Bad Luck in Fundraising: Evidence from Failed Applications for Government Seed Funding in Korea

Po-Hsuan Hsu, Guijung Kim, WonJoon Kim, and S. Katie Moon*

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ABSTRACT

This study examines the effect of Korea's Tech Incubator Program for Startups (TIPS), a unique government funding initiative that leverages the private sector's expertise and *only* considers applicants recommended by sponsor venture capitalists (VCs). Given the high acceptance rate (around or above 90 percent), being rejected from TIPS constitutes a random negative shock to recommended startups. We construct a unique dataset of TIPS applicants' evaluation scores, firm characteristics, and investor information, and implement difference-in-differences and regression discontinuity analyses. We find that rejected startups receive less follow-on investment, spend less on R&D, produce fewer patents, and post lower revenues. These adverse outcomes can be attributed to the loss of expected funding (the financing mechanism) and the missed opportunity to gain exposure to additional investors and industry experts (the promotion mechanism).

Keywords: Korea, startups, public funding, government subsidies, entrepreneurship

JEL Classification: G24, H20, L26, O20, O30

* Hsu is from the College of Technology Management, National Tsing Hua University (pohsuanhsu@mx.nthu.edu.tw), Kim and Kim are from the Department of Business & Technology Management, Korea Advanced Institute of Science and Technology (winterhearts@kaist.ac.kr; wonjoon.kim@kaist.edu), and Moon is from the Leeds School of Business, the University of Colorado Boulder (katie.moon@colorado.edu). We thank Joshua Graff Zivin, Suting Hong, Sina Khoshsokhan, Michael Meurer, Lucy Xiaolu Wang, Yanzhi Wang, Arvids Ziedonis and seminar/conference participants at TPRI brownbag and Taiwan Symposium on Innovation Economics and Entrepreneurship. All errors are our own.

1. Introduction

While government subsidies or grants for the private sector's R&D and/or entrepreneurship are a prevalent policy tool to foster technological development and to create externalities (Lerner, 2002; Trajtenberg, 2005; Bai, Bernstein, Dev, and Lerner, 2023), the efficiency and effectiveness of such programs have been under debates (Lerner, 2002, 2009). Common concerns about the implementation of such subsidies include bureaucracy, delay, and officials' lack of expertise and network (Lerner, 2002, 2009; Wei, Xu, Yin, and Zhang, 2023; Howell, 2024).

How to evaluate all applicants for government funding is a major challenge to governments, even for the most well-functioning ones. One common solution to the lack of expertise in evaluating applicants is to recruit experts to review the pool of applications. Another possible solution is to directly seek the nomination from these experts. This nomination idea is adopted in the Korean government's Tech Incubator Program for Startups (TIPS), an R&D-funding program that collaborates with selected partner VCs ("sponsor VCs" hereafter) and subsidizes the startups recommended by these VCs.

The TIPS began with five sponsor VCs and has grown to have more than 100 sponsor VCs in 2023. On average, a sponsor VC recommended about 3.5 startups in the seed or pre-A stage each year. Startups being accepted for the TIPS ("accepted startups" henceforth) receive a capital infusion of up to 342,000 USD (KRW 500 million) to be used for R&D activities over two years.[1] In addition, the TIPS also provides non-financial support to accepted startups, which includes mentoring and incubation programs for commercialization, networking events, and a dedicated workspace called "TIPS Town". In its first year (2013), the program accepted 15 startups with a budget of 20 million USD. In 2023, it accepted 500 startups with a budget of 320 million USD in 2023 – such growth makes this program being considered as one of the most influential policy initiatives worldwide.[2]

[1] This amount in USD is commensurate to other R&D grants or subsidy projects: $300,000 in Israeli Office of the Chief Scientist (OCS) program (Trajtenberg, 2000), 170,000 Euros in a program in Italy (Bronzini and Iachini, 2014), $150,000 in Phase 1 of DOE's SBIR (Howell, 2017), $100,000 or less in Phase 1 of Department of Defense's (DoD) SBIR Phase I (Audretsch, Link, and Scott, 2019), $100,000 in China's Innofund (Wang, Li, and Furman, 2017).

[2] In 2023, the TIPS program was ranked 4th in the Top 10 Most Active Startup Accelerators by CB Insights (Crunchbase). This recognition highlights the program's significant impact in fostering innovation and supporting startups. https://www.cbinsights.com/research/report/most−active−startup−accelerators/

Given its two-layer screening procedure, the TIPS features a high acceptance rate: the acceptance rate for recommended startups is 100% in the *first two* years and is in the range between 82% and 92% for subsequent years. Such a high acceptance rate makes the TIPS very different from the typical government grants studied in the literature, which often feature low acceptance rates,[3] and suggests that the sponsor VCs exert reasonably effective screening of potential applicants for the TIPS. On the other hand, sponsoring VCs carry reputation costs in recommending applicants to the TIPS and are likely more knowledgeable and experienced than government officials and reviewers of the program. As a result, the event of a recommended startup failing its TIPS application (especially when it only marginally misses the bar) is likely due to "bad luck".[4] To ensure our analysis truly focuses on luck, we also specifically examine applications that are closest to the acceptance cutoff, improving the comparability between accepted and rejected applicants.

The TIPS thus offers us a quasi-natural experiment on the effect of losing government grants and recognition on startups. It features several advantages in identification. First, one major challenge for prior studies on government subsidy programs is the potential for selection bias (Lach, 2002; Conti, 2018), where firms self-select into the application process. We are not subject to this bias because both rejected and accepted startups are recommended by sponsor VCs and thus have the intention to apply for subsidies. Second, the opportunity for future government procurement may create estimation bias (Lichtenberg, 1987). This is not a concern for us because there is no government procurement involved in the TIPS. Third, we observe both rejected and accepted startups at the same time with detailed evaluation scores, which allows us to implement appropriate econometric analyses for causality.

We first collect the application information on all 2,460 recommended startups that had applied for the TIPS in 2014-2021. We dropped the first two years (i.e., 2014 and 2015 application years) to avoid any bias related to the 100% acceptance rate and to mitigate the initial uncertainty

[3] In the U.S., the acceptance rates are 15% in the Phase 1 of DOE's SBIR (Howell, 2017) and 20% in Advanced Technology Program (Feldman and Kelley, 2003). Other programs in other countries appear to be higher, such as 30−40% in the Regional Program for the Industrial Research, Innovation and Technological Transfer of Northern Italy (Bronzini and Iachini, 2014), 40%−60% in China's InnoFund (Wang, Li, and Furman, 2017), and 70% in Israeli Office of the Chief Scientist (OCS) program (Trajtenberg, 2000; Lach, 2002).

[4] We acknowledge that there could be government failures. In the strong form of government failures, sponsor VCs collude with bureaucrats to secure funding for startups they recommended. This seems implausible given VCs' reputation concern and the media coverage of the TIPS.

in the market's expectation of the operations of the program. We then match them to TheVC (a Korean VC database), Pitchbook, and KISLINE (the Korean version of Compustat) and end up with a final sample consisting of 1,182 recommended startups (1,013 accepted and 169 rejected) with available financial/accounting/investor information. For each startup, we focus on an event window of 9 years around its TIPS application year (i.e., [−4 years, +4 years]) and have 6,049 firm-year observations spanning from 2011 to 2022.

To draw a causal effect of the TIPS on startups' subsequent growth, we focus on the new investment amount received by all recommended startups – which corresponds to the primary goal of most public funding programs, which is to attract follow-on investment from the private sector (Lerner, 2002; Gans and Stern, 2003; Toole and Turvey, 2009). We deliberately remove the investment amount from sponsor VCs to ensure that our analyses are not biased by their recommendation decisions. We implement two sets of identification tests: a difference-in-differences (DID) test and regression discontinuity tests using the full sample and subsamples of startups rated near the acceptance cutoff.

In the first full-sample DID analyses, we compare the change in new investment received by accepted startups before and after their TIPS applications to that change by rejected startups. Our DID estimates are statistically significant in various regression specifications, even when we include sponsor VC-by-application year joint fixed effects to absorb all VC-specific factors (such as their funding flows and performance) and the industry-by-year joint fixed effects to absorb all industry-specific factors (such as innovation opportunities and business cycles). The DID estimates suggest that accepted startups receive over 1.79 million USD more per year, which is substantial and economically significant for their growth. In addition, we confirm that the parallel trend assumption is not violated in this setting.

We acknowledge that, even if sponsor VCs nominated their best-quality startups and bear reputation costs, there may still be (minor) quality differences that could be related to some confounding factors. To further mitigate this concern, we focus on two refined samples that include only startups rated near the acceptance cutoff. As the startups received similar evaluation scores on either side of the cutoff are likely of similar quality, their TIPS funding outcomes can be regarded as random assignments. We consider two subsamples for our DID analyses: The first subsample includes 378 firm-year observations using only startups with the closest rankings around the acceptance cutoff (27 accepted and 41 rejected). We then relax the criterion to include

TIPS evaluation scores within ±3 points of the cutoff and create our second subsample of 3,228 firm-year observations (376 accepted and 59 rejected). Our DID estimates in both subsamples are positive and statistically significant across all specifications. Moreover, the magnitude of these estimates is commensurate to that of their counterparts in the full-sample DID.

We further implement a regression discontinuity design (RDD) by focusing on the differential effects of TIPS applications on startup firms just above and below the acceptance cutoff.[5] In particular, we estimate a local linear regression model (Lee and Lemieux, 2014) in a cross-sectional setting (i.e., one startup is an observation). We consider recommended startups in a bandwidth of ±3 or ±5 points of the cutoff. In the pre-TIPS application period, these above-cutoff startups' new investment received over the three years before TIPS applications is indifferent from that of below-cutoff startups. In contrast, in the post-TIPS application period, the former group's new investment received is significantly higher than that of below-cutoff startups. We also show that this pattern is supported by a graphical representation of RDD plots. In terms of economic significance, the estimated discontinuity suggests that above-cutoff startups receive approximately a 3.6-times greater investment amount over the three years following TIPS applications.

All these empirical analyses collectively support a causal effect of the TIPS acceptance on startups' funding performance that is plausibly diagonal to their quality and other confounding factors we can think of. We further discuss several alternative explanations or confounding factors for a causal interpretation.[6]

[5] The use of a RDD design to examine the impact of government subsidy program has been considered by Jaffe (2002), Bronzini and Iachini (2014), Howell (2017), and Gonzalez−Uribe and Leatherbee (2018).

[6] The first set is related to the selection of sponsor VCs and the TIPS: for instance, they may have recommended better-quality startups in the first few years. This concern is mitigated by the fact that our baseline results are robust to using observations from more recent periods, such as 2018–2021 or 2019–2021. It is also possible that the TIPS might have selected firms that already had better funding opportunities to ensure the program's success on records. In other words, accepted startups would show better post-acceptance performance compared to rejected ones, even without the support of the TIPS. This issue is resolved by our DID and RDD results based on startups rated near the acceptance cutoff. Still another concern is industry heterogeneity: startups in some industries that may receive or need more subsequent investment are more likely to be accepted by the TIPS. This issue has been mitigated by our inclusion of industry-by-year joint fixed effects and sponsor VC-by-application year joint fixed effects. Moreover, accepted startups may be required by the TIPS to disclose more information, and such enhanced transparency may reduce information asymmetries for subsequent investors. This concern, however, is likely negligible because startups participating in the TIPS are not required to disclose proprietary information to the public.

Then, how can we interpret the impact of the TIPS? We propose and empirically examine two possible mechanisms that may coexist: financing and promotion.[7] The financing effect is perhaps the most direct and intuitive mechanism. The TIPS subsidy, though modest (up to 342,000 USD), could enhance accepted startups' chances of success by resolving technical or market uncertainty, which attracts more subsequent investments (Lach, 2002; Gonzalez, Jaumandreu, and Pazo, 2005; Bronzini and Iachini, 2014). We empirically examine this mechanism by estimating DID regressions in two subsamples split by the ratio of the amount of expected TIPS grants to the amount of a startup's investment received before its application as a proxy for startups' heterogeneous funding needs. We find that the DID coefficients are larger and significantly positive in the group with high funding needs but statistically insignificant in the group with low funding needs. This finding suggests that the TIPS effect is more pronounced among the startups for which the TIPS grant is more critical and thus supports the financing mechanism.

The promotion mechanism, on the other hand, posits that accepted startups are exposed to more potential investors or become more attractive to them. Different from the certification effect that highlights the grant reception as a new signal about startups' quality (Lerner, 1999; Howell, 2017; Cohen, Fehder, Hochberg, and Murray, 2019), our promotion mechanism focuses more on the visibility and marketing benefits given the TIPS design and our control for startup quality as discussed earlier. To empirically test this mechanism, we decompose a startup's new investment received each year into two new dependent variables: the investment amount from less (more) experienced investors who are more (less) likely to be influenced by the promotion of the TIPS acceptance. We find larger DID coefficients for investments from less experienced investors, supporting the promotion mechanism. If TIPS acceptance served as a valid additional signal of startup quality (which is *unknown* to external investors), we would expect more experienced investors to react to such a signal earlier and invest at least as much, if not more, in those higher-quality startups.

Lastly, we examine the real effects of the TIPS acceptance through the lens of accepted startups' revenues and R&D investment. Our DID estimations indicate that accepted startups have

[7] Lerner (2002), Trajtenberg (2005), and Howell (2024) have discussed the incentives for governments to design public subsidies or government VCs: the certification and the spillovers. Toole and Turvey (2009) review why public financing programs incentivize private investments in small firms, and summarize that this is an underexplored topic. Potential mechanisms include financing, certification or halo effect (Lerner, 1999, 2002; Feldman and Kelly, 2003), future procurement (Feldman and Kelly, 2003), and resolution of technical or market uncertainty (which is close to the prototyping mechanism of Howell (2017)).

approximately nine, 0.2, and 0.6 times higher R&D expenses, patent outputs, and revenues, respectively, compared to rejected startups following their TIPS applications. These economically significant real effects suggest that the TIPS program substantially influences both startups' financial performance and innovative activities positively.

Our research adds to the literature in the following ways. First, we examine a new public funding program and provide Asia-based evidence to the literature on R&D subsidies and grants, which complements prior studies that deliver a positive effect on startups' R&D input, innovation output, and growth in North America and Europe.[8] Given the rising prominence of Asian entrepreneurial activities in the global technology landscape, further analysis of entrepreneurial activities and policies in this region is called for.

Second, the TIPS emphasizes VCs' roles in government subsidies, particularly in screening, monitoring, and fostering competition, and offers new perspectives on how to mitigate bureaucracy or administration costs and achieve efficient resource allocations. Thus, the positive effects of the TIPS on supported startups echoes the policy recommendations from Lerner (2002), Brander, Du, and Hellmann (2015), and Bai, Bernstein, Dev, and Lerner (2023) on the need for government officials to form a stronger relationship with VCs and learn from industry experts in program designs and implementation.[9] Such features of the TIPS differ from prior programs that tend to focus on the government's role in assessing applicants' qualifications, shaping research collaboration (e.g., government-sponsored research consortium), offering government procurement (e.g., federal design and technical competition), promoting spillovers and regional

[8] An extensive list of studies suggested the positive effects in the U.S., which include Lerner (1999), Audretsch et al. (2002), Feldman and Kelley (2003), Toole and Turvey (2009), Howell (2017), Lanahan and Feldman (2018), Azoulay, Graff Zivin, Li, and Sampat (2019), Myers and Lanahan (2022), and Babina, He, Howell, Perlman, and Staudt (2023). However, some studies suggest estimation errors (Lichtenberg, 1988) or even negative effects (Wallsten, 2000). In other countries, the positive effects have been presented in Lach (2002), González, Jaumandreu and Pazó (2005), Almus and Czarnitzki (2013), Jaffe and Le (2015), Conti (2018), and Bai, Bernstein, Dev, and Lerner (2023). Nevertheless, some programs are subject to crowd-out criticism or no-effect (Bronzini and Iachini, 2014; Wang, Li, and Furman, 2017).

[9] The survey of Bai, Bernstein, Dev, and Lerner (2023) indicates that 35% of government subsidy programs involve private investors in investment committees, and 43% of the government subsidy programs are matching to other funding from the private sector.

ecosystems, and supporting minority entrepreneurs.[10] The empirical evidence we present in this paper on the "hybrid" model of the TIPS suggests an alternative approach to public funding.

Third, while the certification effect that centers on the information about startup quality from government program evaluations (Lerner, 1999, 2002; Feldman and Kelly, 2003, Howell, 2017) is relevant, it does not fully explain our results as we find that the additional information generated from the TIPS evaluation influence less experienced potential investors more. Instead, our results support the promotion effect, which emphasizes the enhanced visibility of startups following their acceptance into a government program. This could be a new mechanism for government funding programs to facilitate entrepreneurs and calls for further investigation.

2. Institutional Backgrounds

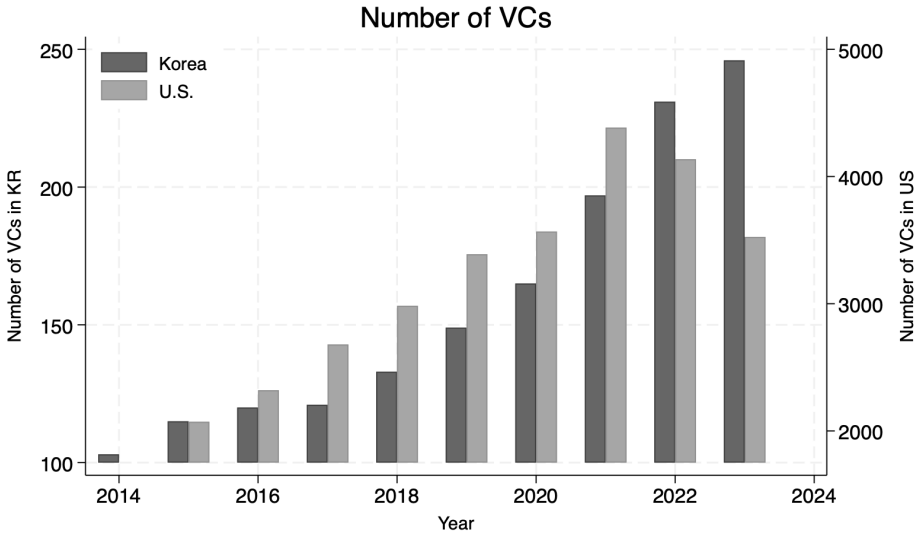
2.1. VCs and VC-Funded Startups in Korea

The entrepreneurial ecosystem in South Korea has expanded dramatically over the past decade. In particular, the number of VCs and their funding volumes have seen substantial growth. As shown in the figures below, between 2014 and 2023, the number of VCs increased by 138.8% (from 103 to 246), outpacing the U.S. market's growth of 101.3% over the same period.[11] The funding landscape has experienced even more dramatic progress, with annual VC investments rising by 229% (from $1.23b to $4.05b), compared to the U.S. market's increase of 73.7%. Consequently, the number of VC-funded startups grew from 901 in 2014 to 2,281 in 2023, reflecting a 153% increase. Compared to the U.S., the growth rate of Korea's VC market shows a relatively stronger trajectory, which may be attributed to the expanding Asian market, increasing

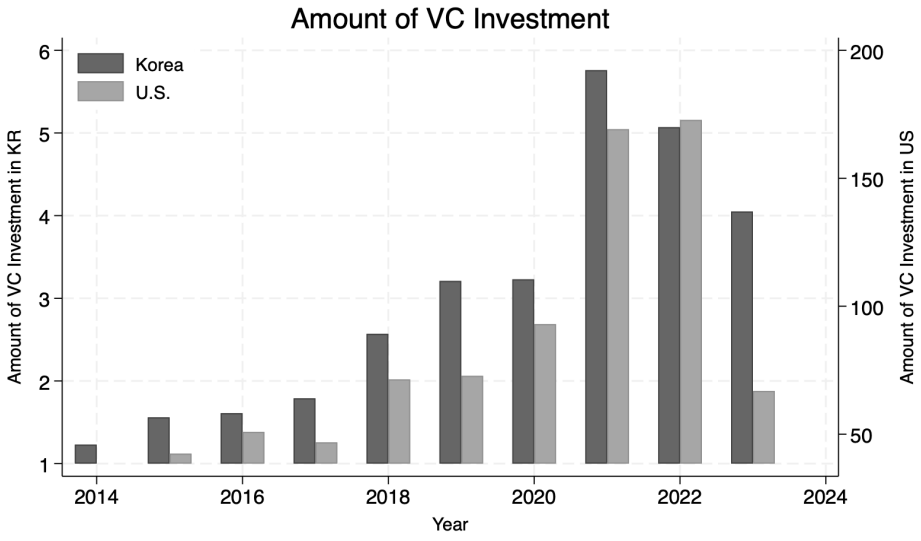
[10] For government−sponsored consortia, see Irwin and Klenow (1996) and Branstetter and Sakakibara (1998). For government procurement, see Lichtenberg (1988) and Gross and Sampat (2023). Advanced Technology Program (ATP), on the other hand, is an example for spillover−focused programs (Feldman and Kelley, 2003). Belenzon and Cioaca (2021) focus on US government R&D contracts. For regional ecosystems, see Guzman, Murray, Stern, and Williams (2024). For government programs to support minority entrepreneurs, see Ewens (2022).

[11] The data sources for these figures are from www.index.go.kr for Korean data (https://www.index.go.kr/unity/potal/main/EachDtlPageDetail.do;jsessionid=U0Ih70mMVCPretcTrirfGkjs4sxZ1nJCGFXjpgsh.node11?idx_cd=1196) and the 2024 NVCA Yearbook (https://nvca.org/wp−content/uploads/2024/05/2024−NVCA−Yearbook.pdf) and Pitchbook−NVCA Venture Monitor Q1 2024 (https://nvca.org/wp−content/uploads/2024/04/Q1−2024−PitchBook−NVCA−Venture−Monitor.pdf) for the U.S. data.

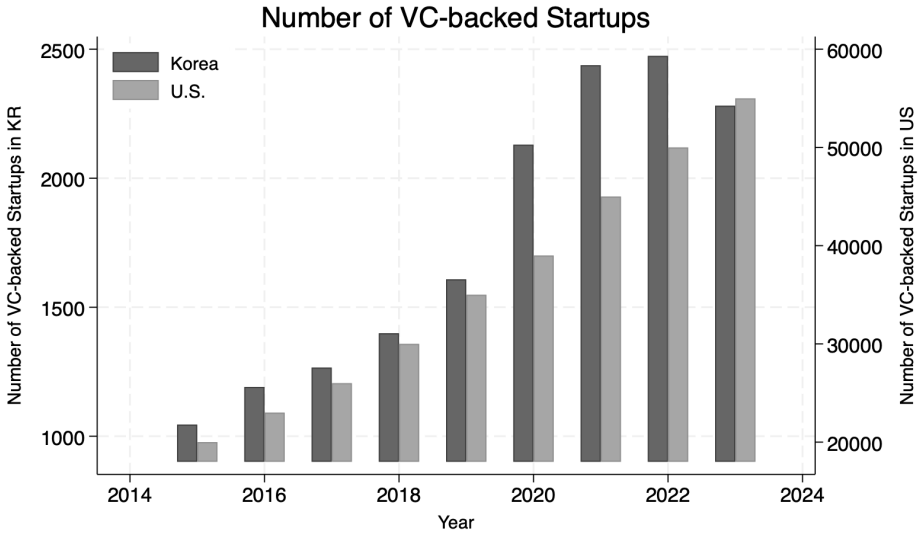
innovation opportunities for Korean talents, strengthened infrastructure in Korea, and/or government interventions.



(a) Growth in the number of VCs



(b) Growth in the amount of VC investment



(c) Growth in the number of VC-backed startups

In addition, the Korean government allocated policy funds for venture capital to foster specific industries through fund of funds, which shaped the funding landscape across sectors, with Information and Communication Technology (ICT) leading the way at approximately 42% of the total VC investments, followed by Bio/Medical at about 25% (KVCA, 2022).

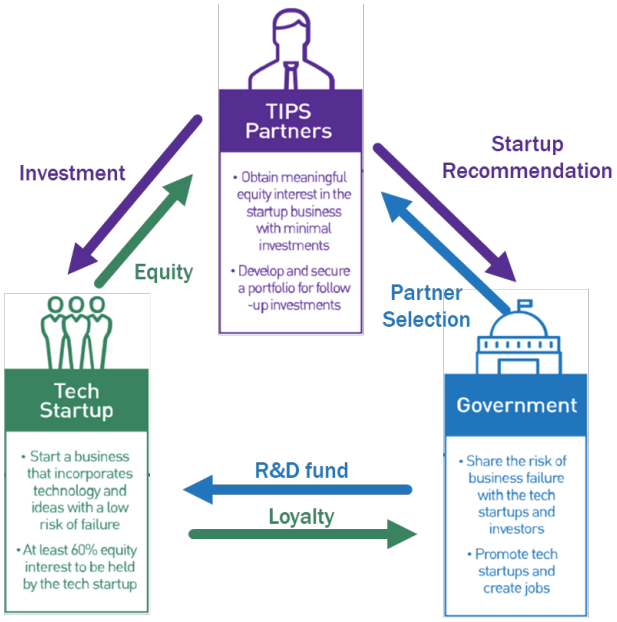
One of the most distinctive characteristics of Korean VC investments is VCs' high risk aversion, which manifests in their investment stage preferences and exit strategies. While U.S. VCs allocate approximately 35% of their investments to seed and early-stage ventures, Korean VCs invest less than 30% of investments in these early stages and predominantly focus on follow-on investments in more established companies (KVCA, 2024; NVCA, 2024).[12] This risk-averse investment tendency can be attributed to the conservative cultural disposition that shows a relatively low tolerance for failure (Park et al., 2017).

2.2. Details of the TIPS

To promote entrepreneurship and mitigate the financing gaps for early-stage startups particularly, the Korean government has introduced a number of policy initiatives. The most prominent one is the Tech Incubator Program for Startups (TIPS) that is based on public-private partnership and was launched in 2013. Unlike traditional government subsidy programs that rely

[12] For the mentioned statistics, see the online magazine managed by the Korea Venture Capital Association (KVCA) at https://webzine.kvca.or.kr/202405/?idx=11.

solely on public evaluation, the TIPS uniquely incorporates the expertise of sponsor VCs (TIPS partners) in their evaluation process. Sponsor VCs can recommend startups in which they have invested (or committed to invest) at least 77,000 USD in seed or pre-A stage.



Source: The official TIPS website (https://www.jointips.or.kr/global/)

In the TIPS structure shown in the above figure, the government provides a comprehensive support package including both financial and non-financial assistance. Selected startups can access up to 342,000 USD (i.e., KRW 500 million) in R&D funding over two years. This subsidy is a one-time capital infusion, rather than stage financing where the government imposes specific tasks and disburses funds only upon their completion. Recipients of the subsidy will prepare reports to justify their use in R&D activities.[13] Unlike other accelerator programs, the government does not hold equity or convertible debt positions of the accepted startups. Beyond such financial support, the TIPS also provides various other supports, including mentoring from industry experts, incubation programs for business development, and support for commercialization and global market entry. The TIPS also offers a dedicated workspace, TIPS Town, where startups can benefit

[13] Eligible uses of the subsidy in R&D activities include acquisition costs for intangible assets such as patents, personnel costs, material costs (salaries, wages, etc.), outsourcing costs, machinery and equipment (tools, instruments, fixtures, software, etc.), transaction fees, travel expenses, education and training costs, advertising and promotional expenses, meeting expenses.

from a collaborative environment and extensive networking opportunities with other entrepreneurs, investors, and industry partners.

Since its inception, the TIPS has experienced substantial expansion in both partnerships and startup participation. While the program began with five sponsor VCs and 15 accepted startups in 2013, it had grown by 2022 to have more than 100 partners and 500 startups, supported by a government budget increase from 20 million USD in 2014 to about 320 million USD in 2023. TIPS-funded startups have shown remarkable success in attracting follow-on investments, with 10.71 billion USD in private investments collectively in more than 2,800 selected startups by the end of 2024.[14]

In addition to the funding and investment, the unique structure of the TIPS has transformed the landscape of Korea's entrepreneurial financing. The TIPS's model that relies on its partnership with sponsor VCs, who serve as the primary screeners in identifying promising startups, ensures that recommended startups are vetted through the same rigorous market-oriented criteria. This market-driven screening approach may illustrate a more effective mechanism for selecting startups that are genuinely attractive to the market, instead of just validating innovation and spillover potential that serves government objectives.

Nevertheless, we also observe some promising startups bypassing TIPS opportunities and instead focusing on securing large-scale investments directly from the market. Notable examples include Shift Up Corporation (a video game developer that recently completed an IPO), Daangn Market Inc. (the developer of a second-hand marketplace platform), and several pharmaceutical startups. These companies have received initial investments ranging from 1 to 10 billion KRW (approximately 714,000 to 7.14 million USD), far exceeding the TIPS subsidy cap of 500 million KRW (approximately 342,000 USD).

3. Data

Our primary data source is the proprietary dataset of the Tech Incubator Program for Startups (TIPS), which we obtained from the Korean government. The TIPS dataset provides detailed information on all 2,460 startups that had applied for the program, including application dates,

[14] For the mentioned statistics, see the press release from the Ministry of SMEs at https://www.mss.go.kr/site/eng/ex/bbs/View.do?cbIdx=244&bcIdx=1054920&parentSeq=1054920.

evaluation dates, evaluation scores, selection status, recommended startups' financial and operating information, and their early-stage investor/investment information. Because the information on recommended startups from the TIPS dataset is only a snapshot at the time of their applications, we supplement the data with annual investor/investment information from TheVC, another Korean venture investment database, and Pitchbook, and firm financial metrics from KISLINE (Korean version of Compustat). In Internet Appendix Section IA1, we discuss the coverage and details of these three Korean datasets. Among the 2,460 recommended startups between 2014 and 2021 from the raw TIPS data, 1,775 startups with 9,969 firm-year observations remain matched with TheVC and Pitchbook for investment records and with KISLINE for financial information.[15]

Table 1 presents the outcomes of 1,775 TIPS applications from the sample by application year. Among all 1,775 recommended startups, 1,577 have been accepted into the program and 192 rejected. The average acceptance rate for the entire sample period is 88.9%. We note that the acceptance rates in the first two years (2014 and 2015) are 100%. This indicates that the process was solely dependent on the sponsor VCs' suggestions initially; thus, we drop the first two years in our analyses. Therefore, the sample is further refined to cover the TIPS application years from 2016 to 2021 only. We also eliminated startups that have applied to TIPS multiple times and ultimately received TIPS funding and those with no pre-TIPS observations. Finally, we limit our sample to have a [−4 year, +4 year] event window around the TIPS application year.[16] Accordingly, our final sample consists of 1,182 startups that applied for the TIPS from 2016 to 2021, with 6,049 firm-year observations spanning from 2011 to 2022.[17]

[Insert Table 1 Here]

Our main variable of interest is the amount of new investment (*funding*) that the startup receives in a given year. When calculating the amount of new funding that a startup receives, we include investment from all sources, such as VCs, corporations, and banks but *exclude* the funding

[15] The matching between the TIPS dataset and TheVC or Pitchbook is based on company names and registration numbers.

[16] For nearly all firms, the application year and evaluation year are identical. In cases where they differ, we use the evaluation year as the center of the event window instead of the application year. For example, if a startup applied for the TIPS in 2015 but was evaluated in 2016, we consider the event window from 2012 (year −4) to 2020 (year +4) with 2016 as event year 0.

[17] We note that for more recent TIPS application years, specifically 2019, 2020, and 2021, the [−4 year, +4 year] event window is truncated due to data availability.

amount from the sponsor VC to address the concern that new funding can be part of the stage financing of the sponsor VC.

In Figure 1, we present the average new investment amount received by the accepted startups and the rejected ones in each event year within the [−4 years, +4 years] window. We find that both groups receive very little new investment before their TIPS applications. However, the two groups show a stark difference in the new investment amount received after their TIPS application, with the accepted startups exhibiting remarkably strong growth in attracting new investors. More importantly, this growth is persistent in the following years, indicating superior performance among accepted startups relative to their rejected peers.

[Insert Figure 1 Here]

Table 2 Panels A and B present the sample distribution by year and by the Korean Standard Industrial Classification (KSIC) industries, respectively. As the number of accepted startups increases over time, as shown in Table 1, the number of startups in each year in Panel A increases over time. We find in Panel B that the top two industries of recommended startups are Information Technology (42%) and Bio/Medical (25%), which comprise 67% of the entire sample.[18] Other industries include Machine/Material, Energy/Resource, Electronics, Knowledge-based Service, and Chemistry.

[Insert Table 2 Here]

Panel C of Table 2 presents summary statistics for the variables used in our analyses. On average, a startup in our sample receives 390,000 USD of new investment in a year, after excluding the funding from the sponsor VC. Our treatment variable, *Treated*, is an indicator that is one for the startups accepted to the TIPS program between 2016 and 2021 and zero otherwise. The average acceptance rate is around 88% between 2016 and 2021, and 86.4% of firm-year observations in the sample are from accepted startups. *Post* is an indicator variable that equals one if the firm-year observation is after its TIPS application year and zero otherwise. We also consider the following control variables: firm age (*ln(1+age)*), the amount of cumulative funding[19] that the firm receives

[18] Each startup's industry is classified under one of the major categories of the Korean Standard Industrial Classification (KSIC). The startups in our sample fall into the following seven industries: Information Technology, Bio/Medical, Machinery/Materials, Energy/Resources, Electronics, Knowledge−Based Services, and Chemistry.

[19] The prior funding amount also includes investment from all sources including VCs, corporations, and banks, but excludes the TIPS sponsor VC's investment.

up to a given year (*ln(1+prior funding)*), the ratio of common stock investment to total investment (*Common equity ratio*), the ratio of a firm's revenue over its book assets (*Total asset turnover*), and the growth of a firm's revenue (*Revenue growth*). All control variables are winsorized at the 1% level. We find that the startups in our sample have an average age of 3.58 years, confirming that they are indeed early-stage startups. Prior to applying to TIPS, the average total investment received by a startup is $363,000. Additionally, the average asset turnover ratio is 34%, while the average revenue growth rate is about 350%.

Panel D of Table 2 compares the characteristics between accepted (treated) and rejected (control) startups. The results show that the average amount of new investment received by treated startups is significantly higher than that of control startups, with a difference of $310,000, which is statistically significant at the 1% level. Additionally, the cumulative funding up to a given year (*ln(1+Prior funding*) is significantly greater for treated firms compared to control firms. While *Common equity ratio* and *Total asset turnover* also show differences between the two groups, we do not observe significant differences in firm age and revenue growth between the two groups. We control for all these variables in our regression analyses.

Lastly, in Panels E and F of Table 2, we compare the same characteristics between accepted (treated) and rejected (control) startups, separately for the pre- and post-TIPS application periods, respectively. We note that while the difference in annual funding amounts between the two groups is negligible before the TIPS applications, the gap widens significantly to $645,000, on average, after the TIPS applications.

4. Empirical Designs and Results

4.1. TIPS acceptance and subsequent investment

To examine the effects of TIPS acceptance on the subsequent investment, we employ a difference-in-differences (DID) approach using the firm-year observations in the [−4 years, +4 years] event windows described in the previous section.[20] Specifically, we estimate the following regression model:

[20] Our DID setting with event windows mitigates potential issues related to late treatments and the heterogeneity in treatment that are common in staggered DID analyses (Gormley and Matsa, 2011; Baker, Larcker, Wang, 2022).

$$\mathrm{Ln}(1 + funding)_{it} = \beta_1 Treated_i + \beta_2 Post_{it} + \beta_3 (Treated_i \times Post_{it}) + Controls_{it} + \sigma_i + \delta_t + \theta_{v\tau} + \gamma_{jt}, \quad (1)$$

where *Ln(1+funding)* denotes the logarithm of one plus the amount of new investment that the startup *i* (recommended by sponsor VC *v* and in industry *j*) receives in year *t*. *Treated*, is an indicator that is one for the startups accepted to the TIPS program between 2016 and 2021 and zero otherwise. *Post* is an indicator variable that equals one if the firm-year observation is after its TIPS application year and zero otherwise. Startup fixed effects σ_i control for all firm-specific, time-invariant characteristics, such as founders' talent or corporate culture. Year fixed effects δ_t control for business cycles. $\theta_{v\tau}$ denotes Sponsor VC (ν) by TIPS application year (τ) fixed effects that control for time-varying characteristics of sponsor VCs, such as investment style, capability, liquidity, or the standard of recommendations. Industry-by-year fixed effects γ_{jt} absorb all time-varying industry-specific factors, such as innovation cycles and VC market conditions.

Table 3 presents the results that compare the new investments between the treated and control groups before and after their TIPS applications. Odd-numbered columns estimate the specifications with firm and year fixed effects, and even-numbered columns estimate the specifications additionally with VC-by-TIPS application year fixed effects and industry-by-year fixed effects. The VC-by-TIPS application year fixed effects absorb all VC-specific factors as discussed earlier, and the industry-by-year fixed effects absorb all industry-specific factors. Also, we introduce a set of control variables to further rule out potential confounding factors.

[Insert Table 3 Here]

Throughout all columns in Table 3, we find the coefficient estimates for the interaction term between *Treated* and *Post* are consistently positive and significant at the 1% level. These findings indicate that the startups accepted into the program, compared to their rejected counterparts, are more likely to receive new investment after being accepted. As explained earlier, these startups are all recommended by sponsor VCs to the program and are thus considered the most promising startups. Also, as explained earlier, we have excluded the sponsor VCs' funding from the dependent variable to prevent self-selection issues and have controlled for VC-by-TIPS application year joint fixed effects as well as industry-year joint fixed effects. Hence, these DID findings suggest that the government's financial and non-financial supports are positively related to subsequent entrepreneurial success. The magnitude of the effect is economically significant. For

example, the coefficient estimate for the interaction term between *Treated* and *Post* in column (1) is 1.720, which corresponds to an increase of 1.79 million USD in funding received per year.[21]

It is important to check whether the parallel trends assumption is satisfied for the validity of DID: without the TIPS acceptance, startups in the treated and control groups would have received similar funding. We thus estimate the following equation to test this assumption:

$$\mathrm{Ln}(1+funding)_{it} = \beta_1 Treated_i + \sum_{n=-5}^{5} \beta_2^n EventYear_{it}^n + \sum_{n=-5}^{5} \beta_3^n Treated_i \times EventYear_{it}^n \beta_3 + Controls_{it} + \sigma_i + \delta_t + \theta_{v\tau} + \gamma_{jt}, \qquad (2)$$

where $EventYear_{it}^n$ is an indicator variable that equals one when firm-year observations are n years relative to the startup *i*'s application to the TIPS ($n = -5$ to 5). For example, $EventYear_{it}^{-3} = 1$ if, for startup *i*, year *t* is exactly three years before its application to the TIPS. Similarly, $EventYear_{it}^{0} = 1$ if, for startup *i*, year *t* is exactly the year it applied to the TIPS.

Figure 2 presents the results with a 95% confidence interval from estimating Equation (2), which visualizes the TIPS acceptance effect within the event window of [−4 years, +4 years] around the TIPS application year of each startup. We use the earliest year ($n = -4$) as the base. Hence, the coefficient for $Treated_i \times EventYear_{it}^{-4}$ is omitted. We find insignificant coefficient estimates for the interaction term for n from −3 to 0, which confirms that there is no pre-trend before the TIPS acceptance of the treated startups and supports the parallel trend assumption underlying the DID test. In contrast, almost all coefficient estimates for the interaction terms with n from +1 to +4 are significantly positive. These results indicate that the TIPS effect on new funding starts immediately after the acceptance.

[Insert Figure 2 Here]

4.2. DID analyses for startups near the cutoff point

We acknowledge that although all startups in our sample are recommended by sponsor VCs as the most promising ones, it is possible that their quality (and thus their chances for TIPS acceptance) could vary. Even though such quality differences between the accepted group and the rejected group do not necessarily invalidate our DID, it may still raise concerns about confounding factors or selection issues. For instance, the difference in subsequent investments between

[21] When a recommended startup is funded ($Treated_i \times Post_{it}$=1), it is associated with an increase of 1.79 million USD (=(1+ 390,000)*(exp(1.720) − 1)) increase in its funding received.

accepted and rejected startups could result from their subtle quality difference that the government is able to identify during the evaluation process. To mitigate this potential concern, we focus on a homogenous subsample that includes only startups that are rated near the acceptance cutoff for the TIPS. If these startups received similar scores on either side of the cutoff, they are likely of comparable quality, and their acceptance or rejection by the TIPS can be considered a random assignment.

The homogenous subsample includes 378 firm-year observations using only startups closest to the cutoff, consisting of 27 accepted startups and 41 rejected startups. Since there was no consistent passing score across evaluation rounds, we identified the lowest-scored accepted startups and the highest-scored rejected startups on the same evaluation round. If the score of the lowest-scored accepted startup is lower than that of the highest-scored rejected startup, the pair is excluded, and the second lowest-scored accepted startup and the second highest-scored rejected startup are considered instead. We then re-estimate Equation (1) using this near-cutoff sample of startups with comparable quality. Table 4 presents the results – all columns in the table follow the same regression specifications as those in Table 3.

[Insert Table 4 Here]

We find that the coefficient estimates for the interaction term between *Treated* and *Post* are positive across all four columns. The estimates are all significant, although they are stronger in the last two columns, where we additionally include control variables beyond firm age. We note that the statistical significance of the TIPS effect in Table 4 appears smaller compared to those reported in Table 3 based on the full sample. The weaker results in Table 4 can be merely due to the much smaller sample size (378 vs. 6,049) and therefore, lower statistical power.

For robustness, we create the second homogenous sample of 3,228 firm-year observations from recommended startups for the 2016-2021 TIPS programs that have TIPS evaluation scores within ±3 points of the cutoff (i.e., lowest) TIPS score for acceptance in each TIPS round. *Treated* equals one for the startups accepted to the TIPS program with their actual TIPS evaluation scores higher than the cutoff in the corresponding TIPS program year and zero otherwise. Table 5 presents the results using this second homogenous subsample. All columns in Table 5 also use the same regression specifications as those in Table 3.

[Insert Table 5 Here]

The coefficient estimates for the interaction term between *Treated* and *Post* are positive and statistically significant across all four columns in Table 5. Similar to the results in Table 4, the statistical significance is stronger in the last two columns, where we additionally include control variables beyond firm age. Overall, our findings in Tables 3, 4, and 5 consistently suggest that startups accepted by the TIPS receive more subsequent investment.

4.3 Regression discontinuity design

In this section, we further reinforce a causal interpretation of our findings by employing a regression discontinuity design. We focus on the differential effects of the TIPS application on startups above and below the TIPS acceptance cutoff in each TIPS program year. To do so, we estimate the following local linear regression model that is consistent with the regression discontinuity design literature (Lee and Lemieux, 2014):

$$\text{Ln}(1 + funding)_i = \beta_1 Treated_i + \beta_2 Relative\ score_i + \beta_3(Treated_i \times Relative\ score_i) + controls_i + \gamma_j + \theta_v + \xi_k, \quad (3)$$

where *Relative score* is startup i's TIPS score minus the cutoff (i.e., lowest) TIPS score for acceptance in each TIPS round, and γ_j, θ_v, and ξ_τ are industry fixed effects, sponsor VC fixed effects, and TIPS application year fixed effects, respectively. The regression is cross-sectional with one observation for each recommended startup, and thus, we cannot include year fixed effects. The main variable of interest is *Treated*, whose coefficient estimates the discontinuity or jump in the new investment amount above the cutoff. The interaction term between *Treated* and *Relative score* allows for the slope of the regression to differ above and below the cutoff.

Table 6 presents the results from estimating Equation (3). We estimate regressions separately for the pre-TIPS application period using the average values over the three years preceding each startup's TIPS application in Panel A, and for the post-TIPS application period, using the average values over the three years following its TIPS application in Panel B. Our results are robust to using the average values over the two years or one year before and after each startup's TIPS application.

[Insert Table 6 Here]

Column (1) shows the results with the full sample of 1,182 observations. We also consider two different bandwidths of |*Relative score*| ≤ 5 and |*Relative score*| ≤ 3 in columns (2) and (3),

respectively. We find in Panel A of Table 6 for the pre-TIPS application period that all the coefficients on *Treated* are insignificant for any of the bandwidths. These results indicate no significant difference in the new funding amount for the startups whose TIPS evaluation scores are above and below the acceptance cutoff in the TIPS evaluation scores before they apply to the TIPS program. In contrast, we find in Panel B for the post-TIP application period that the coefficients on *Treated* are statistically significant throughout all columns with different bandwidths. For example, in the bandwidth with $|Relative\ score| \leq 3$ in column (3), the estimated coefficient for *Treated* suggests that above-cutoff startups receive approximately a 3.6-times[22] greater funding amount in the following year on average, compared to below-cutoff startups. On the other hand, we also note that the coefficients on *Relative score* and *Treated* × *Relative score* are insignificant, suggesting that startups with higher scores do not further attract more investments.

[Insert Figure 3 Here]

Figure 3 graphically illustrates the discontinuity in new funding amounts for the pre-TIPS application period in Panel (a) and for the post-TIPS application period in Panel (b) using the tightest bandwidth with $|Relative\ score| \leq 3$. Consistent with the results in column (3) in Panel A of Table 6, we find no discernible break in the amount of new funding for above-cutoff startups is just below and above the TIPS acceptance threshold before applications, as shown in Panel (a) of Figure 3. Startups whose evaluation scores right below the acceptance threshold appear to have marginally higher funding compared to those right above the cutoff during the pre-TIPS application period. However, this difference is neither statistically nor economically significant. Conversely, in Panel (b) of Figure 3 for the post-TIPS application period, we observe a clear jump in the amount of new funding around the TIPS acceptance cutoff. These results corroborate prior findings based on DID tests that the TIPS acceptance has a significantly positive effect on the amount of subsequent funding for the startups accepted into the TIPS programs.

5. Mechanisms

Thus far, we have presented an extensive list of tests that collectively support a causal effect of the TIPS acceptance on startups' performance in terms of attracting new investment. While

[22] The coefficient estimate for *Treated* in column (3) of Panel B is 1.519, which corresponds to an approximate 357% higher amount, calculated as $(\exp(1.519)-1)\times 100$.

there is no way to exhaust all possible mechanisms underlying such an effect, we attempt to explore the most relevant and important ones in this section.

5.1. Financing mechanism

Howell (2017) demonstrates that small government grants are crucial for startups for prototyping and market experimentation, and do not crowd out private equity. Building on this, we first explore the most direct mechanism that our finding of increased subsequent investment following the TIPS acceptance may be driven by the additional capital infusion provided by the TIPS subsidy itself. For startups struggling to secure funding, the TIPS subsidy, although modest, could enhance their chances of survival and success. To test this mechanism, we conduct an analysis similar to Table 3, focusing on subsamples of recommended startups with high vs. low financing needs.

We consider the relative size of the maximum subsidy amount a recommended startup can receive from the TIPS compared to the total funding that the startup has received until its TIPS application as a proxy for its needs for the subsidy. Specifically, we calculate the maximum potential TIPS subsidy in log minus the logarithmic value of one plus all investments received prior to the TIPS application.[23] For robustness, we also consider another measure that compares the relative size of the potential TIPS subsidy to the total investment from the sponsor VCs only. A larger value in either of these measures indicates that the potential TIPS subsidy would be substantial for the recommended startup relative to the funding it has received so far. We then split the full sample into two subsamples based on the sample median and estimate Equation (1) using each subsample. The summary statistics and DID results are presented in Table 7.

[Insert Table 7 Here]

Panel A of Table 7 reports the summary statistics for these two measures of startups' funding needs. We find that the TIPS subsidy is approximately two times larger than the total previous investments received by the average recommended startup prior to the TIPS application. Although the TIPS subsidy amount of 342,000 USD could be regarded as modest overall, for an average recommended startup in its early stages (within 7 years of being founded), this government subsidy could be crucial to its survival. When comparing the two groups, the TIPS subsidy is smaller than

[23] We adjust the sum of all prior investments by adding one because some firms have no pre-TIPS investment.

the total previous funding for startups classified as having low financing needs, while it is roughly four times larger than the total previous funding for startups with high financing needs. We observe nearly identical results when considering only the previous funding from sponsor VCs, suggesting that most prior funding comes from sponsor VCs.

In Panel B of Table 7, we present the results from estimating the DID regression model in column (3) of Table 3 separately for the subsamples. We find in the first two columns that the effect of the TIPS acceptance is larger in magnitude and statistically significant only in the first group of firms with higher values in the ratio of the potential TIPS subsidy to the total previous funding. We find consistent results in the last two columns when we use the ratio of the potential TIPS subsidy to the previous funding from sponsor VCs.

These results indicate that the financing mechanism is indeed in play in our TIPS setting. The observed increase in the follow-up investments after the TIPS acceptance is related to the effect of the one-time capital infusion of the TIPS subsidy itself, as the capital infusion enhances the chances of survival of accepted startups compared to rejected startups.

5.2. Promotion mechanism

Another important mechanism that can explain our finding of increased subsequent investment following the TIPS acceptance is government promotion. This mechanism predicts that accepted startups will have greater opportunities to access more potential investors or to become more attractive to them. The promotion mechanism focuses on the visibility and marketing benefits given the same quality; in contrast, the certification/signal effect focuses on the award outcome that separates the quality of startups as in Lerner (1999), Howell (2017), and Cohen, Fehder, Hochberg, and Murray (2019). We argue that our results are more likely attributable to the promotion mechanism instead of the certification/signal effect for the following three reasons: first, all recommended startups have already been certified by the sponsor VCs and, more broadly, by the market. Second, our regressions include a control variable of *Ln(1+prior funding)* that serves as a proxy for the market's assessment of a startup's quality. Third, as we have shown in Panel B of Table 6, accepted startups' scores do not explain the subsequent investment they receive.

We empirically test the promotion mechanism by decomposing a startup's new investment received each year into two new dependent variables – the investment amount from less vs. more experienced investors who rely more vs. less on the promotion of the TIPS. We posit that more

experienced investors are less likely to be affected by government promotion, as they have sufficient or better information from their own experience/network. Therefore, we expect the observed effect of increased subsequent investment to be more pronounced among less experienced investors.

We take three different approaches to classify investors as more or less experienced. First, we consider each investor's investment stage focus and classify investors as more experienced if they primarily focus on early-stage investments, such as seed investments, rather than later-stage investments, and less experienced otherwise. Second, we consider each investor's industry experience and classify an investor as more experienced when a given startup's industry is one of the top three industries where the investor has made investments. Third, we consider the number of each investor's investments up to a given year and classify investors as more or less experienced when the number of their prior investments is above and below the median, respectively. We then compare the effects of the TIPS acceptance on subsequent investments from more and less experienced investors. It is noteworthy that we calculate the new investment from more and less experienced investors separately, and then use each of them as the dependent in our DID analyses based on Equation (1). The results from these analyses are presented in Table 8.

[Insert Table 8 Here]

The dependent variable in the odd-numbered columns is the amount of investments from more experienced investors, while the dependent variable in the even-numbered columns is the amount of investments from less experienced investors. Consistently across all columns, we find that the estimated coefficients for *Treated* × *Post* are larger in magnitude for the investments from less experienced investors. The difference in the estimated coefficients for *Treated* × *Post* between investments from more and less experienced investors is statistically significant at the 1% level in the first two columns, while in other columns, the difference is not statistically distinguishable.

Overall, the results in this section support the conclusion that TIPS acceptances serve as a form of government promotion, attracting less experienced investors to invest more in accepted startups because these investors are less connected to investment targets. On the other hand, if TIPS acceptances serve as new signals or certification of startup quality (which are *unknown* to external investors), then such new information should be perceived and processed by more experienced investors earlier than less experienced ones. As a result, we would expect more

experienced investors to invest more than, or at least as much as, less experienced investors. However, our findings in Table 8 suggest otherwise.

5.3. Other alternative explanations

We note an alternative explanation that the TIPS support could be "stage-financing" by the government or sponsor VCs. However, as discussed earlier, the TIPS subsidy is a one-time capital infusion of up to 500 million KRW (approximately 342,000 USD) rather than stage financing, where capital providers impose specific tasks and disburse funds only upon completion.

Also, we acknowledge that the quality of recommended startups and the selection order of sponsor VCs may explain our findings. The high acceptance rates observed in the first two years (2014 and 2015) likely reflect the initial recommendation of only the highest-quality startups by sponsor VCs. Since earlier recommended startups tend to be of higher quality, they are more likely to succeed, potentially driving our results. We have addressed this concern throughout our analyses by excluding startups that have applied to TIPS during the first two years and also including a control variable of *Ln(1+prior funding)* under the assumption that prior funding serves as a proxy for the market's assessment of a startup's quality. Also, we find in an unreported analysis that our results are robust to using observations from the very recent TIPS application periods, such as application years of 2018–2021 or 2019–2021.

Lastly, one may be concerned that acceptance into the TIPS program requires the disclosure of information about the accepted startups. Thus, potentially enhanced information transparency could increase visibility, attracting greater attention from investors and leading to more subsequent funding. However, this explanation is not plausible because startups accepted by the TIPS are not required to disclose proprietary information.

6. Real Outcomes

In this section, we investigate the real effects of TIPS acceptance beyond its impact on subsequent investment. Specifically, we hypothesize that the increased investment resulting from TIPS acceptances should lead to positive real economic outcomes, such as higher R&D investments, more patent outputs, or improved sales. To capture such real effects, we construct the following three variables: *Ln(1+R&D investment)* as the logarithm of the startup's R&D investment amount in a given year, *Ln(1+Patents)* as the logarithm of the number of a startup's

patent applications filed in a given year (which were granted later), and *Ln(1+ Revenues)* as the logarithm of the startup's revenues amount in a given year. We report the summary statistics and the DID results based on Equation (1) for these variables in Table 9.

[Insert Table 9 Here]

Panel A of Table 9 presents the summary statistics of the three outcome variables. In Panel B for R&D investment, we find that the coefficient estimates for *Treated* × *Post* range between 2.30 and 2.49, all positive and statistically significant at the 1% level. This result indicates that startups accepted into the TIPS program invest an additional $1.23 million annually more in R&D compared to their rejected counterparts. This pattern is also found in Panel C for patent output, in which the estimated coefficients on *Treated* × *Post* range between 0.20 and 0.23, all significant at the 1% level. This suggests that accepted startups produce 0.56 more patents, which echoes their increased R&D investment. Finally, in Panel D, we observe that startups accepted to TIPS generate an additional $0.226 million revenue than those rejected, as the coefficient estimates for *Treated* × *Post* are positive and significant in columns (3) and (4). However, the revenue effects are weaker than those for R&D investment and patents, likely because many startups at this stage do not generate any revenue.

It is worth noting that the DID coefficients also translate into substantial economic magnitude. The estimated DID coefficients translate into approximately 9, 0.2 and 0.6 times greater R&D expenditures, patent applications, and revenues for accepted startups, as shown in columns (4) of Panel B to D, respectively, for example. Overall, the findings in this section suggest that the economic effects of TIPS acceptance extend beyond financing and drive up real investments and revenues.

7. Conclusions

While abundant evidence has been presented for the effect of government subsidies or grants on promoting entrepreneurship, the efficiency and associated administration costs of such programs remain under debate. Even though prior studies have highlighted the private sector's expertise and resources may complement governments' roles, most of such programs still rely on governments' planning, evaluation, and direction. In this paper, we examine a novel, large-scale funding program initiated by the Korean government that greatly emphasizes the role of VCs in

screening and evaluating – startups must be recommended by selected VCs to apply to the program, and 90% of them will receive a substantial subsidy for R&D.

The program thus offers us a quasi-natural experiment to examine the effect of government funding because recommended startups failing their applications can be regarded as a bad luck event. Startups that failed their application received significantly lower investment from the private sector relative to their peers that succeeded – a pattern that is robust in the full sample or subsamples consisting of applicants barely missing or passing the threshold. This effect can be attributed to missing the opportunity for financial resources and government promotion, and further results in less R&D expenditures, fewer patents, and lower revenues.

This research not only illustrates a new public funding model that leverages the private sector's expertise but also shows how such a hybrid funding model can uniquely support early-stage entrepreneurship. Given the increasingly important role of entrepreneurship and innovation in Asia, this paper offers timely empirical evidence to the literature and delivers managerial and policy implications.

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Appendix A. Variable Definitions

Variables	Definition
Ln(1+funding)	Logarithm form of the amount of funding from investments in the year
Treated	An indicator variable equal to one if the firm is accepted into the TIPS program
Post	An indicator variable equal to one for the years after the firm receives a TIPS evaluation, and zero otherwise
Ln(age)	Logarithm form of the startup's age
Ln(1+prior funding)	Logarithm form of cumulative previous investments, defined as the natural logarithm of the total investments up to the previous year
Common equity ratio	The proportion of total investment represented by common stock, calculated as the ratio of common stock investment to total investment
Total asset turnover	Logarithm form of total asset turnover, defined as the natural logarithm of current year revenue divided by the book value of total assets
Revenue growth	Logarithm form of revenue growth rate, calculated as the logarithm of one plus the current-year revenue minus the logarithm of one plus the previous-year revenue

Figure 1. Mean Funding and Observation Count by TIPS Acceptance Status

The figure presents the average funding amount received by accepted and rejected startups across event years. The investment from the sponsor VCs is excluded. Event year = 0 indicates the TIPS application year for each recommended startup in the sample. The solid line represents recommended startups that are accepted to the TIPS, while the dashed line represents the recommended startups that are rejected.

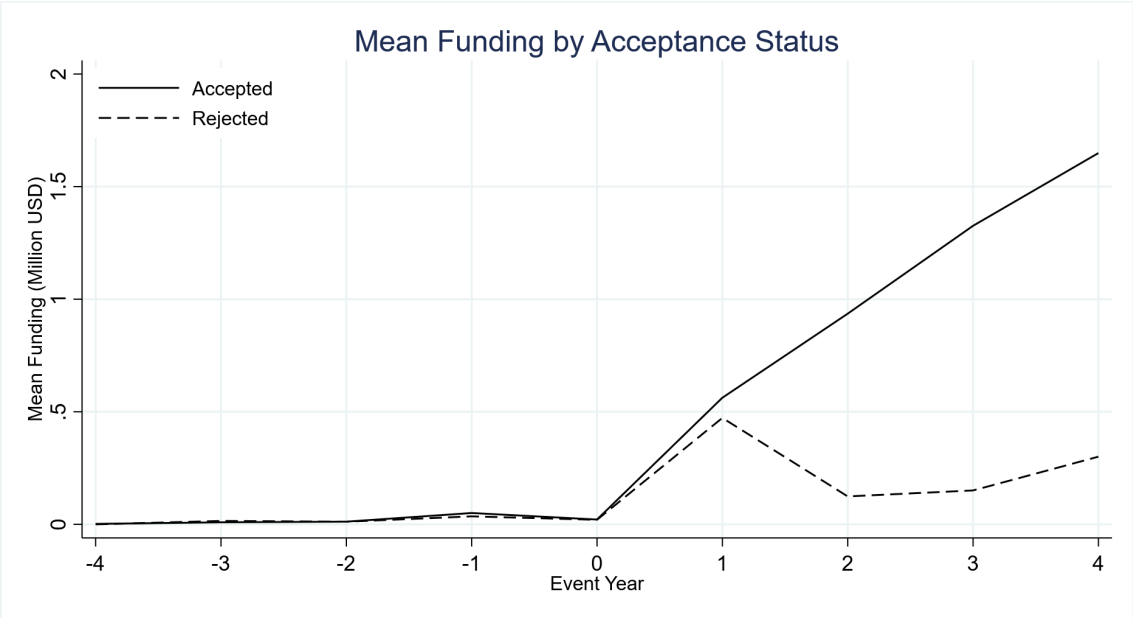


Figure 2. Dynamic Effects of TIPS Acceptance on Subsequent Funding

This figure presents the dynamic effects of TIPS acceptance on subsequent funding. We consider firm-year observations of an event window [−4, +4] around the TIPS application year (Time=0). We specifically estimate the following regression model: $\text{Ln}(1+funding)_{it} = \beta_1 Treated_i + \sum_{n=-4}^{4} \beta_2^n EventYear_{it}^n + \sum_{n=-4}^{4} \beta_3^n Treated_i \times EventYear_{it}^n + Controls_{it} + \sigma_i + \delta_t + \theta_{v\tau} + \gamma_{jt}$. We use the earliest years (Time = −4) as the base. A capped spike shows the 95 percent confidence interval of each estimate.

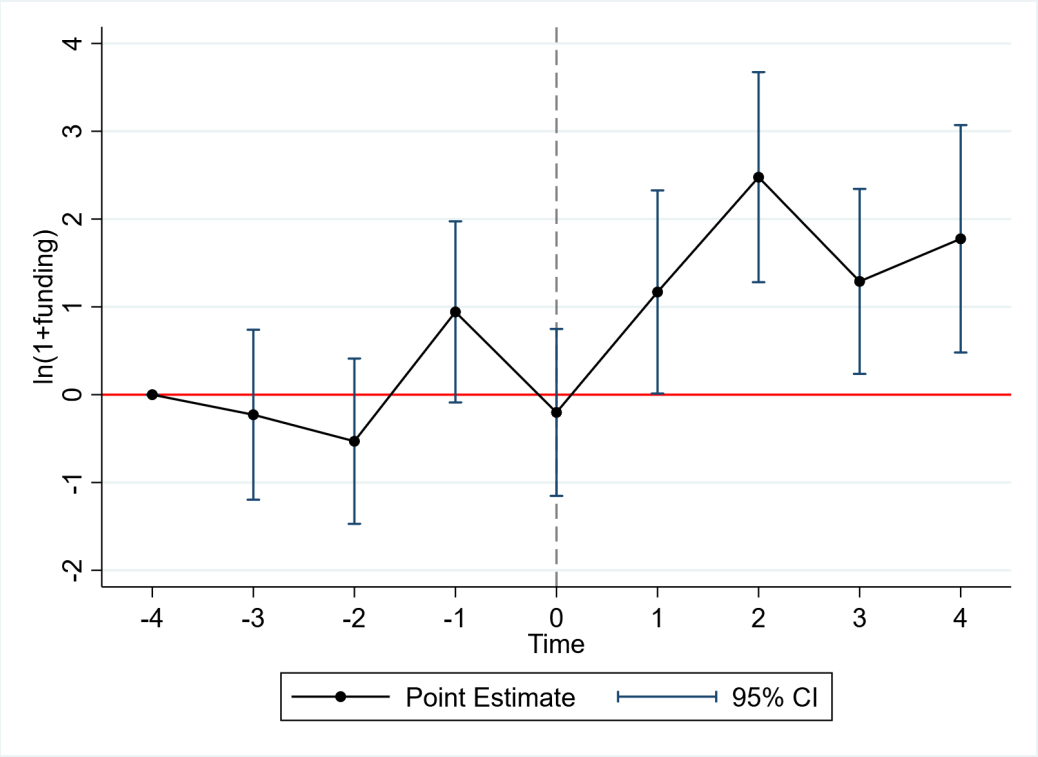
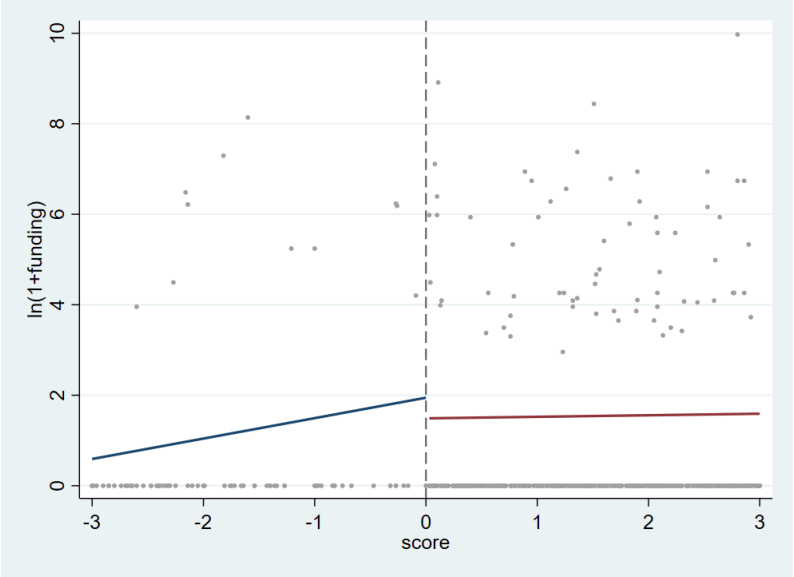
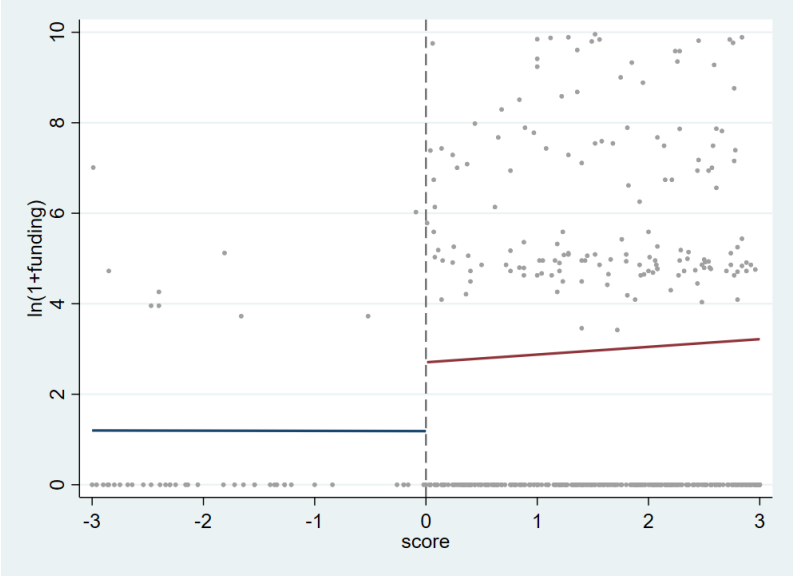


Figure 3. Regression Discontinuity around TIPS Acceptance Cutoff

This figure presents a graphical illustration of the fitted values from the regression discontinuity model specification in column (3) of Table 6 for the tightest bandwidth of |*Relative score*|≤ 3. The solid lines are the predicted values of *Ln(1+funding)*, while the scattered dots are the actual values of *Ln(1+funding)*. The dots are clustered at zero because not all startups have VC investments every year. Panel (a) shows the results for the pre-TIPS application period using the average values over the three years preceding the TIPS application, and Panel (b) shows the post-TIPS application period using the average values over the three years following the TIPS application.



(a) Pre-TIPS Application Period



(b) Post-TIPS Application Period

Table 1. TIPS Applications, Acceptances, and Subsidies

The table presents the numbers of sponsor VCs, TIPS applications, accepted and rejected applications, along with acceptance rates and subsidy amounts over application years for our sample from 2014 to 2021. The units for the total and average subsidies are in millions of USD.

Application Year	Sponsor VCs	Total Applications	Accepted Applications	Rejected Applications	Acceptance Rate	Total Subsidies	Average Subsidies
2014	12	39	39	0	100.00%	12.857	0.357
2015	22	76	76	0	100.00%	25.536	0.355
2016	23	105	86	19	81.90%	29.207	0.356
2017	45	224	203	21	90.63%	69.524	0.349
2018	50	277	254	23	91.70%	89.057	0.355
2019	52	292	257	35	88.01%	90.306	0.356
2020	54	342	296	46	86.55%	101.509	0.355
2021	65	420	372	48	88.57%	101.906	0.257
Total	83	1775	1577	192	88.85%	519.903	0.330

Table 2. Sample Distribution and Summary Statistics

Panels A and B of the table describe the main sample by year and industry. The industry classification is based on the major categories of the Korean Standard Industrial Classification (KSIC). The sample consists of 6,049 firm-year observations for the sample period of 2011–2022. Panel C reports the descriptive statistics for variables used in our analyses. Panel D compares mean statistics between the treated and control groups. The treated group consists of startups accepted to the TIPS program during the sample period, coded as one, and zero otherwise. The control group consists of all other recommended startups. Panels E and F compare mean statistics between the treated and control groups, separately for the pre-TIPS and post-TIPS application periods, respectively. Detailed descriptions of all variables are available in Appendix A.

Panel A. Sample distribution by year

Year	Frequency	Frequency (Accepted)	Frequency (Rejected)
2012	13	8	5
2013	38	29	9
2014	82	66	16
2015	219	178	41
2016	405	342	63
2017	640	548	92
2018	844	726	118
2019	1020	885	135
2020	1130	984	146
2021	1023	897	126
2022	635	563	72
Total	6049	5226	823

Panel B. Sample distribution by industry sector

Industry	Frequency	Frequency (Accepted)	Frequency (Rejected)
Machine/Material	487	424	63
Bio/Medical	1487	1294	193
Energy/Resource	63	51	12
Electronics	618	562	56
Information Technology	2589	2203	386
Knowledge-based Service	625	533	92
Chemistry	180	159	21
Total	6049	5226	823

Panel C. Summary Statistics

Variable	Mean	Std. Dev.	Min	10%	50%	90%	Max	Obs.
Funding (Million USD)	0.390	1.899	0	0	0	0.321	32.143	6049
Ln(1+funding)	2.006	4.864	0	0	0	12.681	16.475	6049
Treated	0.864	0.343	0	0	1	1	1	6049
After	0.428	0.495	0	0	0	1	1	6049
Age	2.583	2.014	0	1	2	6	11	6049
Ln(1+age)	1.097	0.633	0	0	1.098	2.398	2.398	6049
Prior funding (Million USD)	0.363	1.950	0	0	0	0.375	47.928	6049
Ln(1+prior funding)	3.918	8.057	0	0	0	23.764	23.764	6049
Common equity ratio	0.187	0.381	0	0	0	1	1	6049
Total asset turnover	0.339	0.395	0	0	0.199	1.764	1.764	6049
Revenue growth	1.496	4.987	−15.303	−14.225	0.404	14.604	15.640	6049

Panel D. Treated vs. Control Samples

Variable	Mean Treated (Obs=5226)	Mean Control (Obs=823)	Mean Difference
Funding (Million USD)	0.433	0.123	0.310***
Ln(1+funding)	2.137	1.179	0.957***
Age	2.591	2.533	0.057
Ln(1+age)	1.099	1.080	0.019
Prior funding (Million USD)	0.408	0.081	0.326***
Ln(1+prior funding)	4.114	2.674	1.439
Common equity ratio	0.205	0.075	0.130***
Total asset turnover	0.327	0.416	−0.088***
Revenue growth	1.475	1.635	−0.160

Panel E. Treated vs. Control Samples of Pre-TIPS

Variable	Mean Treated (Obs=2930)	Mean Control (Obs=529)	Mean Difference
Funding (Million USD)	0.027	0.021	0.006
Ln(1+funding)	1.145	1.096	0.482
Age	1.380	1.571	−0.190***
Ln(1+age)	0.717	0.787	−0.070***
Prior funding (Million USD)	0.026	0.019	0.006
Ln(1+prior funding)	1.757	1.726	0.031
Common equity ratio	0.153	0.059	0.093***
Total asset turnover	0.321	0.390	−0.069***
Revenue growth	3.220	3.003	0.217

Panel F. Treated vs. Control Samples of Post-TIPS

Variable	Mean Treated (Obs=2296)	Mean Control (Obs=294)	Mean Difference
Funding (Million USD)	0.950	0.305	0.645***
Ln(1+funding)	3.402	1.328	2.075***
Age	4.136	4.265	−0.129
Ln(1+age)	1.587	1.607	−0.020
Prior funding (Million USD)	0.895	0.192	0.703***
Ln(1+prior funding)	7.122	4.382	2.740***
Common equity ratio	0.272	0.102	0.170***
Total asset turnover	0.336	0.462	−0.126***
Revenue growth	−0.753	−0.828	0.075

Table 3. TIPS Acceptance and Subsequent Funding

The table reports results from the regressions of the new funding amount on the TIPS acceptance. The sample consists of 6,049 firm-year observations for the sample period of 2011–2022, comprising 1,182 unique recommended startups for the 2016−2021 TIPS programs. We exclude the TIPS program years of 2014 and 2015 because the acceptance rates in those years are 100%. We specifically estimate the following regression model: $\text{Ln}(1+funding)_{it} = \beta_1 Treated_i + \beta_2 Post_{it} + \beta_3(Treated_i \times Post_{it}) + Controls_{it} + \sigma_i + \delta_t + \theta_{v\tau} + \gamma_{jt}$. The dependent variable is *Ln(1+funding)*, the logarithm of the funding amount that the startup receives in a given year. *Treated* equals one for the startups accepted into the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS application and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

	Ln(1+funding)			
	(1)	(2)	(3)	(4)
Treated × Post	1.720***	1.661***	2.318***	2.254***
	(4.41)	(4.19)	(5.61)	(5.19)
Post	0.438	0.466	−0.527	−0.526
	(1.12)	(1.17)	(−1.08)	(−1.22)
Ln(1+age)	0.784***	0.792***	1.959***	1.780***
	(2.96)	(2.86)	(6.06)	(5.64)
Ln(1+prior funding)			−0.215***	−0.223***
			(−5.00)	(−15.99)
Common equity ratio			−1.878***	−1.954***
			(−4.98)	(−9.17)
Total asset turnover			−2.900***	−2.935***
			(−4.22)	(−12.75)
Revenue growth			0.00756	0.00616
			(0.55)	(0.47)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
N	6049	6049	6049	6049

Table 4. TIPS Acceptance and Subsequent Funding with Similar TIPS−Rankings

The table reports results from the regressions of the new funding amount on the TIPS acceptance among the TIPS applications with comparable TIPS rankings. The sample consists of 378 firm-year observations from 67 unique recommended startups for the 2016−2021 TIPS programs that passed with the lowest score or failed with the highest score based on the TIPS evaluation scores. For cases where the lowest-scored accepted startup's score is lower than the highest-scored rejected startup's score, the pair is excluded. For such cases, we include the second lowest-scored accepted and second highest-scored rejected startups instead. We exclude the TIPS program years of 2014 and 2015 because the acceptance rates in those years are 100%. The dependent variable is *Ln(1+funding)*, the logarithm of the funding amount that the startup receives in a given year. *Treated* equals one for the startups accepted to the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS application and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

	Ln(1+funding)			
	(1)	(2)	(3)	(4)
Treated × Post	1.798**	1.641	2.798**	2.795**
	(2.07)	(1.45)	(2.61)	(2.06)
Post	0.586	0.917	−0.209	−0.0846
	(0.66)	(0.77)	(−0.23)	(−0.07)
Ln(1+age)	2.497***	2.637**	2.862***	3.368**
	(2.83)	(2.35)	(2.98)	(2.63)
Ln(1+prior funding)			−0.210***	−0.259***
			(−4.20)	(−4.83)
Common equity ratio			−1.993***	−2.410***
			(−2.81)	(−3.07)
Total asset turnover			−1.821	−1.767
			(−1.61)	(−1.25)
Revenue growth			−0.0595	−0.0620
			(−1.60)	(−1.22)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
N	378	378	378	378

Table 5. TIPS Acceptance and Subsequent Funding with Similar TIPS Scores

The table reports results from the regressions of the new funding amount on the TIPS acceptance among the TIPS applications with comparable TIPS scores. The sample consists of 3,228 firm-year observations from 636 unique recommended startups for the 2016−2021 TIPS programs that have TIPS evaluation scores within ±3 points of the threshold (i.e., lowest) TIPS score for acceptance in each TIPS program year. We exclude the TIPS program of 2014 and 2015 because the acceptance rates in those years are 100%. The dependent variable is *Ln(1+funding)*, the logarithm of the funding amount that the startup receives in a given year. *Treated* equals one for the startups accepted to the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS application and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

	Ln(1+funding)			
	(1)	(2)	(3)	(4)
Treated × Post	1.097**	1.147**	1.691***	1.740***
	(2.12)	(2.14)	(2.92)	(3.00)
Post	0.737	0.659	−0.204	−0.280
	(1.37)	(1.18)	(−0.34)	(−0.47)
Ln(1+age)	0.816**	0.756**	1.457***	1.414***
	(2.25)	(1.97)	(3.57)	(3.34)
Ln(1+prior funding)			−0.232***	−0.239***
			(−13.22)	(−13.23)
Common equity ratio			−1.581***	−1.715***
			(−5.62)	(−6.05)
Total asset turnover			−2.761***	−2.852***
			(−9.00)	(−8.66)
Revenue growth			−0.0203	−0.0191
			(−1.31)	(−1.17)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
N	3228	3228	3228	3228

Table 6. TIPS Acceptance and Subsequent Funding with Regression Discontinuity

The table reports results from the regressions estimating the following regression discontinuity model: *Ln(1+funding) = β1 Treated + β2 Relative score + β3 Treated × Relative score*. The dependent variable is *Ln(1+funding)*, the logarithm of the average funding amount that the startup receives in a given year. *Relative score* is the actual TIPS evaluation score minus the threshold (i.e., lowest) TIPS score for acceptance in each TIPS program year. The model uses three different bandwidths of the full sample, |Relative score|≤5, and |Relative score|≤3, reported in columns (1), (2), and (3), respectively. Panel A shows the results for the pre-TIPS application period using the average values over the three years preceding the TIPS application. Panel B shows the results for the post-TIPS application period using the average values over the three years following the TIPS application. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

Panel A: Pre-TIPS Application

	Ln(1+funding)		
	(1)	(2)	(3)
	Full sample	|Relative score|≤5	|Relative score|≤3
Treated	0.0916	−0.0384	0.0469
	(0.32)	(−0.11)	(0.11)
Relative score	−0.0185	0.391	0.807
	(−0.13)	(0.82)	(1.12)
Treated × Relative score	−0.219	−0.754	−0.950
	(−1.03)	(−1.35)	(−1.02)
Ln(1+age)	−0.0954	−0.232	−0.179
	(−0.44)	(−0.94)	(−0.60)
Ln(1+prior funding)	0.182***	0.175***	0.167***
	(5.25)	(4.45)	(3.17)
Common equity ratio	−0.687**	−0.643**	−0.650*
	(−2.55)	(−2.06)	(−1.69)
Total asset turnover	8.968***	8.884***	8.610***
	(19.96)	(16.80)	(12.92)
Revenue growth	0.0642***	0.0578**	0.0341
	(2.59)	(2.01)	(0.95)
Industry FE	Yes	Yes	Yes
Application Year FE	Yes	Yes	Yes
VC FE	Yes	Yes	Yes
N	1182	952	636

Panel B: Post-TIPS Application

	Ln(1+funding)		
	(1)	(2)	(3)
	Full sample	|Relative score|≤5	|Relative score|≤3
Treated	1.727***	1.380***	1.461**
	(4.04)	(2.64)	(2.54)
Std. TIPS score	−0.109	0.179	0.220
	(−0.51)	(0.26)	(0.22)
Treated × Std. TIPS score	0.486	0.823	−0.578
	(1.54)	(1.02)	(−0.45)
Ln(1+age)	1.362***	1.345***	1.255***
	(4.70)	(4.21)	(3.40)
Ln(1+prior funding)	0.195***	0.195***	0.182***
	(10.78)	(9.48)	(7.39)
Common equity ratio	−1.917***	−1.898***	−1.859***
	(−4.94)	(−4.37)	(−3.64)
Total asset turnover	−3.290***	−3.257***	−2.702***
	(−8.27)	(−7.02)	(−4.93)
Revenue growth	−0.0620	−0.0514	−0.156**
	(−1.17)	(−0.85)	(−2.20)
Industry FE	Yes	Yes	Yes
Application Year FE	Yes	Yes	Yes
VC FE	Yes	Yes	Yes
N	1182	952	636

Table 7. Financing Mechanism: Different Funding Needs

The table reports results from the regressions of the new funding amount on the TIPS acceptance by startup firms' different funding needs. The sample consists of 6,049 firm-year observations for the sample period of 2011–2022 by 1,182 unique recommended startups for the 2016−2021 TIPS programs. We exclude the TIPS program years of 2014 and 2015 because the acceptance rates in those years are 100%. We estimate the regression model in Table 3 separately for the two groups of firms with high vs. low needs for the TIPS subsidy. We use the logarithmic ratio of the TIPS subsidy amount to one plus the total funding amount that each firm has received before its TIPS application as a proxy for the TIPS funding needs. We consider the total amount of all previous investments and the total investments from each startup's sponsor VCs separately. The dependent variable is *Ln(1+funding)*, the logarithm of the funding amount that the startup receives in a given year. *Treated* equals one for the startups accepted into the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS application and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

Panel A. Summary Statistics of Financing Needs Measures

		Mean	Std. dev.	Min	10%	50%	90%	Max	Obs.
TIPS subsidy / Total prev. funding	Full sample	0.705	0.998	−3.296	−0.693	0.916	1.609	3.219	5985
	Above Median	1.437	0.312	0.916	0.916	1.609	1.609	3.219	3155
	Below Median	−0.111	0.857	−2.89	−1.386	0	0.839	0.916	2830
TIPS subsidy / Sponsor VC's prev. funding	Full sample	0.742	0.974	−3.295	−0.693	0.916	1.609	3.219	5985
	Above Median	1.457	0.305	0.915	0.916	1.61	1.609	3.219	3034
	Below Median	0.006	0.873	−2.89	−1.386	0.223	0.839	1.607	2951

Panel B. DID Analysis

	Ln(1+funding)			
	TIPS subsidy / Total prev. funding		TIPS subsidy / Sponsor VC's prev. funding	
	(1)	(2)	(3)	(4)
	Above Median	Below Median	Above Median	Below Median
Treated × Post	2.569***	1.094	2.546***	0.848
	(6.72)	(1.42)	(6.48)	(1.01)
Post	−0.764*	0.493	−0.883*	0.788
	(−1.82)	(0.62)	(−2.11)	(0.92)
Ln(1+age)	1.609***	1.883**	1.425***	2.256**
	(4.81)	(2.33)	(3.81)	(3.17)
Ln(1+prior funding)	−0.205***	−0.251***	−0.237***	−0.231***
	(−5.05)	(−4.51)	(−5.29)	(−4.59)
Common equity ratio	−1.496***	−2.608***	−1.364***	−2.832***
	(−3.83)	(−4.55)	(−3.57)	(−4.81)
Total asset turnover	−2.881***	−2.687**	−2.734***	−3.245***
	(−3.88)	(−2.78)	(−3.95)	(−3.65)
Revenue growth	−0.00395	0.0165	−0.00253	0.0130
	(−0.24)	(0.89)	(−0.15)	(0.78)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
N	3207	2838	3035	2959

Table 8. Promotion Mechanism: Funding from More or Less Experienced Investors

The table reports results from the regressions of the new funding amount from more or less experienced investors on the TIPS acceptance. The sample consists of 6,049 firm-year observations for the sample period of 2011–2022 by 1,182 unique recommended startups for the 2016−2021 TIPS programs. We exclude the TIPS program years of 2014 and 2015 because the acceptance rates in those years are 100%. We estimate the regression model in Table 3 separately for the two versions of the dependent variables, *Ln(1+funding)*, the logarithm of the new funding amount that the startup receives in a given year from more experienced (in odd-numbered columns) vs. less experienced investors (in even-numbered columns). In columns (1) and (2), we classify investors as more experienced when they primarily focus on early-stage investments, such as seed investments, rather than later-stage investments, and less experienced otherwise. In columns (3) and (4), we classify investors as more experienced when the startup's industry is one of the top three industries where they have made investments and less experienced otherwise. In columns (5) and (6), we classify investors as more or less experienced when their total number of investments up to a given year is above and below the median, respectively. *Treated* equals one for the startups accepted into the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS application and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

	Ln(1+funding)					
	Investment Focus		Industry Experience		Number of Investments	
	(1)	(2)	(3)	(4)	(5)	(6)
	Early stage	Other	Industry Expert	Non-Industry Expert	More Frequent	Less Frequent
Treated × Post	0.660***	1.263***	1.123***	1.399***	1.113***	1.229***
	(2.71)	(5.87)	(3.93)	(4.52)	(4.04)	(4.54)
Post	−1.134***	−0.819***	−0.425*	−0.890**	−0.595**	−0.679**
	(−4.60)	(−3.68)	(−1.97)	(−2.89)	(−2.76)	(−2.63)
Ln(1+age)	1.222***	0.751***	1.193***	1.338***	1.024***	1.131***
	(5.35)	(3.86)	(5.95)	(7.58)	(6.08)	(6.42)
Ln(1+prior funding)	−0.0631***	−0.0145	−0.0281	−0.0465*	−0.0233	−0.0426*
	(−5.61)	(−1.27)	(−1.05)	(−2.05)	(−0.99)	(−1.93)
Common equity ratio	−1.234***	−0.932***	−1.332***	−1.318***	−1.032***	−1.253***
	(−7.32)	(−6.56)	(−6.76)	(−7.13)	(−5.83)	(−6.21)
Total asset turnover	−0.890***	−1.375***	−1.633***	−1.695***	−1.557***	−1.822***
	(−4.43)	(−7.82)	(−4.16)	(−3.53)	(−3.94)	(−4.14)
Revenue growth	−0.0105	0.00725	0.0145*	0.00404	0.0130	−0.000843
	(−1.14)	(0.86)	(1.86)	(0.32)	(1.11)	(−0.09)
Diff. of DID coefficients	−0.603*** (P>|t| = 0.0055)		−1.418 (P>|t| = 0.3160)		−0.297 (P>|t| = 0.6139)	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
VC × Application Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6049	6049	6049	6049	6049	6049

Table 9. TIPS Acceptance and Real Effects

The table reports results from the regressions of the new funding amount on the TIPS acceptance. The sample consists of 6,049 firm-year observations for the sample period of 2011–2022 by 1,182 unique recommended startups for the 2016−2021 TIPS programs. We exclude the TIPS program years of 2014 and 2015 because the acceptance rates in those years are 100%. The dependent variables are *Ln(1+R&D investment)*, the logarithm of one plus the startup's R&D investment amount in a given year in Panel A, *Ln(1+Patents)*, the logarithm of one plus the number of the startup's patent applications filed in a given year (which were granted later) in Panel B, and *Ln(1+ Revenues)*, the logarithm of one plus the startup's revenues amount in a given year. *Treated* equals one for the startups accepted into the TIPS program during the sample period and zero otherwise. *Post* equals one if the firm year is after the TIPS acceptance and zero otherwise. The *t*-statistics (in parentheses) are robust and adjusted for firm clustering. Detailed descriptions of all variables are available in Appendix A.

Panel A. Summary Statistics of Real Effects

	Mean	Std. dev.	Min	10%	50%	90%	Max	Obs.
Ln(1+R&D investment)	7.601	5.493	0	0	10.602	13.062	14.594	5413
Ln(1+Patents)	0.587	0.713	0	0	0	1.609	4.263	6049
Ln(1+Revenues)	8.939	4.806	0	0	10.719	13.936	15.304	6049

Panel B. DID Analysis of R&D Investment

	Ln(1+R&D investment)			
	(1)	(2)	(3)	(4)
Treated × Post	2.322***	2.420***	2.296***	2.237***
	(4.21)	(4.54)	(4.37)	(4.12)
Post	−2.220***	−2.275***	−2.095***	−2.082***
	(−4.24)	(−4.50)	(−4.19)	(−4.04)
Ln(1+age)	6.517***	6.481***	6.843***	6.853***
	(18.72)	(18.94)	(18.96)	(18.66)
Ln(1+prior funding)			0.00550	0.00476
			(0.47)	(0.40)
Common equity ratio			−1.468***	−1.328***
			(−6.18)	(−5.41)
Total asset turnover			0.754***	0.661**
			(2.83)	(2.40)
Revenue growth			0.0601***	0.0584***
			(4.46)	(4.20)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × year FE	No	Yes	No	Yes
N	5409	5409	5409	5409

Panel C. DID Analysis of Patent Applications

	Ln(1+Patents)			
	(1)	(2)	(3)	(4)
Treated × Post	0.230***	0.223***	0.209***	0.203***
	(4.05)	(3.89)	(3.70)	(3.57)
Post	−0.257***	−0.256***	−0.227***	−0.226***
	(−4.48)	(−4.41)	(−3.96)	(−3.92)
Ln(1+age)	0.466***	0.466***	0.486***	0.481***
	(11.13)	(10.79)	(11.37)	(10.87)
Ln(1+prior funding)			0.00647***	0.00665***
			(3.64)	(3.64)
Common equity ratio			−0.116***	−0.0956***
			(−4.48)	(−3.47)
Total asset turnover			0.0664*	0.0626
			(1.76)	(1.59)
Revenue growth			0.00365*	0.00330*
			(1.93)	(1.68)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
N	6049	6049	6049	6049

Panel D. DID Analysis of Revenue

	Ln(1+Revenues)			
	(1)	(2)	(3)	(4)
Treated × Post	0.418	0.477	0.446**	0.465**
	(1.44)	(1.63)	(2.11)	(2.17)
Post	−0.296	−0.334	−0.316	−0.327
	(−1.04)	(−1.16)	(−1.54)	(−1.57)
Ln(1+age)	5.714***	5.713***	6.847***	6.889***
	(24.12)	(23.36)	(39.11)	(38.63)
Ln(1+prior funding)			0.00625	0.00679
			(0.99)	(1.05)
Common equity ratio			2.776***	2.716***
			(21.57)	(21.28)
Total asset turnover			−0.192	−0.145
			(−1.32)	(−0.98)
Revenue growth			0.397***	0.400***
			(84.39)	(83.89)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
VC × Application Year FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
N	6049	6049	6049	6049

Internet Appendix

Section IA1. Coverage of Datasets for Korean Startups

In this paper, we combine multiple data for Korean startups collected from various data sources. In this section, we provide a detailed explanation of those data sources.

1. **TIPS (Tech Incubator Program for Startup)**

   This proprietary dataset is from the Korea Technology and Information Promotion Agency for Small and Medium Enterprises (SMEs) and contains information on 2,460 startups that applied to the TIPS program between 2014 and 2021. The dataset includes application and evaluation details, firm characteristics, and sponsor venture capital investment information. Firm−level information includes firm name, founding date, and industry classifications. The TIPS application and evaluation details include the evaluation dates, evaluation scores, acceptances, and subsidy amounts. The dataset also provides information on the names of sponsor VCs, their pre-TIPS investment amounts, and equity types.

2. **TheVC**

   TheVC is a venture investment database platform focused on the Korean market. The platform provides information about VC, VC−backed startups and funding, including invested startups' basic details, investment records, and industry news. We use theVC for getting the annual investment information on recommended startups. Of the 2,460 TIPS participants, we have collected comprehensive information for 1,895 startups. The investment data includes funding dates, amounts and investor names. We use the investment dates and amounts to construct annual funding amounts for each firm. Additionally, we excluded investments made by sponsor VCs using the investor names.

3. **Pitchbook**

   Pitchbook is a global venture capital investment database that provides detailed information on venture capital investments. The database includes firm characteristics, investment records, and investor−level information such as investment styles, assets under management, and investment histories. We use Pitchbook to cross−validate data from TheVC and fill potential information gaps in other datasets.

4. **KISLINE (now NICE BizLINE)**

   KISLINE is a corporate information database providing financial and credit information for Korean firms. We used KISLINE for the 1,895 startups identified by TheVC and Pitchbook. Among them, 1,775 startups have KISLINE financial information. The financial information collected included annual values of total assets, debt, revenues, and operating incomes.

Table IA1. Sample Selection

The table describes our sample selection procedure.

Sample selection procedure	Firm-year Obs.	Firm-years Excluded	Firm Obs
All TIPS participants from 2014 to 2021			2460
Exclude missing data from Pitchbook or TheVC	11915		1895
Exclude missing observations from KISLINE	9969	1946	1775
Exclude observations with 100% acceptance ratio year (2014 & 2015)	8322	1647	1631
Exclude observations of multiple applied and ultimately accepted startups	7432	890	1458
Exclude observations with no information before TIPS subsidies	6329	1103	1182
Exclude observations outside the [−4 years, +4 years] event window	6049	280	1182
Final sample	6049		1182