020; Tian and Xu, 2021), while others find no evidence of such effects (e.g., Wallsten, 2000; Gans and Stern, 2003; Lee, 2018). For programs providing funds through financial intermediaries, Leleux and Surlemont (2003) provide evidence that the participation of government VCs attracts investment to the industry as a whole. In the angel investment context, Denes, Howell, Mezzanotti, Wang, and Xu (2023) confirm that angel investor tax credits increase angel investments. However, they find no significant effect on state-level entrepreneurial activity. At the micro level, Alperovych, Hübner, and Lobet (2015) provide evidence that government VC–backed firms are less efficient than both private VC–backed and non-VC-backed firms. Also Andonov, Li, and Smeets (2025) find limited evidence that government VCs address market failures and their impact on firm is muted. De Haas and Gonzalez-Uribe (2024) provide the most recent literature review on the effectiveness of debt- and equity-related public policies.

that funding subsidies, implemented via either investment tax credits or return subsidies—as opposed to founding-related subsidies and incentives—are the optimal policy. The closest related empirical work is Pless (2025), who studies whether direct grants and R&D tax credits act as complements or substitutes for firms' R&D investment. This paper instead evaluates the interaction of simultaneously implemented direct funding programs within one ecosystem.

The remainder of the paper proceeds as follows. Section 2 describes the data and sample construction. Section 3 analyzes program entry: who applies where, why (using survey evidence), and how application behavior shifts around first decisions. Section 4 studies screening: who gets approved conditional on applying, and how selection differs across instruments. Section 5 tests whether grants causally shift later program participation using the IV design, and Section 6 concludes.

2 Data and Sample Construction

Norwegian administrative data are widely recognized for their quality and detail, and have been prominently used in research across labor economics, finance, and innovation (e.g., Meling, 2021; Fagereng, Mogstad, and Rønning, 2021; Ring, 2023). This study relies on comprehensive, firm-level administrative data compiled from multiple sources. The starting point is the full population of new establishments (411,200 firms) in Norway from 2000 to 2018, as recorded in the national business registry.

Firms that received government grants or loans are identified using application records from Innovation Norway, the governments innovation agency. In addition, I obtained records of all firms that received any government VC funding from the government-owned VC fund,

which also has a fund-of-funds seed capital mandate.[3] To obtain full deal-flow data—including information on rejected applicants—I contacted each government-supported VC fund individually. Because several management teams were subsequently dissolved, collecting complete data posed logistical challenges. Nevertheless, I was able to obtain deal-flow records from 12 of the 14 relevant government-supported VC funds.

Firm-level market-based share prices are constructed using equity transaction records derived from annual tax declarations filed with the Norwegian Tax Authorities. These records include every purchase, sale, and liquidation of equity by investors in Norwegian firms, as reported for wealth tax purposes. The data provide detailed information on transaction dates, amounts, and the number of shares traded, enabling the construction of firm-specific share prices from the date of firm inception.[4]

All datasets are linked via a unique firm identifier (*organisasjonsnummer*), assigned to all firms registered in Norway as well as to foreign institutional shareholders. This identifier is used consistently across administrative records and allows reliable merging of data on financial statements and business registry entries. Appendix A provides details on the institutional background.

3 Who Applies, Where and Why?

3.1 Application Patterns

A total of 13,631 firms applied for at least one form of public funding. Figure 1, Panel A, shows that grants attract the largest share of applicants—81%. Grants are non-repayable and

[3] I am extremely grateful to Christian Wolff-Skjelbred (Investinor AS, Seed Capital Scheme) for providing this data and facilitating contact with all current and former seed fund management teams.

[4] The detailed description of the equity transaction data and calculation of market share prices can be found in Kisseleva, Mjøs, and Robinson (2026).

therefore carry no financial risk, which may explain their widespread appeal. Government loans account for only 22% of applicants, suggesting a more selective appeal—possibly due to repayment obligations or stricter eligibility. Together, grants and loans account for the vast majority of applicants. In contrast, government VC programs receive significantly fewer applications: government-supported VC (GVCs) attract slightly fewer than loans—18% of applicants—while government-owned VC (GVCo) attracts only 9%. Lower application volume may be due to specific portfolio firm targeting or may reflect barriers such as complexity, investor-readiness requirements, or limited awareness among potential applicants.

Insert Figure 1 here.

Panel B presents distinct application paths, capturing the unique combinations of programs to which each firm applied. The majority of firms—approximately 60%—applied only for grants, reinforcing the central role of grants in the public funding landscape. Loan-only applicants make up 10% of the total, while GVCs-only and GVCo-only applicants account for 4.8% and 1.9%, respectively. Approximately 23% of firms applied to combinations of programs, with the most common being grant + loan (6.7%) and grant + GVCs (6.5%). All other combinations represent each 2% or fewer of applicants. Applications to three or more programs are rare: all such combinations together account for approximately 6% of firms. This subset of multi-program applicants likely represents a distinct group of firms seeking to layer complementary sources of public support.

3.2 Survey Evidence

To uncover why some entrepreneurs choose to apply for specific public funding programs while others do not, I conduct a large-scale survey in the setting country. The survey invitation was sent to all publicly available email addresses registered with Norway's Brønnøysund

Register Centre as firm contact points. Due to the historical nature of the registry data, some firms no longer exist or may have inactive e-mail addresses. These contact points include both firm-level and individual accounts—plus many non-startup firms. Thus, the effective reach of the target group (entrepreneurs) cannot be precisely determined by the number of email addresses. In total, 611 individuals responded, **439** of whom identify themselves as entrepreneurs and successfully passed the control questions.

The responses portray a picture of a currently active and domestically located entrepreneurial pool. Four out of five respondents are male, and the modal founder is in their early-to-mid 30s. Almost half of respondents hold at least a masters degree—most often in business/economics, or engineering/technology—and reside predominantly in Oslo and the broader South-East. One-third of respondents launched just one venture, and 44% of respondents founded their most recent startup during 2020–2025. Approximately 30% of respondents have sought a grant, 15% a loan, 16% have pitched to GVCo, and just 4% have approached GVCs. This distribution implies that the pool of respondents is biased towards greater familiarity with GVCo and less familiarity with GVCs, as the actual application rates in the data reveal a reversed pattern between two equity programs.

The survey reveals that grant applicants are overwhelmingly motivated by immediate liquidity needs: 62% seek capital for startup and operations, while smaller shares are driven by R&D (16%) or growth ambitions (12%). Market validation and the replacement of private capital are rare motivations. In contrast, the main reasons for not applying are perceived lack of qualification or relevance (41%), bureaucracy or skepticism (20%), and information gaps (14%). Only a minority cite a lack of need (14%) or low belief in securing support (10%). Thus, grant demand is shaped primarily by capital constraints, while non-application reflects eligibility perceptions, administrative barriers, and knowledge gaps, rather than an absence of interest.

For government loan programs, the leading motivation is again the need for capital (50%), with growth (16%) and favorable terms (16%) also being important. R&D and lack of alternative funding are less common drivers (9% each). Among non-applicants, 32% cite no need for a loan, but process barriers—bureaucracy or skepticism (27%) and doubts about qualification or success (23%)—are nearly as frequent. Additional deterrents include lack of knowledge (9%) and a desire to avoid debt (9%). Loan uptake is thus shaped by both capital requirements and perceived accessibility, with significant frictions from the process itself.

By contrast, applications for both GVCs and GVCo are primarily motivated by scaling and growth—especially for GVCo (60%) and, to a lesser extent, for GVCs (32%). Other motivations include financing opportunities, strategic alignment, and partnerships; for GVCo, investor demands and R&D are also reported. The principal barriers to applying are lack of knowledge (GVCs: 38%, GVCo: 26%) and perceived irrelevance to the firms stage or industry (GVCs: 21%, GVCo: 32%), with smaller shares citing lack of need or a desire for independence. Bureaucracy and skepticism are cited less often. Taken together, the equity segment appears governed not only by demand for capital and strategic resources, but also by information frictions and perceived program fit.

The survey yields three testable implications. First, if information frictions and perceived fit are central barriers, then prior public-program experiences should predict not only re-application to the same program but also transitions across programs, as initial participation reduces informational and administrative fixed costs and updates beliefs about eligibility and fit. Second, if grants and loans primarily address liquidity needs, then applications should be concentrated among more financially constrained firms (e.g., lower profitability and weaker balance sheets), conditional on age and local conditions. Third, if equity programs are primarily about scaling and investor readiness, then equity applications should be more tightly linked to indicators of capitalization and organizational build-out (e.g., paid-in

equity, employment, assets) than to contemporaneous profitability.

3.3 Determinants of Applications

To test these predictions in the rich administrative data, I estimate the following firm-year application regression model on the full population of all new establishments in Norway from 2000–2018 (411,200 firms).

$$\text{Apply}_{ijt} = \beta_1 + \beta_2 H_{ijt-1} + \beta_{3k} \sum_{k \neq j} H_{ikt-1} + \beta_4 X_{it-1} + \mu_{it} + \varepsilon_{ijt}. \tag{1}$$

Apply_{ijt} is a dummy variable equal to one if firm i applies to program j in year t. H_{ijt-1} summarizes firm i's prior history in program j (prior application and prior approval indicators), and $\sum_{k \neq j} H_{ikt-1}$ analogously summarizes histories in the other programs. X_{it-1} is a vector of observable pre-application firm characteristics measured at $t-1$ and μ_{it} denotes firm age, calendar year, municipality, and industry fixed effects.

Table 1 isolates program histories and cross-program linkages in a parsimonious specification, while Appendix Table C1 adds rich pre-application controls and the full set of fixed effects. Table 1 shows strong within-program persistence: prior interaction with a program predicts applying to that same program again. For grants, a prior grant application (approval) is associated with a 3.85 (8.94) percentage point increase in the probability of applying again (Column (1)). Relative to a mean application rate of 0.44%, these magnitudes correspond to roughly a nine-fold (twenty-fold) increase. For loans, a prior loan application predicts an increase of about four percentage points in subsequent loan applications (Column (3)), roughly a 36-fold increase relative to the mean of 0.11%. Persistence is even stronger in the equity segment. Prior GVCs and GVCo applications are associated with increases of 5.32 and 6.13 percentage points, respectively, and prior approvals predict

much larger continuation: a prior GVCs approval raises subsequent GVCs applications by 24.23 percentage points (Column (5)) and a prior GVCo approval raises subsequent GVCo applications by 35.69 percentage points (Column (7)).

Insert Table 1 here.

Beyond within-program persistence, Table 1 documents economically meaningful and asymmetric cross-program linkages. Grant experiences are especially predictive of later engagement elsewhere: conditional on other histories, a prior grant approval is associated with higher probabilities of applying for a loan (1.61pp; Column (4)) and for GVCs (1.68pp; Column (6)), with a smaller but still positive association for GVCo (0.63pp; Column (8)). Notably, cross-program linkages appear not only for approvals but also for applications, consistent with the surveys emphasis on informational and administrative fixed costs: once a firm navigates one public program, the marginal cost of approaching another appears lower.

Interplay is also pronounced within the equity segment. Prior GVCs application predicts GVCo application (3.64pp; Column (8)), and prior GVCo application predicts GVCs application (1.43pp; Column (6)), consistent with the two equity channels operating as partially overlapping routes for scaling finance. Finally, a linkage runs from equity into debt: a prior GVCo approval is associated with a higher probability of subsequent loan applications (4.65pp; Column (4)), consistent with equity-backed firms layering loans as complementary financing.

Appendix Table C1 shows that these history-based patterns persist when adding firm observables and fixed effects. The covariate patterns also align with the survey evidence. Across programs, applications are negatively related to pre-application profitability, consistent with financing needs motivating demand. For grants in particular, applications are more common among firms with lower revenues and lower profits, consistent with grants serving earlier-stage or liquidity-constrained ventures. In contrast, equity applications are

more strongly associated with capitalization and organizational build-out—especially paid-in equity, but also assets and employment—while remaining negatively related to profitability, consistent with equity participation reflecting scaling and investor readiness rather than short-run operating liquidity.

These patterns connect to a latent-quality view of selection in the spirit of Chodorow-Reich, Nenov, Santos, and Simsek (2024). In that framework, agents differ in latent productivity (quality), and observed entry decisions reflect threshold rules that shape the composition of the observed sample. In my setting, applying to program j is an endogenous entry decision into program-specific screening, so applicant pools can differ systematically because programs target different regions of an underlying state space. One dimension relates to financial slack and constraints (central for grants and loans), while another relates to scalability and investor readiness (central for equity screening). Observable pre-application characteristics X_{it-1} proxy for these latent states imperfectly: profitability, revenues, and cash proxy for internal funding capacity; paid-in equity and employment proxy for capitalization and organizational build-out; and bank debt proxies for external debt reliance and access. Differential loading of these proxies across programs implies that programs draw applicants from distinct regions of the latent state space. This compositional heterogeneity is central for interpretation: differences in approval rates and later outcomes across programs will partly reflect differences in who chooses to apply, not only differences in programs themselves.

3.4 Entry Sorting

If programs serve distinct regions of the firm-state space, segmentation should be visible at system entry: observables should predict which program a firm approaches first. Figure 2 evaluates entry sorting by comparing predicted and realized first-program choice. For each

program, the x-axis plots the predicted probability that the firms first public-funding application is to that program, estimated from a multinomial logit using pre-entry firm characteristics and fixed effects. The y-axis plots the realized share of firms whose first application is to that program, computed within 20 bins of the predicted-probability distribution (one observation per firm at its first application year). Across programs, realized entry shares increase monotonically with predicted propensities, indicating strong segmentation at entry: observable pre-entry fundamentals jointly organize whether firms enter first via broad-access direct programs (grants/loans) or via selective equity programs (GVCs/GVCo), consistent with targeting complementarity across instruments.

Insert Figure 2 here.

Table 2 quantifies overlap in predicted entry propensities across programs. For each row (the realized first program applied to), entries report the share of firms whose predicted probability of entering via the columns program falls in that programs top decile of predicted probabilities in the full entry sample. By construction, 10% of firms in the full entry sample are in the top decile for each program; values above (below) 10% indicate concentration (low overlap) and thus stronger segmentation. Loan entrants are highly concentrated among firms with high predicted loan propensity: 43.1% of loan-first firms fall in the loan top decile, compared with 6.8% of grant-first firms. Equity entry is similarly concentrated: 37.0% of GVCs-first firms are in the GVCs top decile, and 49.6% of GVCo-first firms are in the GVCo top decile. Cross-segment overlap is low: grant-first firms rarely lie in the equity top deciles (8.4% for GVCs; 8.2% for GVCo), and equity-first firms rarely lie in the grant top decile (7.2% for GVCs-first; 4.5% for GVCo-first). Overall, entry paths are strongly segmented, consistent with targeting complementarity rather than interchangeable take-up at entry. Within the equity segment, however, cross-over in propensities is meaningful, consistent with GVCs and GVCo operating as adjacent screening gates for firms with similar investor-readiness

characteristics.

Insert Table 2 here.

3.5 Follow-on Applications

I next examine application dynamics around firms first decisions. Figure 3 plots event-time application hazards to other programs around the first decision in an origin program. The patterns are timed to decisions, indicating re-optimization rather than slow-moving differences in levels. Around first grant decisions, hazards for loan and equity applications rise in the event year and remain elevated after approvals, consistent with grants often preceding broader financing attempts. Around grant rejections, the increase is more concentrated in the event year, consistent with rapid redirection when grant funding does not materialize. Around first loan decisions, grant hazards increase contemporaneously and equity hazards shift more modestly, consistent with bundling or sequencing of debt and grants within the same financing episode. Around equity decisions, reallocations are strongest: following approvals, hazards tilt toward continued participation within the equity segment (including the other equity channel), while hazards toward grants decline; following rejections, hazards shift toward broader-access instruments.

Insert Figure 3 here.

Figure C1 complements this evidence by focusing on firms next-step application choices after their first interaction with a given origin program, among firms that apply again at least once.[5] Two patterns stand out. First, approvals generate strong same-program continuation, especially in the equity segment: after a first GVCs approval, roughly 70% of firms apply to

[5]Because multiple applications can occur in the same next application year, the probabilities do not necessarily sum to one.

GVCs again in their next observed application year, compared to roughly 30% after rejection; for GVCo, the analogous probabilities are roughly 85% versus roughly 30%.

Second, equity rejections are associated with substitution toward broader-access funding. After a first GVCs (GVCo) rejection, firms shift disproportionately toward grants (next-step grant probabilities of about 60% and 45%, respectively), whereas after equity approvals, grant applications fall (to roughly 25% after GVCs approval and roughly 30% after GVCo approval). This pattern is consistent with learning about investor-readiness and program fit: rejection in selective equity screening induces firms to redirect search toward instruments with lower screening thresholds and lower application costs, while approval reduces the relative attractiveness of broad-access funding. By contrast, next-step loan applications are comparatively stable across origin outcomes, consistent with loans being layered as a complement rather than serving as a strict alternative to grants or equity.

Taken together, the evidence shows that application behavior is highly state-dependent and adjusts around decisions, consistent with re-optimization after new information arrives. The resulting sequences make the public funding system resemble a ladder. The next section asks whether this ladder is also enforced by program screening: conditional on applying, do programs select systematically different firm states?

4 Who Gets Funded?

This section turns to the second stage of navigating the public funding: conditional on applying, which firms are approved, and which forces shape approval rates within and across programs. Figure 4 presents annual approval rates for four public funding programs over 2005–2018, measured as the share of applicants approved in each program-year. Grants and loans exhibit consistently high approval rates—typically above 60% and often close to

80%—and are comparatively stable over time. This pattern is consistent with both programs operating as broad-access policy tools, where screening is present but not designed to ration support to a small minority of applicants.

Insert Figure 4 here.

In contrast, the two equity programs are much more selective. GVCs approval rates are lower and more variable, ranging from about 4% in the programs inception year to roughly 22% at their peak. GVCo approval rates are lower still and generally closer to 10%, with occasional deviations (as low as 3% in its inception year and as high as 15%). This is a key complement to the application patterns in Section 3: equity programs are not only applied to by fewer firms, but they also approve a much smaller share of those applicants, indicating a substantially tighter second-stage screen.

This raises the natural question: what predicts approval within each program? I estimate the following approval regressions to identify participating determinants:

$$\text{Approve}_{ijt} = \beta_1 + \beta_2 \,\text{Applicants}_{rjt} + \beta_3 \,\widehat{\Pr}\big(\text{Apply}_{ijt} = 1\big) + \mu_{it} + \varepsilon_{ijt}, \tag{2a}$$

$$\text{Approve}_{ijt} = \beta_1 + \beta_2 \,\text{Applicants}_{rjt} + \beta_3 H_{ijt-1} + \beta_{4k} \sum_{k \neq j} H_{ikt-1} + \beta_5 X_{it-1} + \mu_{it} + \varepsilon_{ijt}, \tag{2b}$$

where Approve_{ijt} equals one if firm i is approved to program j in year t. Applicants_{rjt} is the number of applicants to program j in region r and year t, capturing local applicant volume (congestion). $\widehat{\Pr}(\text{Apply}_{ijt} = 1)$ is the predicted application probability from (1), which summarizes selection into the applicant pool. H_{ijt-1} contains within-program history indicators (prior application and prior approval), and $\sum_{k \neq j} H_{ikt-1}$ contains analogous histories in other programs. X_{it-1} includes pre-application firm characteristics measured at $t-1$, and μ_{it} denotes firm age, calendar year, region, and industry fixed effects.

Table 3 reports the results. First, selection into applying is tightly aligned with

approval. In Equation 2a, the predicted application probability is a strong positive predictor of approval in every program. The coefficients imply economically large gradients: a 10 percentage point higher predicted application propensity is associated with about a 16.8 percentage point higher grant approval probability, 15.4 percentage points higher loan approval probability, 30.1 percentage points higher GVCs approval probability, and 22.8 percentage points higher GVCo approval probability (Columns (1), (4), (7), and (10)). The gradient is steepest for the equity programs, where baseline approval rates are low. In a latent-quality framework, $\widehat{\Pr}(\text{Apply})$ is an estimated index of program-specific fit, so its strong predictive power for approval is consistent with monotone selection into the applicant pool. This also motivates the richer decomposition in Equation 2b, which replaces the single-index propensity control with its underlying components to identify which dimensions of prior experience and firm state drive approval.

Insert Table 3 here.

Second, local competition matters—but differently across program types. The coefficient on Applicants_{rjt} is negative for grants, loans, and GVCo, consistent with tighter screening or limited capacity in high-demand region-years. For GVCs, however, the coefficient is positive and statistically significant, indicating higher approval rates in high-applicant region-years. In venture environments, thicker deal flow can raise approval rates if investment capacity expands in high-activity states or if match quality improves when the applicant pool is deeper, whereas fixed capacity would predict the opposite.

Third, approval depends strongly on program histories, and the structure differs sharply between broad-access and equity programs. For grants, prior approval substantially increases approval probabilities among repeat applicants (approximately 18.9 percentage points; Column (2)), while a prior unsuccessful grant application has little effect. This asymmetry suggests that the grant screen rewards demonstrated fit or implementability but

does not strongly stigmatize past rejection. For loans, history effects are sharper: a prior unsuccessful loan application reduces the probability of approval by approximately 13.4 percentage points, while prior loan approval raises it by about 12.5 percentage points (Column (5)), consistent with credit-style screening in which past failure remains informative for subsequent underwriting.

For the equity programs, the contrast is concentrated at the rejection margin. A prior rejection in GVCo is not penalized (Column (11)), and in GVCs it is positively associated with approval (Column (8)). A natural interpretation is that rejection in VC-style screening is not a persistent low-quality label: it can reflect timing, mandate fit, and readiness. Conditional on reapplying, previously rejected firms are plausibly positively selected on persistence and improved readiness—a mechanism that aligns with the surveys emphasis on informational barriers and perceived fit in the equity segment. Figure 5 visualizes these history gradients by plotting predicted approval probabilities by within-program history group.

Insert Figure 5 here.

Columns (3), (6), (9), and (12) restrict to first-time applicants, for whom there is mechanically no within-program history. Within the broad-access segment, grants and loans appear to share information: prior grant approval predicts higher loan approval for first-time loan applicants (Column (6)), consistent with certification within the same allocator. By contrast, grant and loan approvals have limited predictive power for approval in the equity programs. In addition, prior loan rejection is negatively associated with GVCs approval for first-time GVCs applicants (Column (9)), consistent with segmentation: VC-style screeners do not appear to treat broad-program approvals as sufficient evidence of investor readiness, while a negative debt-screening signal remains informative about fit in the VC segment. Within the equity segment, cross-certification is strongest: prior GVCs approval predicts substantially higher GVCo approval among first-time GVCo applicants (Column (12)), consistent with

the two equity channels operating as adjacent gates.

Appendix Table C2 confirms that these history patterns are not purely compositional artifacts of firm scale and fixed effects. Conditional on applying, approvals in grants and loans tilt toward firms with stronger implementability proxies—in particular higher profits and liquidity for grants, and stronger liquidity for loans—consistent with execution and repayment capacity being central at the approval stage even if liquidity needs motivate applying. In contrast, the equity programs tilt away from contemporaneous profitability, consistent with investing in growth options rather than current cash flow, and display stronger connections to capitalization and balance-sheet structure. This two-stage pattern complements the application results in Appendix Table C1: financially tighter firms disproportionately apply to broad-access programs, but conditional on applying, the approved firms in those programs skew toward stronger fundamentals, while equity programs screen on investor-readiness rather than short-run profits.

Finally, Table 4 translates these regression patterns into levels by describing firms characteristics before and after the first application. Grants and GVCs primarily attract younger firms, while loans and GVCo draw relatively older, more mature ventures. Approved firms tend to be slightly younger in all programs except loans, with grant recipients particularly skewed toward new ventures (median age zero versus one among rejections). Total funding amounts per firm increase sharply across programs, from grants (mean 2.58 million NOK) to loans (mean 7.08 million NOK), and further to equity (GVCs: mean 15.46 million NOK; GVCo: mean 38.08 million NOK), reflecting both program design and the capital intensity of recipients.

Insert Table 4 here.

A striking feature is the prevalence of zero pre-application revenues, salaries, and profits among grant and GVC applicants, reflecting the early-stage nature of these firms. For grants

and loans, approved applicants are observably larger and more economically active even *before* applying: higher mean revenues, higher wage bills, higher assets, and substantially higher paid-in equity. This fits a screening environment where the primary goal is broad support, but implementability and baseline viability still matter. For GVCs and GVCo, approved firms are not simply larger in revenues or assets; instead, approval is associated with balance-sheet structure that is more consistent with investor readiness: higher paid-in equity and lower reliance on bank loans. Post-application patterns are especially stark for equity programs, where approved firms exhibit large increases in paid-in equity relative to rejected firms, consistent with the institutional form of equity finance and the survey emphasis on scaling as the primary motive for approaching government VC.

Taken together, Sections 3 and 4 make the public funding ecosystem look like a ladder: grant recipients are more likely to engage with other programs. The key question is whether this pattern reflects a causal gateway—grant approval changes later public-finance participation—or sorting and learning, where latent high-type firms both win grants and pursue additional programs. The next section distinguishes these explanations.

5 Grants as a Gateway

5.1 Empirical Design

Empirically estimating the causal effects of entrepreneurship support programs poses well-known challenges, and the descriptive evidence in previous sections makes clear why. Both entry into the applicant pool and receipt of funding are highly non-random: firms self-select into applying based on histories and fundamentals (Section 3), and approvals then screen on

closely related dimensions (Section 4).[6]

I use an instrumental-variable (IV) strategy that exploits quasi-exogenous variation in grant screening tightness across region–year cells. The key idea is that, conditional on the applicant pool, changes in capacity relative to inflow shift the effective approval threshold and move marginal applicants from rejection to approval, generating a LATE interpretation (e.g., Angrist and Krueger, 1991; Angrist and Pischke, 2008). Concretely, I start from a leave-one-out region–year grant acceptance rate among grant applicants and interpret it as a proxy for local screening generosity.

In a latent-quality framework, an unobserved state (quality/fit/sophistication) can jointly affect (i) application, (ii) approval, and (iii) later multi-program participation, mechanically producing a spurious "gateway" pattern. This induces a central threat to exclusion that raw acceptance rates can reflect applicant composition: in some region–years, better firms may apply, raising acceptance even absent any supply shift. To isolate the plausibly exogenous component, I construct an applicant-weighted *residualized* grant tightness shifter, $\widetilde{Z}^{G}_{rti}$, by purging the part of the raw region–year acceptance rate that is predictable from predetermined applicant-pool composition and fixed effects, in the spirit of purified supply shifters (e.g., Barrot, Martin, Sauvagnat, and Vallee, 2024).

Let the raw leave-one-out acceptance rate for grants in region r and year t be

$$Z^{G,\text{raw}}_{rti} \equiv \frac{N^{G}_{rt,-i}}{A^{G}_{rt,-i}},$$

[6] As described in the institutional background in Appendix A, there are no observable program threshold cutoffs to utilize for a regression discontinuity design (RDD). Standard difference-in-differences (DiD) designs therefore face three practical obstacles. First, approved and rejected applicants differ in pre-application scale and financial strength (Table 4), making parallel trends implausible without additional structure. Second, grants are often awarded at very early firm ages, and many applicants have zero pre-application outcomes (revenues, wages, profits), limiting pre-trend diagnostics and restricting identification to a non-representative older subset. Third, treatment is inherently multi-dimensional: firms frequently layer instruments, and approval in one program changes subsequent applications to others (Figure 3 and Figure C1).

where $A^G_{rt,-i}$ is the number of grant applicants (measured in hundreds) in cell (r,t) excluding firm i and $N^G_{rt,-i}$ is the corresponding number approved. I then residualize $Z^{G,\text{raw}}_{rt}$ on predetermined measures of applicant composition: (i) cell means of lagged firm characteristics $\overline{X}_{rt-1}$ (constructed among applicants), and (ii) cell means of prior grant application and approval history $\overline{H}_{rt-1}$ (also among applicants) and an extensive set of fixed effects. Formally,

$$Z^{G,\text{raw}}_{rti} = \beta_0 + \beta_1 \overline{X}_{rt-1} + \beta_2 \overline{H}_{rt-1} + \delta_{region} + \delta_{\text{industry}\times t} + \delta_{\text{age}} + \delta_{region\times\text{industry}} + \varepsilon_{rti}, \quad (3)$$

and define the residualized shifter as $\widetilde{Z}^G_{rti} \equiv \widehat{\varepsilon}_{rti}$. Intuitively, $\widetilde{Z}^G_{rti}$ compares region–years with similar observable applicant pools but different ease of approval. Empirically, the purge is substantial: the residualized shifter is only 0.39 correlated with the raw grant acceptance rate.

A second concern may arise that grant tightness may proxy for broader policy cycles shared across programs. First, the residualized grant shifter is only modestly correlated with residualized shifters for other programs (0.36 with loans, -0.12 with GVCs, and 0.03 with GVCo). Second, further purging $\widetilde{Z}^G_{rti}$ of any component predictable from other programs' residualized shifters yields a twice-residualized instrument that remains extremely similar to the baseline instrument (correlation 0.94). Together, these diagnostics support interpreting $\widetilde{Z}^G_{rti}$ as capturing grant-specific screening tightness rather than common shocks.

The instrument enters the first stage for the grant approval among first-time grant applicants:

$$\text{Approve}_{ij=Gt} = \beta_0 + \beta_1 \widetilde{Z}^G_{rti} + \beta_2 \hat{p}^G_i + \beta_3 H_{i,t-1} + \beta_4 X_{i,t-1} + \delta_{region} + \delta_{\text{industry}\times t} + \delta_{\text{age}} + \varepsilon_{ijt}, \quad (4)$$

where $\hat{p}^G_i$ is the firm-specific predicted propensity to apply for a grant measured at the

firms first grant-application year. In a monotone-selection framework, $\hat{p}_i^G$ proxies for latent program fit/quality, so including it absorbs selection on observables that jointly drives application and approval. $H_{i,t-1}$ and $X_{i,t-1}$ are the same predetermined histories and lagged firm characteristics used in Section 3.

Table 5 reports the first-stage estimates and associated weak-instrument diagnostics. The F-statistic is comfortably above the conventional threshold of ten in all specifications. The standard deviation of $\widetilde{Z}_{rti}^G$ is 0.039, and a one-standard-deviation increase raises the probability of grant approval by about 1.6–1.8 percentage points. Table C3 provides balance tests within the grant-applicant sample: $\widetilde{Z}_{rti}^G$ is not systematically related to predetermined public-funding histories or pre-application firm fundamentals, consistent with the shifter moving approval through screening tightness rather than applicant selection.

Insert Table 5 here.

5.2 Why Grant Approval May (Not) Trigger a Ladder

The survey evidence suggests that grant approval can affect subsequent applications through offsetting channels.

Learning and fixed-cost reductions. Many non-applicants cite bureaucracy, skepticism, information gaps, and perceived lack of fit. This naturally maps into fixed costs of navigating public programs. Entering the system—often already at the application stage—can lower informational and administrative costs within a program and, potentially, across programs, making later applications more likely even absent changes in firm fundamentals. This mechanism is consistent with strong within- and cross-program persistence in applications (Table 1) and with the re-optimization of application choices around initial approvals and rejections (Figure 3 and Figure C1). At the same time, because information acquisition

and bureaucracy costs may be paid upon applying (not only upon approval), this channel need not generate a large approval-induced gateway effect, especially for marginal applicants.

Reduced need and a stronger outside option. Grant applicants primarily seek liquidity for operations and near-term execution. For firms near the margin, receiving a grant can relax constraints and improve the continuation value outside further public funding. In the spirit of Howell (2017), early-stage grants can finance prototyping and progress that increases subsequent private VC and improves innovation and revenue outcomes, thereby strengthening the outside option. A stronger outside option can reduce the incremental value of applying for additional public instruments, even if the grant improves firm performance.

Certification. A separate possibility is that grant approval conveys information to other public funding allocators. However, Howell (2017) emphasizes the real input channel rather than (private) investor certification as a primary mechanism. In a broad-access setting with high grant approval rates, the grant decision may be an informationally thin signal for more selective equity screens, limiting any certification-based gateway into GVCs/GVCo. Certification may be more plausible within the direct allocator (grants→loans), where evaluators and criteria overlap more closely.

Taken together, these channels imply an ex ante ambiguous prediction for whether grant approval increases subsequent participation in other public programs: learning can push toward further applications, while improved slack and a better outside option can push away from them.

5.3 Grant Approval and Subsequent Participation

I estimate whether grant approval causally affects subsequent participation in other public programs using the following second-stage specification:

$$Y_{ih}^{j\neq G} = \beta_0 + \beta_1 \,\text{Approve}_{ij=Gt_0} + \beta_2 \,\hat{p}_i^G + \beta_3 \,H_{i,t_0-1} + \beta_4 \,X_{i,t_0-1} + \delta_{region} + \delta_{\text{industry}\times t_0} + \delta_{\text{age}} + \varepsilon_{ih}, \tag{5}$$

where $Y_{ih}^j \in \{\text{Apply}_{ih}^j,\ \text{Approve}_{ih}^j\}$ captures firm i's subsequent application to, or approval in, destination program $j \neq G$ over horizon $h \in \{1, 3, 5\}$ years after the first grant application year t_0. Table 6 reports OLS estimates of (5) and corresponding 2SLS estimates that instrument $\text{Approve}_{ij=G,t_0}$ with the residualized grant tightness shifter $\widetilde{Z}_{rti}^G$ for the three-year horizon; Appendix Tables C4–C5 report the one- and five-year horizons.

Across horizons, the OLS estimates show that grant recipients are substantially more likely to participate in other programs. This pattern is consistent with a latent-quality view of selection: firms with higher execution capacity, sophistication, or program fit are more likely to clear the grant screen and more likely to pursue multi-program financing strategies. In addition, learning and fixed-cost reductions can reinforce this correlation: firms that successfully engage with one program may find it easier to navigate others.

In contrast, the 2SLS estimates isolate the effect of grant approval for marginal applicants whose approval status changes when local screening tightness shifts. These compliers are, by construction, close to the approval threshold and therefore distinct from the high-type firms that disproportionately generate the OLS ladder. The 2SLS estimates imply limited approval-induced transitions into the equity programs: the large positive OLS associations for GVCs/GVCo largely disappear once grant approval is instrumented. This is consistent with the mechanisms in Section 5.2 and with the survey evidence: equity participation is primarily about scaling and investor readiness, and a marginal grant approval need not move

a firm into the equity-ready region or materially change perceived fit. More broadly, it fits the view that grants operate mainly through real inputs ((e.g., prototyping and progress) Howell, 2017) rather than through strong certification into selective equity screens.

Insert Table 6 here.

By contrast, a gateway into loans is conceptually more plausible because grants and loans are administered by the same direct allocator and rely on more overlapping information sets. Consistent with this, the 2SLS point estimates for loan transitions are the largest among the destination programs and appear more pronounced at longer horizons (Appendix Table C5). While imprecisely estimated, this pattern is consistent with a delayed certification channel: for some marginal firms, the grant may help cross an internal viability or implementability threshold that later becomes relevant for loan approval. This interpretation also aligns with the survey, where loan demand reflects capital needs and favorable terms and may arise after firms make progress.

Taken together, the OLS–IV contrast maps cleanly into the three channels emphasized above. First, informational and bureaucracy costs are often paid at entry (the first application) rather than at approval, so grant approval need not generate a large additional learning shock. Second, approval can relax need and strengthen the outside option, lowering the incremental value of further public funding. Third, any certification effect is likely to be stronger within the direct allocator (grants→loans) than across segments into selective equity programs.

Figure 6 complements these results by plotting reduced-form event-time coefficients from regressing destination-program application indicators on $\widetilde{Z}^{G}_{rti}$, evaluated at t_0. Pre-period coefficients are close to zero and show no systematic drift, consistent with the shifter not proxying for differential pre-trends. Post-t_0 coefficients remain small and non-monotone,

reinforcing the conclusion that grant approval does not systematically trigger broad causal ladder-climbing into other programs.

Insert Figure 6 here.

Overall, strong sequencing in administrative data primarily reflects sorting and learning in a multi-program environment. Complementarity across instruments is therefore mainly *targeting complementarity*—different programs serve different regions of the firm-state space—rather than *gateway complementarity* from grants into other public funding programs. The causal gateway effect of grant approval for marginal applicants appears limited for selective equity programs and, at most, suggestive for public loans.

6 Conclusion

This paper provides a unified, within-country comparison of the main public funding programs for entrepreneurs—grants, government loans, and equity delivered through government-owned and government-supported venture capital funds—using population-level administrative data from Norway and complementary survey evidence. By observing the full applicant universe and tracking both approvals and rejections, the analysis moves beyond the single-program focus of prior work to characterize who applies where, how each instrument screens conditional on application, and how early decisions shape subsequent navigation of the public funding ecosystem.

These results sharpen how to interpret both firm behavior and policy program interplay. For entrepreneurs, early interactions generate state-dependent re-optimization: approvals and rejections—especially in the selective equity segment—are followed by persistent same-program continuation or redirection toward broader-access instruments, consistent with

learning about fit and with fixed costs of program participation. For policy design and evaluation, the central implication is conceptual: the public funding portfolio operates primarily through targeting complementarity—different instruments cover different regions of the firm-state space—rather than through gateway complementarity, in which early grants causally propel firms into later-stage loan or equity programs. The policy portfolio is therefore best evaluated as a system of segmented allocators, not as interchangeable substitutes or enforced ladder.

Although Norway represents an ideal empirical laboratory—offering high-quality administrative data, well-defined funding programs, and a broadly representative institutional environment for advanced economies—its welfare system and high level of public spending may affect the overall scale of support available to entrepreneurs as well as risk exposure and individuals' selection into entrepreneurship. Nevertheless, the core mechanisms documented here—endogenous program entry, instrument-specific screening, information frictions, and the distinction between selection-based sequencing and causal gateways—are present in many advanced economies, even if magnitudes differ across contexts.

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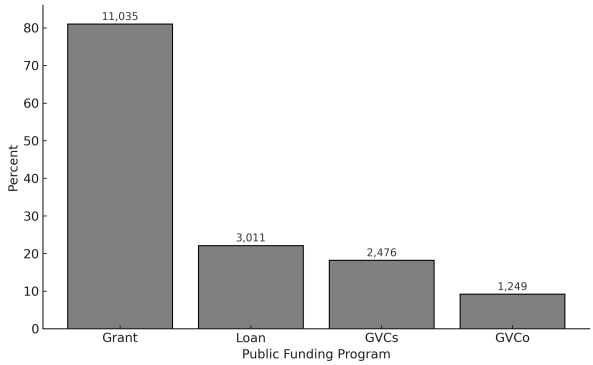
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Figure 1: Distribution of Public Funding Applications

Figure 1 presents the distribution of firms applying to four types of public funding: grants, loans, government-supported venture capital (GVCs), and government-owned venture capital (GVCo). Panel A shows the share of applicants to each program, allowing for multiple applications. Panel B presents mutually exclusive application paths, capturing all observed combinations of program applications. The sample includes all firms applying for public funding between 2005 and 2018.

Panel A: Distribution of Applicants



Panel B: Combination of Applications

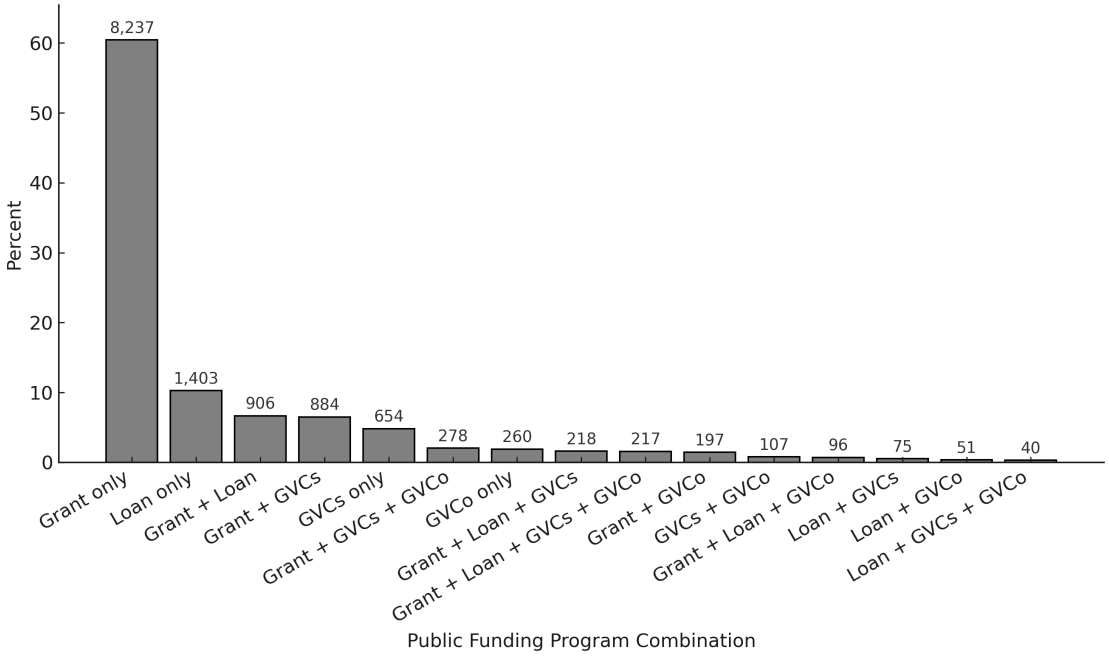


Figure 2: Entry Sorting: Realized First Program vs. Predicted Propensity

Figure 2 assesses if firms sort into different public funding programs at ecosystem entry. For each program j, the x-axis plots the predicted probability that the firms first public-funding application is to program j, estimated from a multinomial logit model using pre-entry firm characteristics and fixed effects as shown in Table 1. The y-axis plots the realized share of firms whose first application is to that program j, computed within 20 bins of the predicted probability distribution (one observation per firm at its first application year).

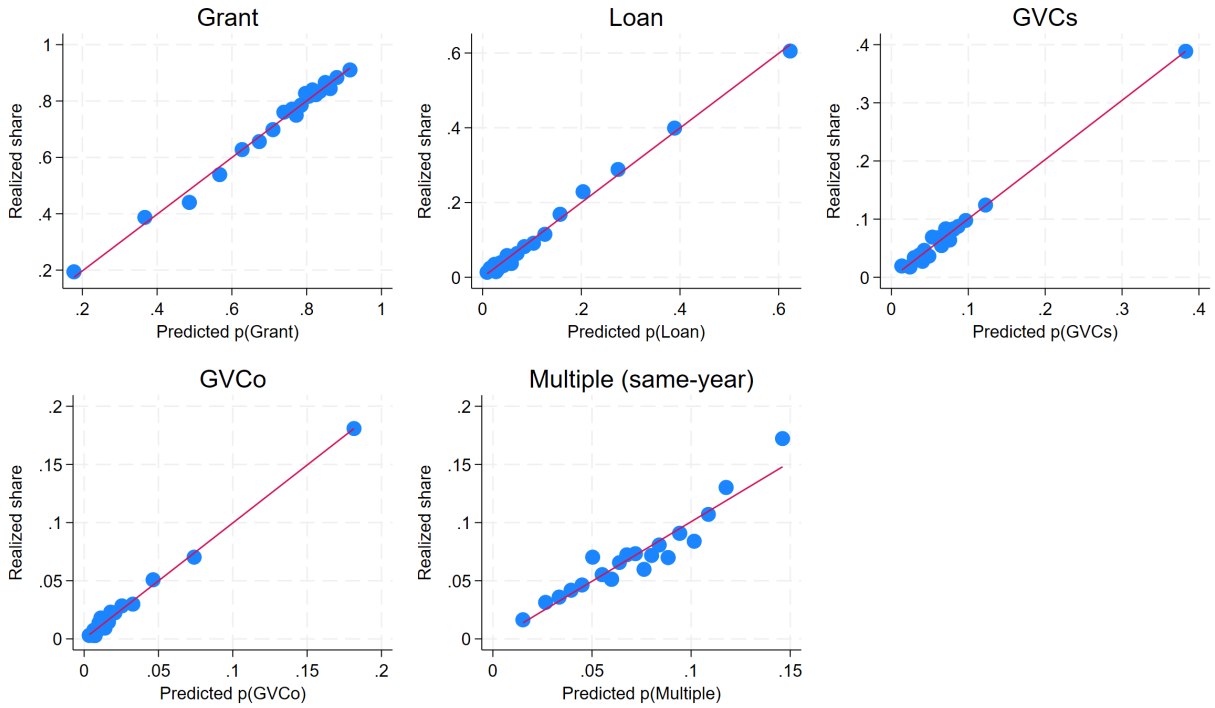


Figure 3: Event-time Application Hazards Around First Decision

Figure 3 plots annual application hazards to other public funding programs in event time around a firms first decision in a given origin program. Each row corresponds to an origin program (Grant, Loan, GVCs, GVCo). The left column conditions on firms whose first application to the origin program is approved; the right column conditions on firms whose first application is rejected. Event time 0 denotes the calendar year of the first decision in the origin program. Lines report the mean probability (in percent) that the firm applies to each of the other programs in year $t_0 + k$, for $k \in [-5, +5]$. The grey dashed series (right axis) reports the number of firm-year observations contributing to each event-time bin. The sample includes all firms applying for public funding between 2005 and 2018.

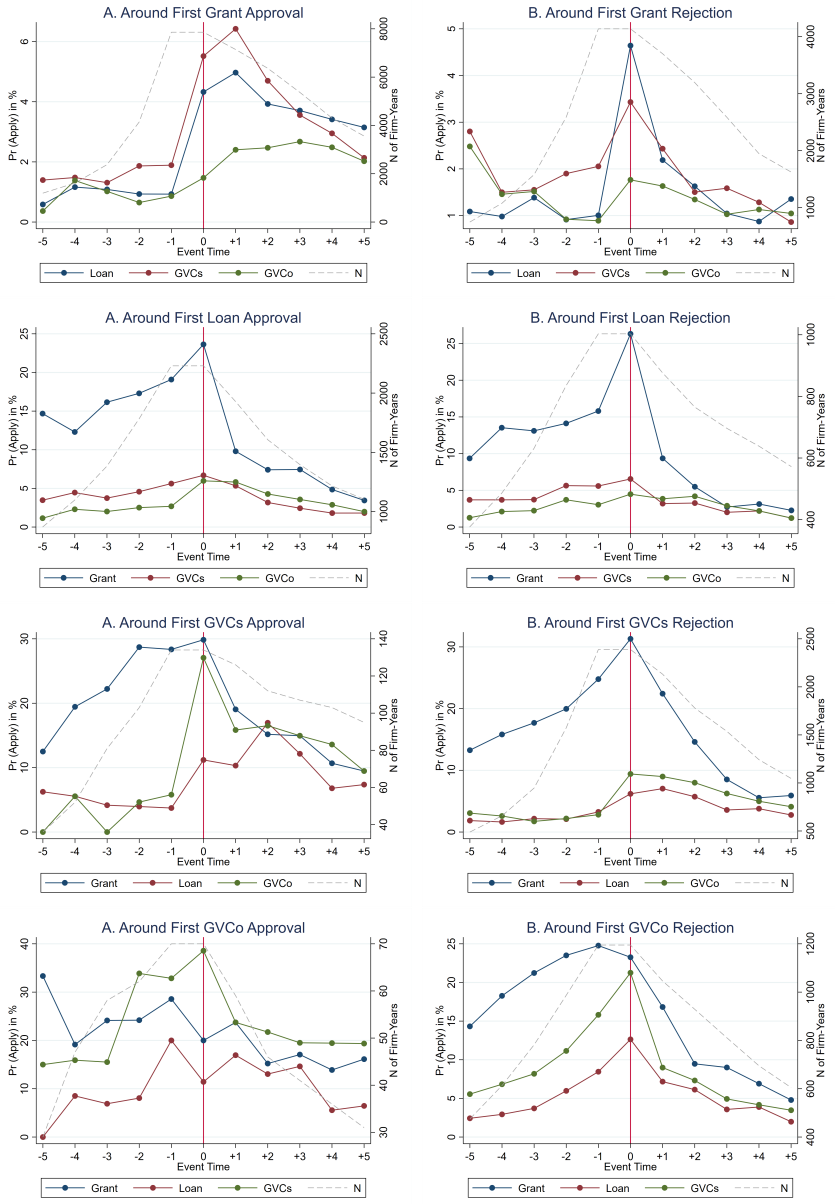


Figure 4: Annual Approval Rates

Figure 4 shows annual approval rates for grants, loans, government-supported VC (GVCs), and government-owned VC (GVCo) from 2005 to 2018. Approval rates are calculated as the percentage of applicants approved each year. The first GVCs were established in 2006 and GVCo in 2009. The figure illustrates program-related differences in selectivity and stability over time.

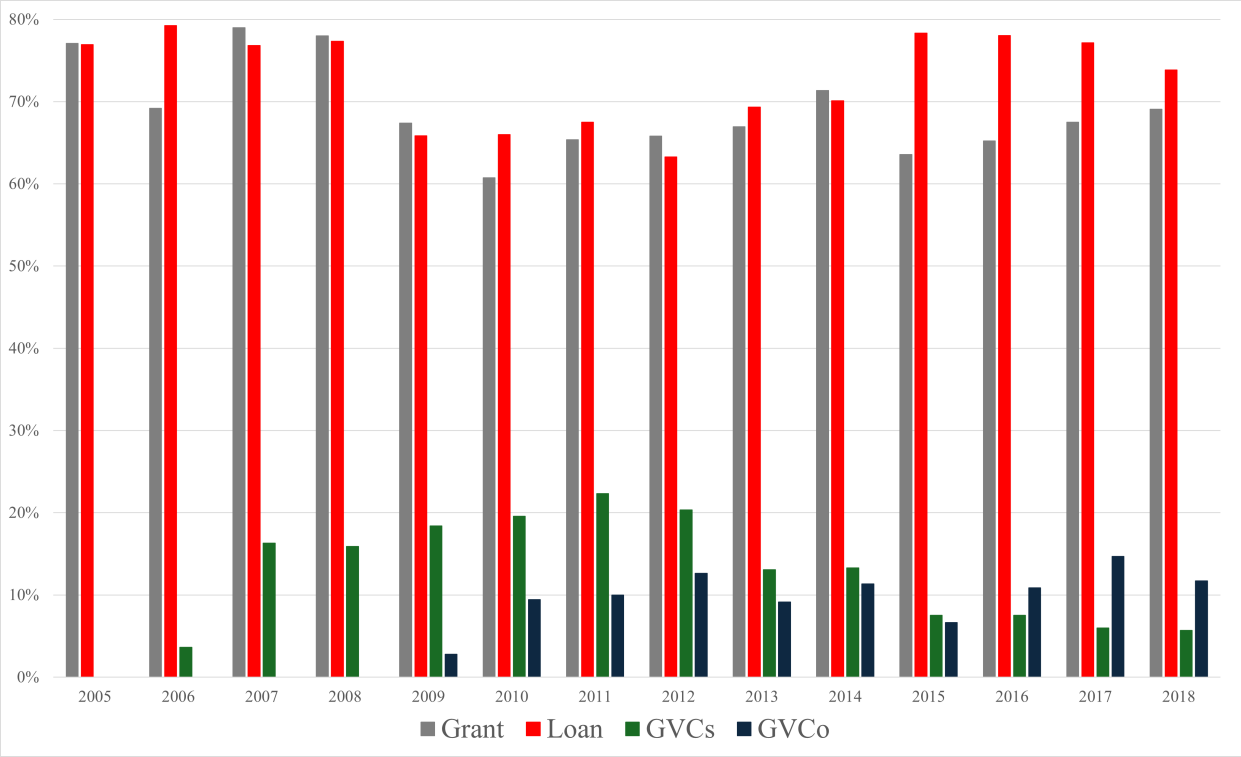
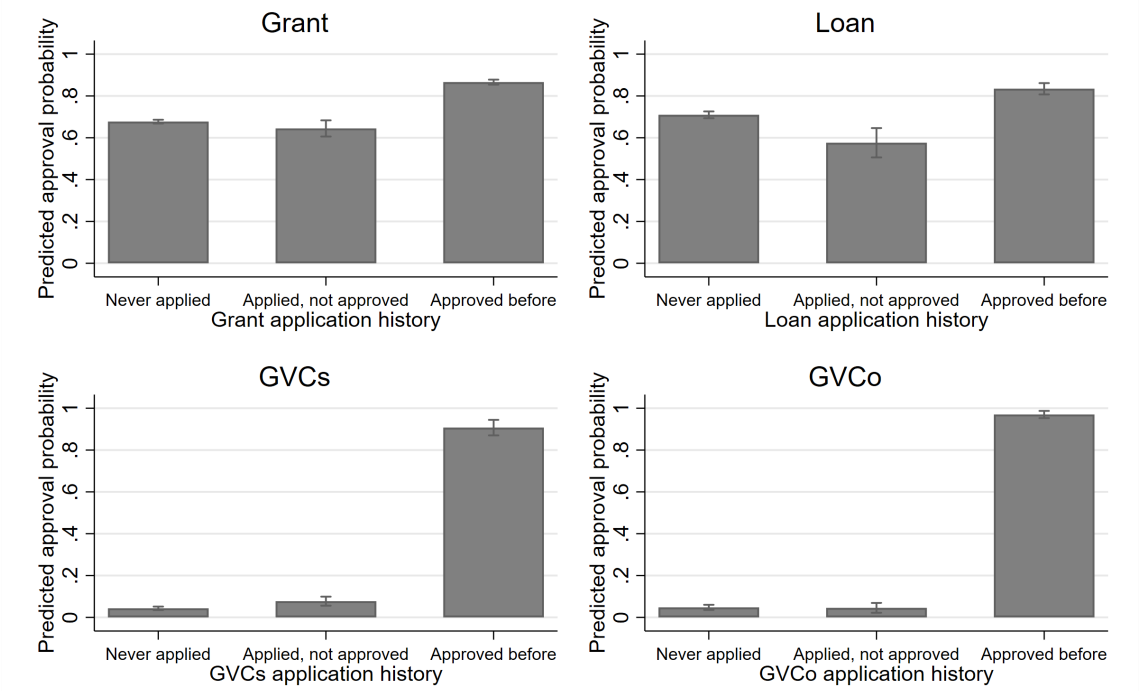


Figure 5: Predicted Program Approval

Figure 5 plots predicted approval probabilities in program j by firms' prior application history in that same program, based on the approval regressions in Equation 2. The bars display predictive margins with 95% confidence intervals, computed after estimating the specifications in Table 3 Columns (2), (5), (8), and (11), respectively. In each panel, the sample is restricted to applicants to the corresponding program j, and firms are grouped into three mutually exclusive history categories: never applied, previously applied but not approved, and previously approved.



Bars show predictive margins; whiskers are 95% confidence intervals.

Figure 6: Event-Time Trends

Figure 6 plots event-time coefficients from reduced-form regressions of program-j application indicators on the residualized grant approval rate shifter, $\widetilde{Z}^{G}_{rti}$. Event time k is defined relative to the first grant application year t_0 ($k = 0$). For each $k \in [-5, +5]$, the plotted point estimate is the coefficient on $\widetilde{Z}^{G}_{rti}$ from a separate regression using firm-year observations at event time k; vertical bars denote 95% confidence intervals. All specifications include region, firm-age, and industry-by-calendar-year fixed effects. Standard errors are clustered at the region–year level.

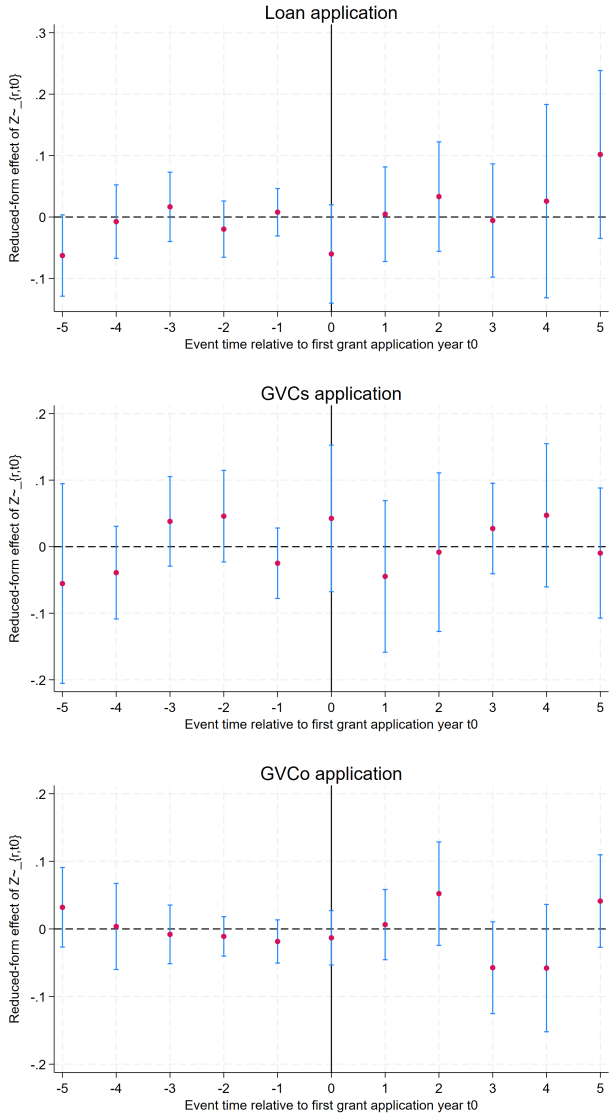


Table 1: Determinants of Public Funding Applications

Table 1 examines which firms apply to each public funding program and reports LPM estimates of the probability that firm i applies for program j (government grants, loans, or equity (GVCs or GVCo)) at time t, as specified in Equation 1. Explanatory variables include indicators for prior application and prior approval history. The sample comprises all new establishments in Norway from 2000 to 2018 (411,200 firms). No fixed effects are included. The constant term is estimated but omitted for brevity. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Grant Application (1/0)		Loan Application (1/0)		GVCs Application (1/0)		GVCo Application (1/0)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prior grant application (1/0)	0.0385***	0.0369***		0.0046***		0.0068***		0.0035***
	(0.0019)	(0.0019)		(0.0008)		(0.0008)		(0.0007)
Prior grant approval (1/0)	0.0894***	0.0855***		0.0161***		0.0168***		0.0063***
	(0.0029)	(0.0030)		(0.0013)		(0.0012)		(0.0010)
Prior loan application (1/0)		-0.0060*	0.0399***	0.0320***		-0.0001		0.0030*
		(0.0034)	(0.0032)	(0.0031)		(0.0020)		(0.0018)
Prior loan approval (1/0)		0.0052	0.0373***	0.0338***		0.0009		0.0066***
		(0.0043)	(0.0044)	(0.0043)		(0.0025)		(0.0024)
Prior GVCs application (1/0)		0.0367***		0.0181***	0.0532***	0.0382***		0.0364***
		(0.0036)		(0.0021)	(0.0025)	(0.0025)		(0.0023)
Prior GVCs approval (1/0)		-0.0143		0.0132	0.2423***	0.2327***		0.0200*
		(0.0123)		(0.0090)	(0.0256)	(0.0251)		(0.0118)
Prior GVCo application (1/0)		0.0048		0.0071**		0.0143***	0.0613***	0.0373***
		(0.0048)		(0.0032)		(0.0036)	(0.0038)	(0.0037)
Prior GVCo approval (1/0)		0.0356		0.0465**		0.0532**	0.3709***	0.3569***
		(0.0265)		(0.0221)		(0.0256)	(0.0398)	(0.0390)
Observations	3,778,126	3,778,126	3,778,126	3,778,126	3,650,797	3,650,797	3,144,549	3,144,549
R-squared	3.9%	4.0%	1.8%	2.5%	3.4%	4.1%	4.3%	5.8%
Mean dependent variable	0.44%	0.44%	0.11%	0.11%	0.09%	0.09%	0.05%	0.05%

Table 2: Entry Segmentation Across Public Funding Instruments

Table 2 quantifies overlap in predicted entry propensities across programs. For each row (the realized first program applied to), the entries report the percentage of firms whose predicted probability of entering via the columns program falls in the top decile of that programs predicted-probability distribution in the full entry sample. Predicted probabilities are obtained from a multinomial logit model of first-program choice using pre-entry firm characteristics and fixed effects as shown in Table C1, estimated on one observation per firm at its first application year. By construction, 10% of firms in the full entry sample belong to the top decile for each program; values above (below) 10% indicate concentration (low overlap) and thus stronger segmentation in entry paths.

		Top-decile			
First Program Application	N	p(Grant)	p(Loan)	p(GVCs)	p(GVCo)
Grant	9,719	14.3%	6.8%	8.4%	8.2%
Loan	1,597	2.6%	43.1%	11.3%	14.6%
GVCs	991	7.2%	9.8%	37.0%	29.7%
GVCo	353	4.5%	13.0%	35.4%	49.6%
Multiple (same year)	971	7.6%	10.3%	10.5%	9.0%

Table 3: Determinants of Public Funding Approval

Table 3 reports LPM estimates of the probability that, conditional on applying, firm i is approved for public program j at time t, as specified in Equation 2. N of applicants is the total number of applicants to program j in year t and region g. Predicted application is the predicted probability from running Equation 1. Explanatory variables include indicators for prior application and prior approval history. Other explanatory variables capture firm characteristics measured in the year prior to application. All specifications include firm age, calendar year, region and industry fixed effects. The constant term is estimated but omitted for brevity. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Grant Approval (1/0)			Loan Approval (1/0)			GVCs Approval (1/0)			GVCo Approval (1/0)		
Applicants to the program	All	All	First-time	All	All	First-time	All	All	First-time	All	All	First-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
N of applicants	-0.019**	-0.020**	-0.025**	-0.124**	-0.121**	-0.086	0.049***	0.035*	0.047**	-0.147**	-0.162***	-0.177**
	(0.008)	(0.008)	(0.011)	(0.051)	(0.051)	(0.060)	(0.019)	(0.018)	(0.019)	(0.058)	(0.056)	(0.071)
Predicted application	1.683***			1.537***			3.087***			2.281***		
	(0.067)			(0.223)			(0.067)			(0.027)		
Prior grant application (1/0)		-0.033				-0.122**			0.003			-0.025
		(0.021)				(0.054)			(0.014)			(0.024)
Prior grant approval (1/0)		0.189***				0.084***			0.014			-0.006
		(0.008)				(0.023)			(0.011)			(0.016)
Prior loan application (1/0)			-0.011		-0.134***				-0.063***			-0.018
			(0.084)		(0.037)				(0.020)			(0.025)
Prior loan approval (1/0)			0.017		0.125***				0.011			0.033
			(0.038)		(0.016)				(0.024)			(0.025)
Prior GVCs application (1/0)			0.105***			0.007		0.034***				0.007
			(0.027)			(0.031)		(0.012)				(0.015)
Prior GVCs approval (1/0)			0.214***			-0.100		0.864***				0.238***
			(0.030)			(0.089)		(0.021)				(0.077)
Prior GVCo application (1/0)			0.026			-0.068			-0.024*		-0.002	
			(0.047)			(0.050)			(0.013)		(0.014)	
Prior GVCo approval (1/0)			0.306***			0.095			-0.039*		0.922***	
			(0.101)			(0.112)			(0.020)		(0.013)	
Observations	16,498	16,498	10,827	4,061	4,061	2,985	3,285	3,285	2,431	1,687	1,687	1,227
R-squared	9.2%	10.3%	9.0%	5.7%	7.8%	8.2%	63.2%	64.9%	12.8%	61.4%	63.8%	11.1%
Mean dependent variable	73.23%	73.23%	73.23%	73.04%	73.04%	73.04%	12.17%	12.17%	12.17%	11.41%	11.41%	11.41%
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Table 4: Description of Approved and Rejected Applicants

Table 4 summarizes descriptive statistics of firms applying to four public funding programs—Grants, Loans, GVCs, and GVCo—separately for approved and rejected applicants. Besides the firm age at first application and the total size of received public funding, a range of firm characteristics measured both before and after the application date, are reported. Amounts are reported in millions of Norwegian kroner (NOK) (1 USD ≈ 6.6 NOK over the sample period, based on average daily interbank mid-quote rates from Norges Bank). The sample covers firms applying between 2005 and 2018.

	Grant				Loan				GVCs				GVCo			
	Rejected		Approved		Rejected		Approved		Rejected		Approved		Rejected		Approved	
N of firms	3,176		7,860		781		2,230		2,343		134		1,179		70	
	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean
Firm age (first application)	1.0	1.7	0.0	1.6	2.0	3.1	2.0	3.4	1.0	1.9	1.0	1.7	3.0	3.5	3.0	3.2
Total amount per firm			0.92	2.58			3.40	7.08			11.42	15.46			17.51	38.08
Funding amount / total assets			109%	799%			44%	625%			22%	76%			31%	31%
Firm characteristics before first application																
Revenues	0	6.07	0	36.66	0.07	6.75	0.18	16.77	0	4.57	0	2.31	0.05	25.74	0.38	8.01
Salaries	0	2.76	0	9.54	0.02	1.94	0.13	4.04	0	1.69	0	1.04	0.16	8.11	0.89	4.42
Operating profit	0	-0.04	0	3.49	0	-1.09	0	-0.89	0	-0.19	0	-1.06	-0.04	-6.58	-0.93	-5.11
Total assets	0	6.77	0	63.39	0.85	7.37	1.60	18.97	0.11	6.49	0.14	4.69	1.36	33.78	4.48	19.89
Cash	0	0.46	0	3.12	0.06	0.80	0.13	2.26	0.02	0.96	0.01	1.03	0.17	4.12	0.81	5.01
Paid-in equity	0	1.28	0	15.73	0.11	2.82	0.20	6.17	0.03	2.00	0.07	3.70	0.23	13.44	2.24	14.53
Outstanding bank loan	0	0.63	0	9.13	0	1.58	0	5.73	0	1.62	0	0.94	0	6.98	0	2.14
Firm characteristics after first application																
Revenues	0.01	8.58	0.17	52.95	0	9.18	0.99	26.47	0.06	10.10	0.09	9.56	0.10	36.42	1.96	22.55
Salaries	0	4.68	0.04	16.35	0	2.28	0.36	5.87	0.01	3.83	0.55	4.64	0.10	12.11	3.94	11.25
Operating profit	0	0.25	0	3.54	0	0.07	0	-0.28	0	-0.65	-0.44	-7.58	0.00	-1.53	-3.69	-12.43
Total assets	0.14	11.07	0.62	86.70	0.68	10.67	4.10	32.57	0.84	17.16	5.15	25.87	1.63	59.24	17.40	56.50
Paid-in equity	0.05	2.23	0.10	25.87	0.10	3.44	0.43	11.10	0.13	8.40	3.69	25.41	0.32	27.10	12.58	55.45
Outstanding bank loan	0	0.78	0.00	4.57	0	3.09	0.00	10.71	0	3.36	0	4.27	0	15.24	0	7.43

Table 5: Instrumenting Grant Approval—First stage

Table 5 reports first-stage estimates for grant approval among grant applicants. The endogenous regressor is an indicator for grant approval, and the excluded instrument is the residualized grant acceptance-rate shifter $\widetilde{Z}^G_{rti}$, constructed at the region–year level as leave-one-out and purged of predictable applicant-pool composition. Columns (1)–(3) use all grant application-years; column (4) restricts the sample to each firm's first grant application. $\hat{p}^G_i$ denotes the predicted probability of applying for a grant measured at the first grant application year. Controls are firm characteristics at $t-1$ and program-application histories. Standard errors are two-way clustered at the firm and region–year level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$\widetilde{Z}^G_{rti}$	0.426***	0.428***	0.452***	0.573***
	(0.088)	(0.088)	(0.086)	(0.119)
$\hat{p}^G_i$		-2.554*	0.677	-20.705**
		(1.455)	(1.787)	(8.368)
Observations	16,483	16,483	16,483	10,813
R-squared	7.4%	7.4%	11.8%	11.0%
Applications	All	All	All	First
Controls	No	No	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry x CY FE	Yes	Yes	Yes	Yes
Firm age FE	Yes	Yes	Yes	Yes
F-Stat	23.45	23.48	27.72	23.14
p-value	0.00	0.00	0.00	0.00
KP rk Wald F				23.14
Cragg-Donald F				26.69
KP rk LM				8.505
KP rk LM p-value				0.00

Table 6: Do Grants Serve as Gateways into Other Public Funding Programs?

Table 6 estimates the effect of grant approval on subsequent participation in other public funding programs within three years of the firm's first grant application year. The dependent variables in Panel A are indicators for applying to other programs at any time in years $t_0 + 1$ through $t_0 + 3$, while the dependent variables in Panel B are corresponding approval indicators. Columns (2), (4), (6) instrument grant approval with the residualized region–year grant acceptance-rate $\widetilde{Z}^G_{rti}$ (Table 5). $\hat{p}^G_i$ denotes the predicted probability of applying for a grant measured at the first grant application year. All specifications include controls, which are firm characteristics at $t-1$ and program-application histories as well as region, firm age and industry by calendar year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Appendix Tables C4–C5 replicate Panel A and Panel B for one-year (t_0+1) and five-year (t_0+1 to t_0+5) transition horizons, respectively.

Panel A: Application in the next three years to:

	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.054***	0.044	0.063***	0.009	0.025***	-0.003
	(0.006)	(0.109)	(0.008)	(0.126)	(0.005)	(0.078)
$\hat{p}^G_i$	2.573*	2.718	7.817**	8.621**	1.702	2.127
	(1.535)	(2.112)	(3.319)	(3.984)	(2.397)	(2.812)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	5.8%	2.1%	8.3%	1.7%	7.7%	2.6%

Panel B: Approval in the next three years to:

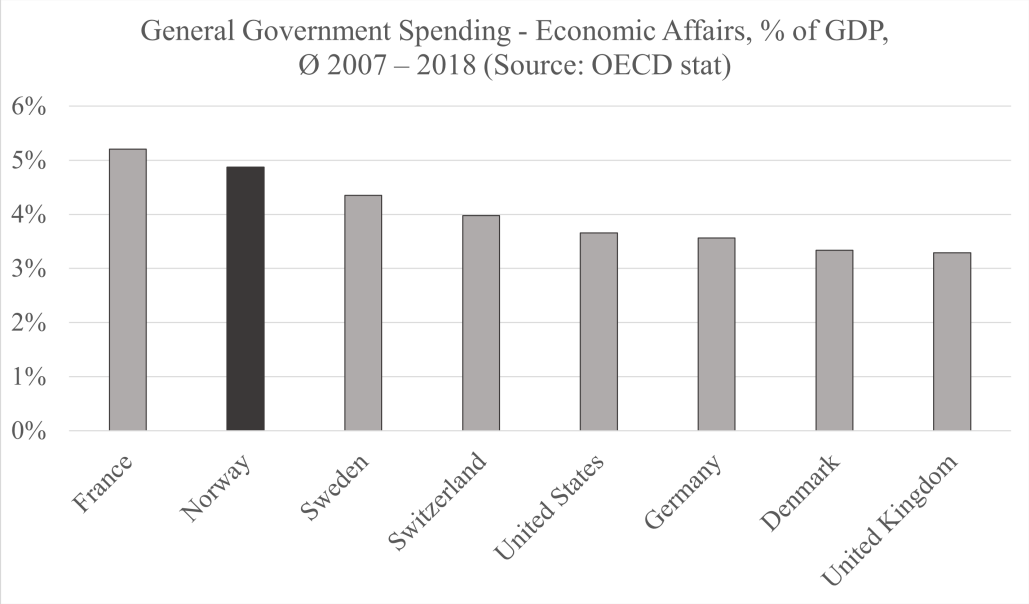
	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.047***	0.028	0.003**	-0.017	0.001*	0.000
	(0.005)	(0.108)	(0.001)	(0.032)	(0.001)	(0.021)
$\hat{p}^G_i$	3.178**	3.467*	-0.568	-0.276	0.094	0.110
	(1.269)	(2.047)	(0.418)	(0.665)	(0.171)	(0.375)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	5.1%	1.8%	8.1%	4.3%	6.3%	4.6%

Appendix A: Institutional Background

The Norwegian government leads all developed countries in terms of general government spending per capita (see Figure A1), making Norway an ideal setting to evaluate various policy designs simultaneously. Despite its small population, Norways economic and financial structure closely resembles that of other advanced Western economies (see Figure A2).

Figure A1: Government Spending on Economic Affairs

Figure A1 shows cross-country averages of general government spending on economic affairs as a percentage of GDP over the period 2007–2018. Norway ranks highest among developed countries, reflecting the states outsized role in the economy. The figure underscores Norways relevance as a setting to study the design and allocation of public entrepreneurial funding. (Source: OECD stat.).

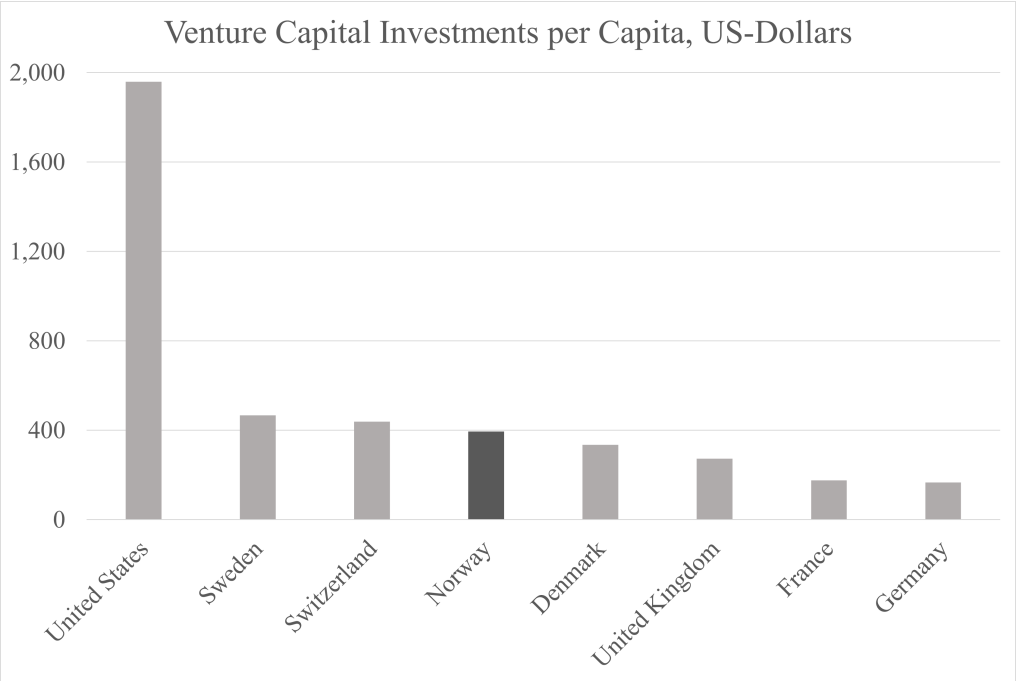


Consequently, insights drawn from the Norwegian context are likely to be relevant to other settings.[7]

[7]Further background on the Norwegian innovation system, startups, and VC market is provided in Appendix V of Hvide and Jones (2018) and in Kisseleva, Mjøs, and Robinson (2026).

Figure A2: Venture Capital Investments per Capita

Figure A2 presents average annual venture capital (VC) investments per capita (in USD) across developed economies from 2007 to 2018. Norway ranks as the third-largest VC market per capita in Europe during this period, following Sweden and the United Kingdom. While Norway's private VC sector remains modest in absolute terms, the per-capita intensity underscores its relevance as a setting for evaluating the role of government-backed venture capital. (Source: OECD stat.).



This study examines three nationally established public funding programs designed to support domestic entrepreneurial firms either directly or through financial intermediaries. Specifically, I evaluate grants, loans, and equity provided through government venture capital (VC) funds.[8]

Both grants and loans are administered by Innovation Norway, a government agency that targets firms with innovation projects. For entrepreneurs, Innovation Norway offers

[8]R&D subsidies are excluded from this analysis because they are provided as tax relief across all firms in Norway and generally exert little immediate impact on early-stage firms with negative earnings (e.g., Färnstrand Damsgaard, Hjertstrand, Norbäck, Persson, and Vasconcelos, 2017; Nilsen, Raknerud, and Iancu, 2020; Pless, 2025). For an overview of public programs worldwide, please refer to Bai, Bernstein, Dev, and Lerner (2021).

market clarification grants, commercialization grants, innovation contract grants, innovation loans, and startup loans—with the possibility of combining grants and loans.[9] Furthermore, a more general grant for innovation projects is available to entrepreneurs. These grants target innovation broadly, including projects from established firms as well. In this case, the public funding component (i.e., the aggregate of grants and loans) typically does not exceed 50% of total financing, with the remainder consisting of working capital, newly raised equity, subordinated loans, or bank loans.[10] Innovation loans and startup loans are high-risk loans. Firms that receive these loans are usually not able to obtain debt financing in the commercial credit market. Both government grants and loans are designed to provide critical liquidity for new business models and innovative products that have not yet entered the market, and—unlike similar programs in Sweden or Germany—they are not earmarked for specific expenditures such as wages.

Government equity is provided through a combination of a wholly state-owned VC fund and several government-supported VC funds (see Brander, Du, and Hellmann, 2015). The state-owned VC fund operates analogously to private VC funds, with one of its mandates being to actively invest equity in order to stimulate wealth creation by offering risk capital to competitive, globally focused, and primarily recently established firms without regional restrictions.[11] The management team actively governs its portfolio companies and may execute follow-up investments, although state ownership is capped at 49%. A notable difference from private VC funds is the adoption of an annual bonus scheme, instead of the fund-typical carried interest, in line with Norwegian state guidelines for executive compen-

[9] `https://en.innovasjonnorge.no/article/startups`

[10] `https://en.innovasjonnorge.no/article/funding-for-innovation-projects`

[11] According to the fund's articles of association, investments are prioritized in sectors with businesses that have potential global competitive advantages, that address the exploitation of key natural resources, that utilize innovative technologies and expertise, and/or that contribute to mitigating the effects of anthropogenic climate change and negative impacts on the environment.

sation of investment managers in state-owned firms.

In addition, the Norwegian government has established several government-supported VC seed funds. The four nationwide funds[12] and the five regional funds[13] were established between 2006 and 2008, with only two funds remaining active today. These funds were given five years to build their portfolios (i.e., 2006-2010 or 2008-2012). The primary objectives of the nationwide schemes were to increase the supply of seed capital and to enhance the commercialization of research-based projects from universities, whereas the regional schemes primarily aimed to boost the supply of seed capital and promote the development of specific regions. Furthermore, four additional nationwide seed funds were established between 2014 and 2018,[14] and these funds have also completed their investment periods. The primary objective of these funds was to increase the supply of seed capital to small and medium-sized enterprises in order to promote innovative business ventures in Norway.

All government-supported VC seed funds are managed by private equity professionals and invest on the same terms and conditions as private VC funds, with clearly defined exit strategies for each investment. Notably, they exhibit several investment specializations: they cannot invest in companies that are older than five years at the time of funding, ensuring that the investments represent first-time financing. In addition, certain sectors are considered off-limits (including oil, gas, financial services such as banking and insurance, mining, real estate,

[12]The Norwegian government contributes up to 50% of a funds total capital in the form of subordinated loans. Private investors finance at least 50% of the total capital, and the funds are 100% privately owned. In addition, the government grants 25% of the subordinated loans to cover potential losses. The loans carry an interest rate of twelve-month NIBOR plus two percentage points. https://www.eftasurv.int/newsroom/updates/two-new-norwegian-seed-capital-schemes-approved-efta-surveillance-authority.

[13]The Norwegian government finances up to 70% of a funds total capital in the form of subordinated loans and partly covers administrative costs. Private investors finance at least 30% of the total capital, and the funds are 100% privately owned. Additionally, the government grants 25% of the subordinated loan to cover potential losses. The loans carry an interest rate of twelve-month NIBOR plus 0.5 percentage points. https://www.eftasurv.int/newsroom/updates/two-new-norwegian-seed-capital-schemes-approved-efta-surveillance-authority

[14]Similar conditions as in the previous nationwide funds: https://www.eftasurv.int/newsroom/updates/state-aid-new-norwegian-seed-capital-scheme-approved

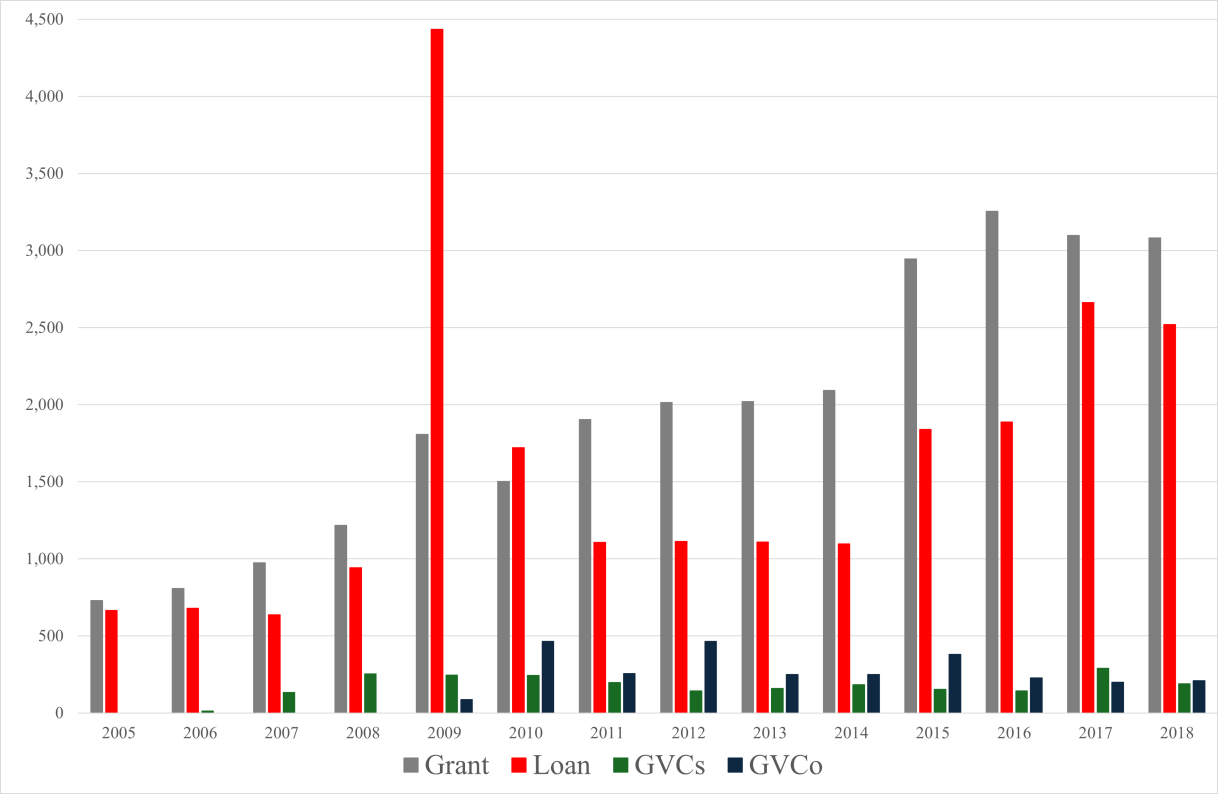
and infrastructure), and public ownership in these funds is capped at 49.9%. Moreover, regional seed funds are subject to geographical limitations.

The annual budget proposals for grants and loans are made by the Ministry of Trade, Industry, and Fisheries, while the budget is approved by parliament. These are nonrolling annual budgets, meaning the allocated budget must be spent within the fiscal year. Similarly to the directly provided funding, the establishment and allocation of capital to the financial intermediaries (government VCs) that administer equity are based on annual budget proposals from the Ministry of Trade, Industry, and Fisheries and are approved by parliament. The allocated government capital is made partially available for investments upon the signing of a contract with the government VC management firm and partially in tranches on call. A time-series overview of the government capital supply into all public funding types is presented in Figure A3.

Overall, this institutional setting underscores the multifaceted approach of the Norwegian government to fostering entrepreneurship and innovation. The design and implementation of these funding programs offer a rich context for evaluating public funding for entrepreneurs.

Figure A3: Public Funding Allocation

Figure A3 displays annual public funding allocations from four types of public funding—grants, loans, government-supported venture capital (GVCs), and government-owned venture capital (GVCo)—from 2005 to 2018. Values are reported in millions of Norwegian kroner (NOK) (on average approximately eight Norwegian kroner to the USD).



Appendix B: Survey Design and Results (Section 3)

Survey Invitation

Nettskjema

Invitation to respond to

Public Funding for Entrepreneurs

Survey link: `https://nettskjema.no/i/9962603?token=325eklasuhoneaoissard9ro`

Norwegian text [...]

English text

Survey Invitation

We invite you to participate in a research survey about how public funding programs support entrepreneurship in Norway. Our broader goal is to better understand how entrepreneurs navigate early-stage financing opportunities, such as government grants, government loans, and government-supported venture capital.

The results of this survey will contribute to an academic study examining how different types of government support relate to key firm-level outcomes, including innovation output, employment, firm operations, and market capitalization. This survey is administered by Professor Aksel Mjøs at the Norwegian School of Economics (NHH) and Professor Katja Kisseleva at Frankfurt School of Finance & Management (Germany).

We are extremely grateful for you taking 5 minutes to complete this survey. Your insights are highly valuable and will contribute to improving the understanding of how public funding supports entrepreneurs in Norway.

Thank you for your participation!

This survey is sent to companies which have submitted their e-mail address to the Brønnøysund Register Centre.

Questionnaire

1. Please choose your preferred language for this survey / Hvilket språk ønsker du å bruke i denne undersøkelsen?

   - Norsk
   - English

2. This survey focuses on your experience with Norwegian public funding programs and startup activity. A startup refers to a newly established company that aims to develop innovative products or services.
   It takes approximately 4–6 minutes to complete.
   No personal information is collected. Your responses remain completely anonymous and cannot be traced back to you or your company.
   Click **Next** to begin.

3. Have you ever founded or co-founded a startup?

   - Yes
   - No

     (If no: Thank you for your interest in the survey. This study is intended for individuals who have founded or co-founded a startup. We truly appreciate your time!)

4. How many startups have you founded?
   (Free text)

5. In which year did you found your most recent startup?
   (Free text: 4-digit year)

All subsequent questions refer only to your most recent startup.

6. Is your most recent startup still active?
   - Yes
   - No
7. What region of Norway does/did your most recent startup primarily operate from?
   - Oslo and the Greater Oslo Region
   - South-East Norway (Østlandet)
   - South-West Norway (Vestlandet)
   - Central Norway (Trøndelag)
   - Northern Norway (Nord-Norge)
8. Has your most recent startup applied (or do you plan to apply) for an Innovation Norway startup or innovation grant?
   - Yes
   - No
9. - *[If Yes]* What were/are your main reasons for applying? (Free text, mandatory)
   - *[If No]* What were/are your main reasons for not applying? (Free text, mandatory)
10. Has your most recent startup applied (or do you plan to apply) for an Innovation Norway loan?
    - Yes

- No

11. - *[If Yes]* What were/are your main reasons for applying? (Free text, mandatory)
    - *[If No]* What were/are your main reasons for not applying? (Free text, mandatory)

12. Has your most recent startup pitched (or do you plan to pitch) to Investinor for venture capital?

    - Yes
    - No

13. - *[If Yes]* What were/are your main reasons for pitching to them? (Free text, mandatory)
    - *[If No]* What were/are your main reasons for not pitching to them? (Free text, mandatory)

14. Has your most recent startup pitched (or do you plan to pitch) to any of the following Norwegian seed funds?
    Please check all that apply:

    - ProVenture
    - Sarsia
    - SakorninVest
    - Alliance
    - KapNor
    - Fjord Invest

- Norinnova
- Midvest
- None of these

15. - *[If at least one selected]* What were/are your main reasons for pitching to them? (Free text, mandatory)
    - *[If None of these]* What were/are your main reasons for not pitching to them? (Free text, mandatory)

16. Are you currently a resident of Norway?

    - Yes
    - No

17. What is your gender?

    - Female
    - Male
    - Non-binary / Other gender

18. How old were you when you founded your first startup?

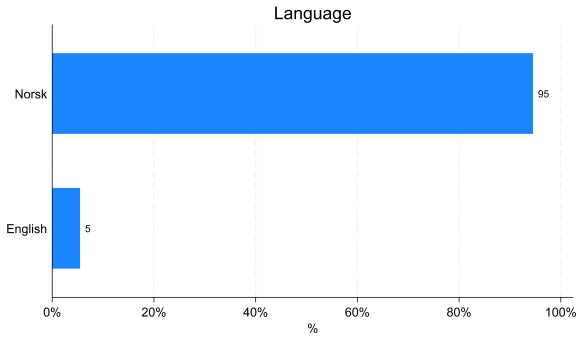
    - Under 20
    - 20–24
    - 25–29
    - 30–34
    - 35–39

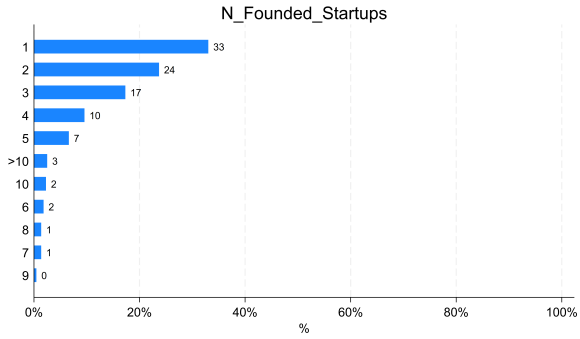
- 40–44
- 45–49
- 50–54
- 55–59
- 60 or older

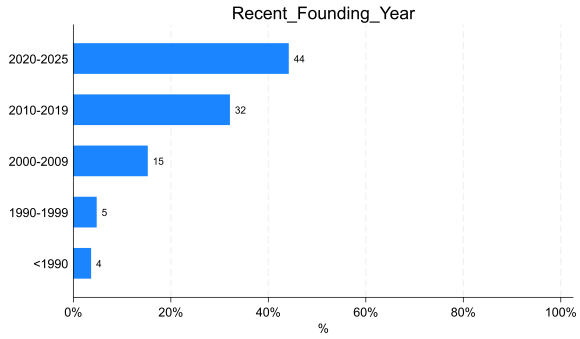
19. What is your highest level of completed education?
    - High school or equivalent
    - Bachelor's degree
    - Master's degree
    - PhD or equivalent
    - Other (please specify): *(Free text)*
20. What was the main field of your education?
    - Business / Economics
    - Engineering / Technology
    - Natural Sciences
    - Social Sciences
    - Humanities / Arts
    - Other (please specify): *(Free text)*
21. **Please press Send to submit your response.**

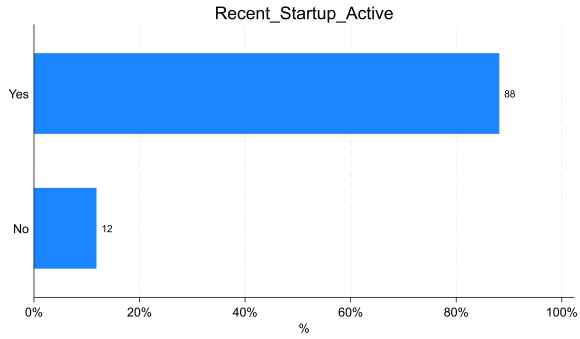
    Thank you for your participation! Your insights are extremely valuable and will contribute to understanding how public funding supports entrepreneurs in Norway.

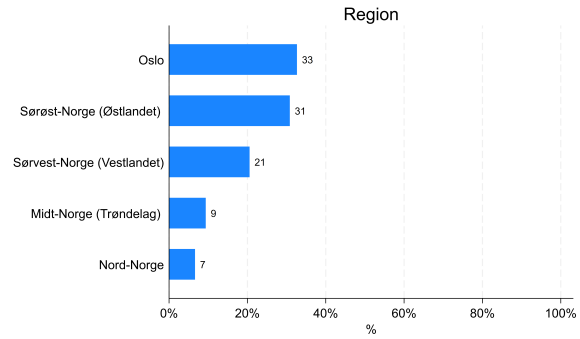
Survey Results

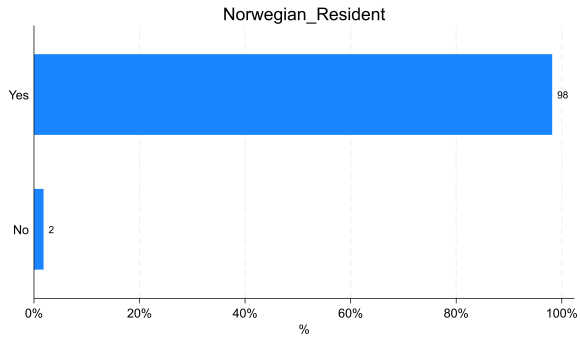


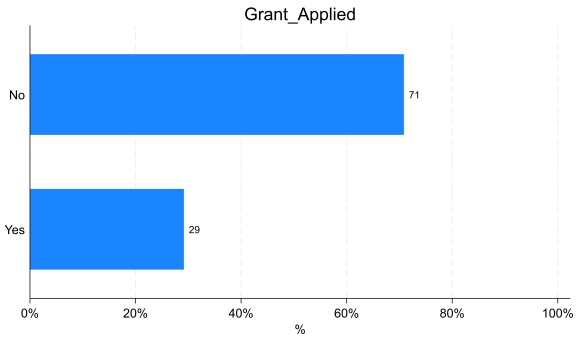


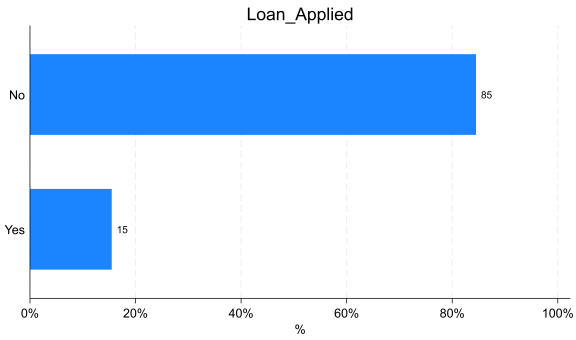


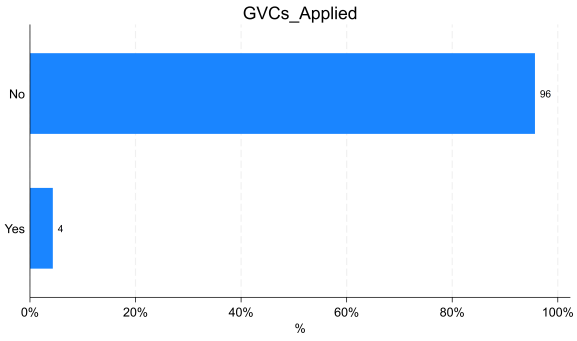


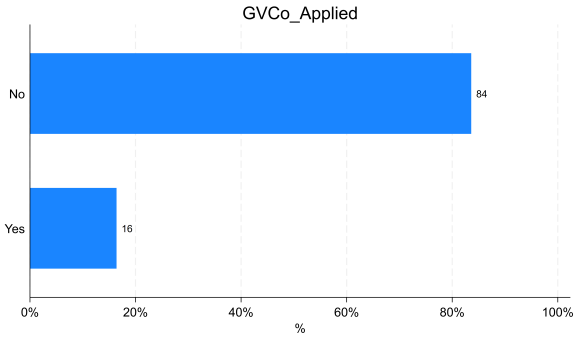


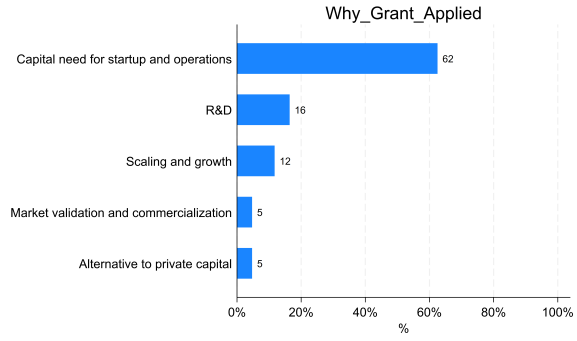


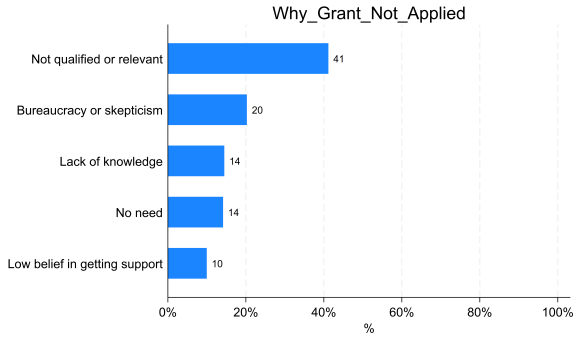

Grant_Applied
No
Yes
71
29
0%
20%
40%
60%
80%
100%
%

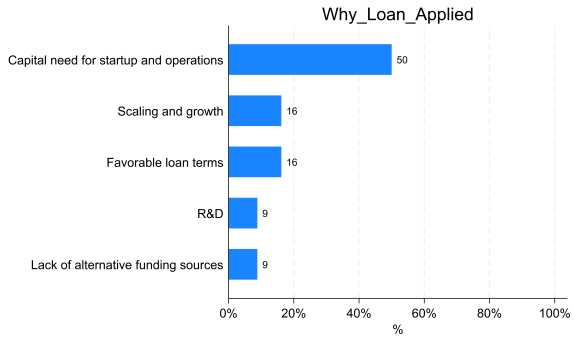

Loan_Applied
No
Yes
85
15
0%
20%
40%
60%
80%
100%
%

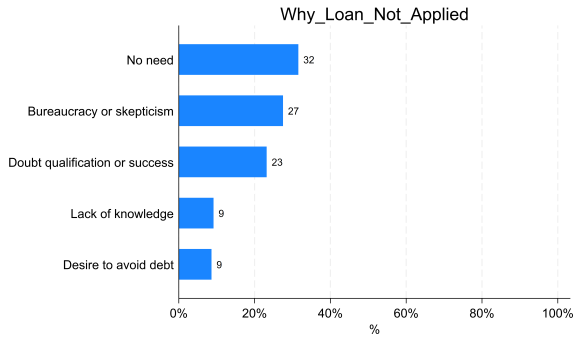

GVCs_Applied
No
Yes
96
4
0%
20%
40%
60%
80%
100%
%

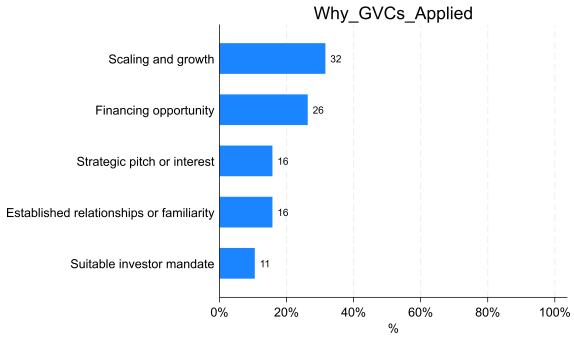

GVCo_Applied
No
Yes
84
16
0%
20%
40%
60%
80%
100%
%

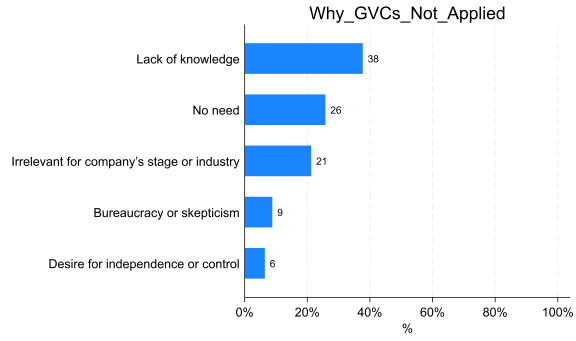

Why_Grant_Applied
Capital need for startup and operations
R&D
Scaling and growth
Market validation and commercialization
Alternative to private capital
62
16
12
5
5
0%
20%
40%
60%
80%
100%
%

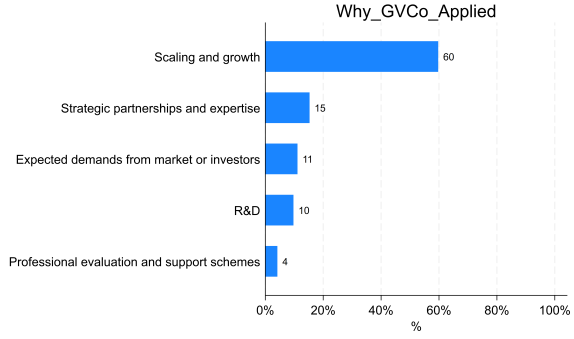

Why_Grant_Not_Applied
Not qualified or relevant
Bureaucracy or skepticism
Lack of knowledge
No need
Low belief in getting support
41
20
14
14
10
0%
20%
40%
60%
80%
100%
%

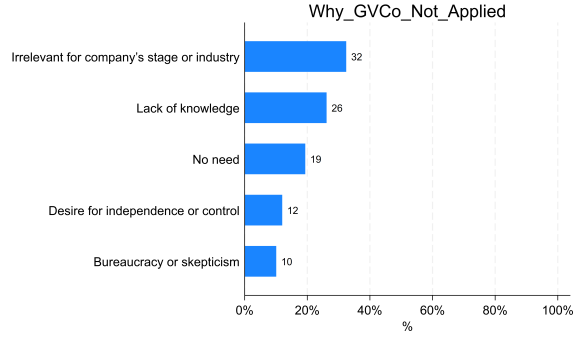

Why_Loan_Applied
Capital need for startup and operations
50
Scaling and growth
16
Favorable loan terms
16
R&D
9
Lack of alternative funding sources
9
0%
20%
40%
60%
80%
100%
%

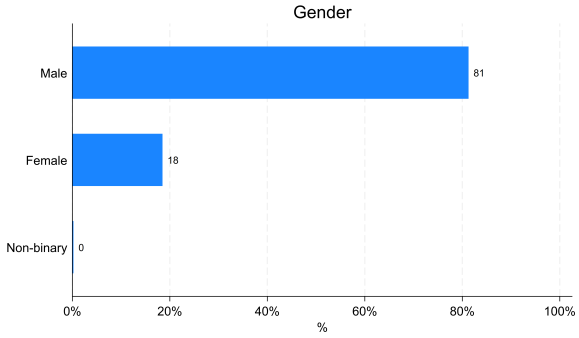

Why_Loan_Not_Applied
No need
32
Bureaucracy or skepticism
27
Doubt qualification or success
23
Lack of knowledge
9
Desire to avoid debt
9
0%
20%
40%
60%
80%
100%
%

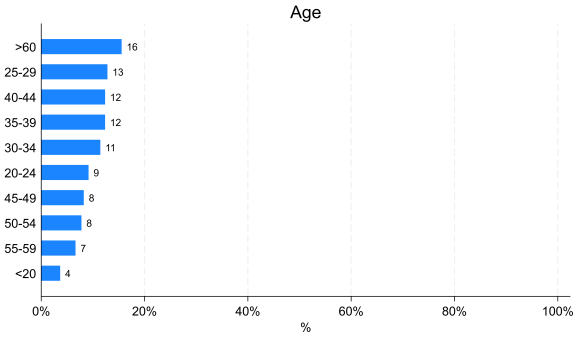

Why_GVCs_Applied
Scaling and growth
32
Financing opportunity
26
Strategic pitch or interest
16
Established relationships or familiarity
16
Suitable investor mandate
11
0%
20%
40%
60%
80%
100%
%

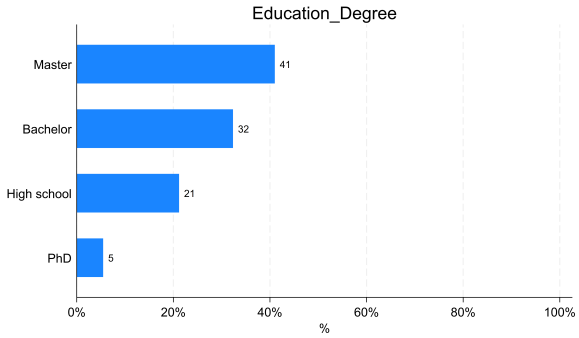

Why_GVCs_Not_Applied
Lack of knowledge
38
No need
26
Irrelevant for company's stage or industry
21
Bureaucracy or skepticism
9
Desire for independence or control
6
0%
20%
40%
60%
80%
100%
%

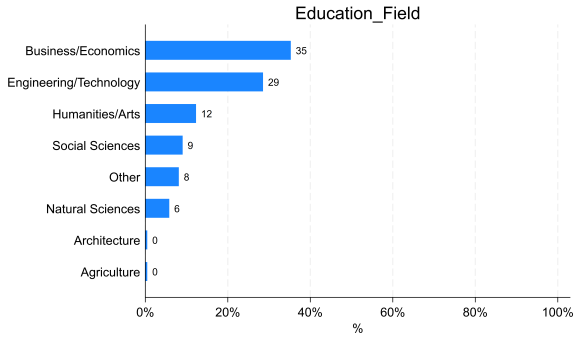

Why_GVCo_Applied
Scaling and growth
60
Strategic partnerships and expertise
15
Expected demands from market or investors
11
R&D
10
Professional evaluation and support schemes
4
0%
20%
40%
60%
80%
100%
%


Why_GVCo_Not_Applied
Irrelevant for company's stage or industry
32
Lack of knowledge
26
No need
19
Desire for independence or control
12
Bureaucracy or skepticism
10
0%
20%
40%
60%
80%
100%
%


Gender
Male
Female
Non-binary
81
18
0
0%
20%
40%
60%
80%
100%
%


Age
>60
25-29
40-44
35-39
30-34
20-24
45-49
50-54
55-59
<20
16
13
12
12
11
9
8
8
7
4
0%
20%
40%
60%
80%
100%
%


Education_Degree
Master
Bachelor
High school
PhD
41
32
21
5
0%
20%
40%
60%
80%
100%
%


Education_Field
Business/Economics
Engineering/Technology
Humanities/Arts
Social Sciences
Other
Natural Sciences
Architecture
Agriculture
35
29
12
9
8
6
0
0
0%
20%
40%
60%
80%
100%
%

Appendix C: Additional Figures and Tables

Figure C1: Probability of Next Application

Figure C1 summarizes firms next-step application choices across public funding programs following their first application to a given origin program. Within each panel, firms are split by the outcome of the origin application (first application rejected vs. approved). For each group, bars report the probability that the firms next observed application year after t_0 (i.e., the earliest year $t > t_0$ in which the firm applies to any program) includes an application to the indicated destination program. Because multiple applications can occur within the same next application year, probabilities need not sum to one. The sample includes all firms applying for public funding between 2005 and 2018.

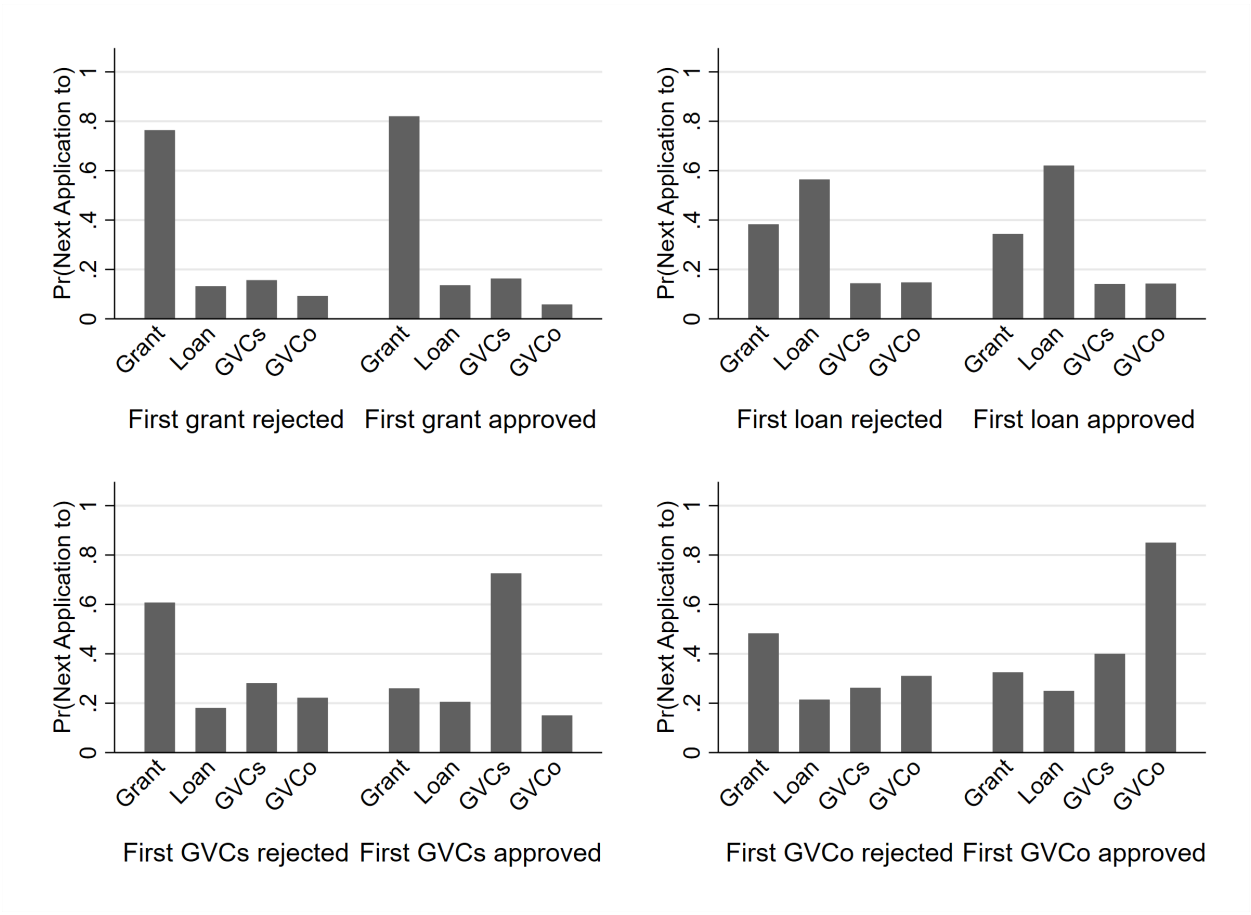


Table C1: Determinants of Public Funding Application—Full Specification

Table C1 reports the full specifications of the application regressions from Table 1. Explanatory variables include indicators for prior application and prior approval history, as well as a vector of pre-application firm characteristics measured at $t-1$. The sample comprises all new establishments in Norway from 2000 to 2018 (411,200 firms). All specifications include firm age, calendar year, municipality and industry fixed effects. The constant term is estimated but omitted for brevity. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Grant Application (1/0)	Loan Application (1/0)	GVCs Application (1/0)	GVCo Application (1/0)
	(1)	(2)	(3)	(4)
Prior grant application (1/0)	0.0324***	0.0042***	0.0061***	0.0033***
	(0.0019)	(0.0008)	(0.0008)	(0.0007)
Prior grant approval (1/0)	0.0838***	0.0155***	0.0175***	0.0066***
	(0.0030)	(0.0013)	(0.0013)	(0.0011)
Prior loan application (1/0)	-0.0060*	0.0295***	0.0008	0.0033*
	(0.0034)	(0.0031)	(0.0020)	(0.0018)
Prior loan approval (1/0)	0.0038	0.0333***	0.0009	0.0067***
	(0.0043)	(0.0043)	(0.0026)	(0.0024)
Prior GVCs application (1/0)	0.0311***	0.0174***	0.0310***	0.0335***
	(0.0036)	(0.0022)	(0.0025)	(0.0023)
Prior GVCs approval (1/0)	-0.0131	0.0126	0.2343***	0.0202*
	(0.0122)	(0.0089)	(0.0244)	(0.0120)
Prior GVCo application (1/0)	0.0023	0.0069**	0.0081**	0.0342***
	(0.0048)	(0.0033)	(0.0038)	(0.0038)
Prior GVCo approval (1/0)	0.0356	0.0466**	0.0600**	0.3597***
	(0.0265)	(0.0221)	(0.0256)	(0.0389)
L1.Subsidiary (1/0)	-0.0031***	-0.0009***	-0.0009***	-0.0006***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
L1.Total assets $0 <= p50$ (1/0)	0.0006***	-0.0000	0.0003***	0.0002***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
L1.Total assets $> p50$ (1/0)	0.0014***	0.0009***	0.0006***	0.0007***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
L1.Revenues (1/0)	-0.0006***	0.0003***	0.0001	0.0002***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
L1.Employees (1/0)	0.0007***	0.0007***	0.0002***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
L1.Profit (1/0)	-0.0017***	-0.0008***	-0.0008***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
L1.Cash $0 <= p50$ (1/0)	0.0011***	0.0002***	0.0001**	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
L1.Cash $> p50$ (1/0)	0.0018***	0.0005***	0.0005***	0.0002***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
L1.Paid-in equity $0 <= p50$ (1/0)	0.0016***	0.0001*	0.0003***	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)
L1.Paid-in equity $> p50$ (1/0)	0.0030***	0.0010***	0.0007***	0.0004***
	(0.0002)	(0.0001)	(0.0001)	(0.0000)
L1.Bank loan (1/0)	0.0002**	0.0005***	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	3,226,524	3,226,524	3,145,637	2,732,313
R-squared	5.3%	2.9%	6.8%	6.7%
Mean dependent variable	0.44%	0.11%	0.09%	0.05%

Table C2: Determinants of Public Funding Approval—Full Specification

Table C2 reports the full specifications of the approval regressions from Table 3. N of applicants is the total number of applicants to program j in year t and region g. Explanatory variables include indicators for prior application and prior approval history. Other explanatory variables capture firm characteristics measured in the year prior to application. All specifications include firm age, calendar year, region and industry fixed effects. The constant term is estimated but omitted for brevity. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Grant Approval (1/0)	Loan Approval (1/0)	GVCs Approval (1/0)	GVCo Approval (1/0)
Applicants to the program	All	All	All	All
	(1)	(2)	(3)	(4)
N of applicants	-0.020**	-0.111**	0.036**	-0.157***
	(0.008)	(0.051)	(0.018)	(0.056)
Prior grant application (1/0)	-0.031	-0.086**	0.005	-0.033*
	(0.021)	(0.043)	(0.015)	(0.018)
Prior grant approval (1/0)	0.188***	0.063***	0.018*	-0.009
	(0.008)	(0.018)	(0.010)	(0.012)
Prior loan application (1/0)	-0.051	-0.132***	-0.021	-0.032**
	(0.037)	(0.037)	(0.014)	(0.016)
Prior loan approval (1/0)	0.012	0.121***	0.011	0.013
	(0.017)	(0.017)	(0.017)	(0.018)
Prior GVCs application (1/0)	0.019	-0.027	0.034***	0.007
	(0.013)	(0.025)	(0.012)	(0.012)
Prior GVCs approval (1/0)	0.014	-0.074	0.855***	0.130***
	(0.032)	(0.061)	(0.022)	(0.034)
Prior GVCo application (1/0)	-0.042*	-0.067**	-0.014	-0.007
	(0.023)	(0.034)	(0.013)	(0.014)
Prior GVCo approval (1/0)	0.039	-0.048	0.064**	0.877***
	(0.051)	(0.078)	(0.030)	(0.024)
L1.Subsidiary (1/0)	-0.022**	-0.059***	-0.017*	-0.014
	(0.009)	(0.018)	(0.009)	(0.012)
L1.Total assets $0 <= p50$ (1/0)	-0.039	-0.250*	-0.043*	-0.076
	(0.043)	(0.131)	(0.026)	(0.162)
L1.Total assets $> p50$ (1/0)	0.048	-0.180	-0.022	-0.034
	(0.045)	(0.133)	(0.028)	(0.164)
L1.Revenues (1/0)	-0.023**	-0.018	-0.021*	-0.026
	(0.011)	(0.023)	(0.012)	(0.017)
L1.Employees (1/0)	-0.001	-0.006	0.011	-0.013
	(0.011)	(0.020)	(0.012)	(0.015)
L1.Profit (1/0)	0.020**	0.020	-0.027**	-0.032***
	(0.009)	(0.017)	(0.011)	(0.012)
L1.Cash $0 <= p50$ (1/0)	0.044*	0.092*	0.025	-0.044
	(0.024)	(0.049)	(0.015)	(0.036)
L1.Cash $> p50$ (1/0)	0.067***	0.134***	0.059***	-0.025
	(0.025)	(0.050)	(0.017)	(0.039)
L1.Paid-in equity $0 <= p50$ (1/0)	0.010	0.218*	0.031	0.122
	(0.036)	(0.121)	(0.025)	(0.153)
L1.Paid-in equity $> p50$ (1/0)	0.046	0.196	-0.001	0.118
	(0.036)	(0.121)	(0.025)	(0.151)
L1.Bank loan (1/0)	0.021*	-0.026	0.009	0.033**
	(0.011)	(0.018)	(0.013)	(0.015)
Observations	16,498	4,061	3,285	1,687
R-squared	10.3%	8.4%	65.0%	64.6%
Mean dependent variable	73.23%	73.04%	12.2%	11.41%

Table C3: Balance Test for the Residualized Instrument

Table C3 reports balance test for the residualized region–year grant tightness shifter, $\widetilde{Z}^{G}_{rti}$, within the grant-applicant sample used in the IV design. Each column reports the coefficient from a separate regression of a predetermined firm characteristic on $\widetilde{Z}^{G}_{rti}$. Columns (1)–(4) use pre-application public-funding history indicators (prior interaction with each program), while columns (5)–(9) use pre-application firm characteristics measured at $t-1$. All specifications include region, firm age, industry-by-calendar-year, and region-by-industry fixed effects. Standard errors are clustered at the region–year level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Pre-application History								
	Grant	Loan	GVCs	GVCo	Subsidiary (1/0)	Assets (1/0)	Cash (1/0)	Paid-in equity (1/0)	Bank loan (1/0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widetilde{Z}^{G}_{rti}$	-0.207	-0.040	-0.024	-0.044	-0.040	0.009	0.019	0.048	-0.072
	(0.176)	(0.063)	(0.059)	(0.027)	(0.062)	(0.050)	(0.055)	(0.053)	(0.055)
Observations	16,483	16,483	16,483	16,483	16,483	16,483	16,483	16,483	16,483
R-squared	30.1%	11.1%	8.4%	7.8%	16.1%	79.3%	72.4%	77.8%	22.5%

Table C4: Grants as Gateways—Next-Year Effect

Table C4 replicates Table 6 and estimates the effect of grant approval on subsequent participation in other public funding programs in the year after the firm's first grant application year. The dependent variables in Panel A are indicators for applying to other programs next year $t_0 + 1$, while the dependent variables in Panel B are corresponding approval indicators. Columns (2), (4), (6) instrument grant approval with the residualized region–year grant acceptance-rate $\widetilde{Z}^G_{rti}$ (Table 5). $\hat{p}^G_i$ denotes the predicted probability of applying for a grant measured at the first grant application year. All specifications include controls, which are firm characteristics at $t-1$ and program-application histories as well as region, firm age and industry by calendar year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Application in the next year to:

	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.026***	0.004	0.034***	-0.088	0.006**	0.019
	(0.004)	(0.061)	(0.005)	(0.102)	(0.002)	(0.043)
$\hat{p}^G_i$	0.639	0.978	3.135	4.980*	2.103	1.904
	(1.279)	(1.520)	(2.659)	(2.890)	(2.057)	(2.241)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	4.9%	1.0%	5.9%	-5.1%	6.5%	1.9%

Panel B: Approval in the next year to:

	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.023***	0.028	0.001**	-0.020	0.001	0.019
	(0.003)	(0.066)	(0.001)	(0.021)	(0.001)	(0.015)
$\hat{p}^G_i$	1.217	1.140	-0.694**	-0.370	-0.118	-0.391
	(1.164)	(1.497)	(0.279)	(0.448)	(0.132)	(0.282)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	4.4%	1.1%	13.1%	7.2%	6.6%	-3.3%

Table C5: Grants as Gateways—Five-Years-Horizon

Table C5 replicates Table 6 and estimates the effect of grant approval on subsequent participation in other public funding programs in the next five years after the firm's first grant application year. The dependent variables in Panel A are indicators for applying to other programs at any time in years $t_0 + 1$ through $t_0 + 5$, while the dependent variables in Panel B are corresponding approval indicators. Columns (2), (4), (6) instrument grant approval with the residualized region–year grant acceptance-rate $\widetilde{Z}^G_{rti}$ (Table 5). $\hat{p}^G_i$ denotes the predicted probability of applying for a grant measured at the first grant application year. All specifications include controls, which are firm characteristics at $t-1$ and program-application histories as well as region, firm age and industry by calendar year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Application in the next year to:

	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.061***	0.186	0.066***	0.007	0.031***	0.008
	(0.006)	(0.141)	(0.008)	(0.130)	(0.005)	(0.079)
$\hat{p}^G_i$	4.161**	2.275	10.704***	11.602***	3.115	3.464
	(1.800)	(2.735)	(3.707)	(4.383)	(2.649)	(3.013)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	6.3%	-1.8%	9.3%	1.8%	8.6%	2.9%

Panel B: Approval in the next year to:

	Loan		GVCs		GVCo	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Grant approved (1/0)	0.054***	0.146	0.003**	-0.027	0.002***	0.008
	(0.006)	(0.132)	(0.001)	(0.033)	(0.001)	(0.024)
$\hat{p}^G_i$	4.714***	3.339	0.112	0.564	0.150	0.065
	(1.573)	(2.526)	(0.605)	(0.854)	(0.294)	(0.461)
Observations	10,813	10,813	10,813	10,813	10,813	10,813
R-squared	5.6%	-0.6%	9.3%	3.6%	5.1%	3.3%