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KATO, Masatoshi
Kwansei Gakuin University

IKEUCHI, Kenta
RIETI

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Picking Winners or Making Them? Evidence from the J-Startup program*

Masatoshi KATO†
School of Economics & Research Center for Entrepreneurship (RECENT), Kwansei Gakuin University

Kenta IKEUCHI
Research Institute of Economy, Trade and Industry (RIETI)

Abstract

Using a longitudinal dataset of Japanese start-ups, this study evaluates the J-Startup program, Japan's flagship initiative aimed at fostering globally competitive start-ups. We estimate the average treatment effect on the treated (ATT) using propensity score matching, finding that program participation significantly enhances firm growth, particularly in employment and sales, and increases the likelihood of generating high-growth firms. Heterogeneity analysis reveals that these effects are particularly pronounced for younger firms, while evidence on firm size remains inconclusive. To explore underlying mechanisms, we examine financing capacity and network expansion as potential channels. We find that program participation enhances financing capacity, which in turn is positively associated with firm growth, which is consistent with a certification-induced financing channel. While program participation also expands investor and customer networks, these channels show limited association with firm growth. Overall, the findings suggest that while the program exhibits elements of "picking winners," its marginal impact is strongest for firms at earlier stages of development, and that growth effects operate primarily through certification-induced improvements in financing capacity.

Keywords: Start-up, acceleration program, treatment effect model, firm heterogeneity, certification effect.
JEL Classification: L26, O38, C23.

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† Corresponding author. E-mail: mkato@kwansei.ac.jp

1. Introduction

Start-ups are widely regarded as key drivers of innovation, job creation, and economic growth (e.g., Aghion et al., 2009; Koellinger and Thurik, 2012; Haltiwanger et al., 2013). Yet, many new firms fail within a few years of entry (Bartelsman et al., 2005). A central explanation is the liability of newness (Stinchcombe, 1965): young firms lack established routines, legitimacy, and, crucially, a track record. As a result, they face pronounced information asymmetries vis-à-vis external stakeholders such as investors and business partners, which constrain their access to critical resources. These market imperfections provide a rationale for public intervention in early-stage start-ups. However, whether such interventions are effective remains an open question, and even when positive effects are documented, it is unclear which types of firms benefit most.

In recent years, start-up policy has increasingly shifted from broad-based support toward selective interventions targeting firms with high growth potential (e.g., Audretsch et al., 2020; Coad et al., 2022; Grilli et al., 2023). Such selective approaches rest on the assumption that governments can identify high-potential firms ex ante and that program participation generates measurable performance advantages (e.g., Colombo et al., 2013). However, it remains unclear which types of firms benefit most from such interventions and when these effects materialize. Systematic evidence on the moderating role of firm characteristics—such as firm age and size—remains limited, despite their theoretical relevance for understanding resource constraints and information asymmetries. This gap is particularly important, as effective policy design requires not only selecting promising firms but also allocating support to those for whom the marginal impact is greatest.

A further, more exploratory question concerns the mechanisms through which any such effects operate. Prior studies, notably on the Small Business Innovation Research (SBIR) program, have shown that government certification can enhance firms' access to external finance by reducing information asymmetries between start-ups and investors (Lerner, 1999; Howell, 2017). However, certification may also generate broader effects beyond financing, such as expanding business networks through increased trading partnerships. Whether these represent distinct and empirically separable channels through which program participation fosters firm growth remains an open question.

Against this backdrop, this study examines the effectiveness of the J-Startup program, Japan's flagship initiative designed to foster globally competitive start-ups. We investigate whether the impact of government support varies systematically with firm characteristics, focusing on firm age and size, and explore the temporal dimension of these effects. Beyond estimating average and heterogeneous treatment effects, we further explore the mechanisms through which program participation affects firm growth, examining financing capacity and network expansion as potential channels. Using a longitudinal dataset of Japanese start-ups covering the period 2018–2024, we model program participation using a logit specification and estimate the average treatment effect on the treated (ATT) via propensity score matching (PSM). We find that the program disproportionately selects firms that are larger, younger, and already possess intellectual property. Participation significantly improves firm performance, particularly in employment and sales growth. Importantly, heterogeneous effects are observed: the gains are most pronounced for younger firms, while the evidence on firm size remains inconclusive. Regarding mechanisms, program participation enhances financing capacity and expands both investor and customer networks. However, only the financing channel shows a consistent positive association with firm growth, suggesting that capital increase plays a more direct role in translating program participation into firm growth.

This study makes four contributions. First, prior studies have predominantly examined discrete policy instruments, such as financial support or matching services. While informative, this approach may underestimate the overall impact of policy when firms receive multiple, complementary forms of support. We instead examine a comprehensive support program that integrates financial, networking, and intellectual property-related assistance, allowing for a more holistic assessment of government intervention. Second, although it is well understood that policy effects are heterogeneous, systematic evidence on which firms benefit most and when such benefits emerge remains limited. We address this gap by explicitly modeling the moderating role of firm age and size and by examining the timing of policy effects, thereby providing new insights into how government support can be more effectively targeted. Third, we provide direct empirical evidence on the mechanisms linking program participation to firm growth, distinguishing between financing and network expansion channels. While certification effects through financing have been theorized, systematic empirical evidence comparing multiple channels within a single program evaluation remains scarce. Fourth, despite the long-standing implementation of start-up policies in Japan, rigorous quantitative evaluations remain scarce. By providing empirical evidence on the effects of a major national initiative, this study contributes to the literature on entrepreneurship policy and offers policy-relevant insights in a context that has received limited attention.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and outlines the methodology. Section 4 presents the results. Section 5 discusses the findings and their implications. The final section concludes.

2. Background and hypotheses development

2.1. Background and related literature

Governments around the world have increasingly promoted entrepreneurial activity through policies and programs designed to accelerate the start-up process (e.g., Hochberg, 2016; Merguei and Costa, 2022). Such policy efforts take various forms, including seed accelerators, start-up competitions, and government-backed loan schemes. Government loan programs have been shown to positively affect firm performance, contributing to employment creation and sales growth (Bertoni et al., 2019; Hottenrott and Richstein, 2020). Loans targeted at research and development (R&D) activities further enhance firm survival and increase the likelihood of attracting venture capital (VC) investment (Zhao and Ziedonis, 2020). Similarly, government venture capital (GVC) has been found to generate a catalytic effect by stimulating private investment without crowding it out, often through certification mechanisms (Brander et al., 2015; Guerini and Quas, 2016). While the direct impact of GVC alone on firm growth may be limited, its effectiveness is significantly enhanced when combined with private VC through syndication (Grilli and Murtinu, 2014). In addition to financial support, "soft" forms of assistance—such as incubation and networking—also improve start-up performance relative to unsupported firms (Colombo and Delmastro, 2002; Soetanto and Jack, 2016).[1]

[1] Colombo and Grilli (2006) provide early evidence from Italy on the effectiveness of public support for high-tech start-ups, documenting positive effects on firm growth.

Recent studies on public acceleration programs provide further evidence on their effectiveness. Gonzalez-Uribe and Leatherbee (2018) show that mentoring and training components can be more impactful than financial support alone, while Autio and Rannikko (2016) find that public support programs significantly accelerate sales growth. Hallen et al. (2020) demonstrate that participation in accelerator programs facilitates faster access to VC funding and exit opportunities, and Gonzalez-Uribe and Reyes (2021) report positive effects on employment and firm scaling.[2] At the same time, concerns have been raised regarding the potential crowding-out effects of public support. For instance, Wallsten (2000) finds no significant impact on employment and provides evidence that public subsidies may substitute for private R&D investment. Similarly, Kösters (2010) finds evidence of deadweight losses in German start-up subsidies, suggesting that subsidized firms would likely have succeeded without public support and highlighting the challenge of targeting firms for whom support generates the greatest marginal impact. Overall, while the evidence is not without exception, the literature broadly suggests that public support tends to improve start-up performance.[3]

However, the impact of public support is unlikely to be uniform across firms. Emerging evidence suggests that firm- and founder-level characteristics moderate the effectiveness of policy interventions. For example, Grilli et al. (2023) show that entrepreneurs with higher levels of human capital benefit more from policy reforms that reduce growth barriers. Similarly, Chapman and Hottenrott (2024) find that the effectiveness of public subsidies is greater for firms led by founders with a strong entrepreneurial orientation. Despite these insights, systematic evidence on which types of firms benefit most from public support remains limited. In particular, the moderating roles of firm age and size have received insufficient attention, despite their theoretical relevance. Younger firms typically face more severe resource constraints and higher levels of information asymmetry due to the lack of established track records, while smaller firms tend to have limited internal resources and weaker access to external financing and networks (Stinchcombe, 1965; Kato et al., 2026). In the Japanese context, Kato and Coad (2024) suggest that the limited effectiveness of the SBIR program may

[2] Similarly, Biancalani et al. (2022) document positive effects of Italy's Start-up Act on firm growth, providing further cross-country evidence on the effectiveness of selective public support programs.
[3] Evidence on the long-term effects of start-up subsidies is more limited. Caliendo and Tübbicke (2020) find positive long-term effects of start-up subsidies on self-employment survival using matching estimates.

be partly attributable to insufficient targeting of young firms in the early stages of their development, further highlighting the importance of firm age as a moderating factor in evaluating policy effectiveness.[4]

A further gap in the literature concerns the mechanisms through which public support translates into firm growth. A recurring finding is that government support confers a certification effect, whereby selected firms gain enhanced credibility and access to external resources (Kim and Wagman, 2014). Consistent with this view, firms receiving support from programs such as the SBIR initiative are more likely to obtain VC financing (Lerner, 1999; Howell, 2017), with particularly strong effects observed among financially constrained firms (Howell, 2017).[5] However, the literature has predominantly focused on financing as the primary channel through which certification operates. Whether program participation also expands business networks—such as increasing trading partnerships or collaborative innovation activity—as a distinct growth channel remains largely untested empirically. Moreover, most prior studies examine specific policy instruments in isolation, leaving the question of which channels are operative within comprehensive support programs underexplored. Identifying and comparing multiple mediating channels within a single program evaluation therefore represents an important gap in the existing literature.

2.2. The J-Startup program: Hypotheses development

The J-Startup program is a public–private acceleration initiative launched in 2018 by Japan's Ministry of Economy, Trade and Industry (METI) in collaboration with private-sector partners, including venture capital firms, large corporations, and accelerators. The program aims to foster high-growth start-ups with the potential to become globally competitive firms. A key feature of the program is its integrated support ecosystem. Selected start-ups receive comprehensive assistance, including opportunities to pitch to investors, support for research and development (R&D) and intellectual property (IP), and strategic business matching with corporate partners. In addition, the program actively promotes international expansion by facilitating participation in global exhibitions and providing access to overseas networks.

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[4] Prior studies on public support for SMEs in Japan have documented positive effects on capital investment and firm growth (Harada and Honjo, 2005; Honjo and Harada, 2006) as well as on productivity improvement (Takahashi and Hashimoto, 2023).

[5] Public grants have also been shown to increase the likelihood of receiving venture capital investment more broadly, consistent with a certification mechanism (Berger and Hottenrott, 2021; Thys et al., 2025). Hottenrott et al. (2018) find that public subsidies increase new ventures' use of bank loans, suggesting that public support may complement rather than substitute private financing.

A distinctive aspect of the program is its selective screening process. Firms are nominated and evaluated by experienced private-sector experts based on their innovativeness and scalability. As a result, only a limited number of high-potential start-ups are selected, making the program highly competitive. From a theoretical perspective, this selective process functions as a certification mechanism. Selection conveys credible information about a firm's underlying quality to external stakeholders, such as investors, business partners, and customers (Spence, 1973; Kim and Wagman, 2014). Because the screening process involves expert evaluation based on difficult-to-observe characteristics, program selection can reduce information asymmetries and facilitate access to external resources. This signaling role provides the theoretical motivation for our empirical strategy: if J-Startup selection functions as a certification mechanism, treated firms should exhibit superior post-selection performance relative to observationally similar non-selected firms.

A central question in the entrepreneurship policy literature concerns whether public support programs generate measurable performance advantages for participating firms. If certification mechanisms are operative, participating firms should gain improved access to external resources such as finance, business partnerships, and market opportunities, which in turn translate into superior firm growth. We therefore propose the following hypothesis:

H1: Participation in selective public support programs positively affects firm growth.

The benefits of certification and resource access are unlikely to be uniform across firms. A key insight from the liability of newness literature is that younger firms face particularly severe information asymmetries (Stiglitz and Weiss, 1981; Honjo et al., 2014). Without an established track record, young firms struggle to credibly signal their quality to external stakeholders, making access to finance, customers, and business partners especially challenging (Stinchcombe, 1965; Coad, 2018; Coad et al., 2025). Government-backed certification can therefore play a disproportionately important role for younger firms by providing a credible quality signal that substitutes for the track record they lack. Similarly, smaller firms tend to have limited internal resources and weaker access to external financing and networks, making them more dependent on external validation to overcome resource constraints (Bercovitz and Mitchell, 2007; Djupdal and Westhead, 2015). In contrast, older and larger firms are more likely to have already established reputations and resource access through prior market interactions, reducing the marginal benefit of government certification. Consistent with this reasoning, Grilli et al. (2023) show that the benefits of policy interventions are greater for firms facing higher growth barriers, and Chapman and Hottenrott (2024) find that the effectiveness of public subsidies varies systematically with firm-level characteristics. Taken together, these arguments suggest that the marginal value of public support is greatest for firms that face the most severe resource constraints and information asymmetries—namely, younger and smaller firms. Accordingly, we propose the following hypotheses:

H2a: The positive effect of selective public support on firm growth is negatively moderated by firm age.

H2b: The positive effect of selective public support on firm growth is negatively moderated by firm size.

Beyond average and heterogeneous effects, a further question concerns the mechanisms through which program participation translates into firm growth. Understanding these mechanisms is important not only for theory but also for policy design, as it allows policymakers to identify which aspects of support programs are most effective. We consider two potential mediating channels.

The first is financing capacity. A well-established finding in the certification literature is that government-backed selection reduces information asymmetries between start-ups and potential investors, thereby enhancing firms' ability to attract external capital. Lerner (1999) and Howell (2017) show that SBIR awardees are significantly more likely to obtain venture capital financing, with effects particularly pronounced among financially constrained firms. We proxy this channel using paid-in capital increase.

The second channel is network expansion. Beyond direct financing, program participation may also facilitate the development of new relationships with investors and business partners. Recent evidence suggests that accelerator programs can serve as intermediaries connecting start-ups with higher-profile investors, thereby expanding their investor base (Dalle et al., 2025). By serving as a credible quality signal, program selection may help firms expand their investor base—captured by shareholder increase—as well as their customer and supplier relationships—captured by customer expansion. Notably, shareholder increase reflects both dimensions simultaneously: it captures the broadening of the investor network and the associated improvement in financing capacity, two aspects that are inherently intertwined in the context of equity financing.

While the financing channel has received empirical support in prior studies, the network expansion channel has received comparatively little systematic empirical attention. Examining both channels within a single program evaluation not only allows us to identify which mechanisms are operative, but also to rule out those that are not—an exercise that itself carries informational value for both theory and policy design. We therefore propose the following hypotheses:

H3a: Government certification enhances start-up growth through improved financing capacity.

H3b: Government certification enhances start-up growth through expanded business networks.

Figure 2 presents the analytical framework underlying our empirical analysis. The framework illustrates the hypothesized relationships between J-Startup selection, firm growth, and the two sets of moderating and mediating factors examined in this study. The direct effect of program participation on firm growth (H1) is hypothesized to be moderated by firm age and size (H2a and H2b). In addition, financing capacity and network expansion are examined as potential mediating channels through which program participation translates into firm growth (H3a and H3b).

3. Methodology

3.1 Data

We first compile a list of firms selected under the J-Startup program from publicly available sources. To characterize these firms in detail, we utilize a comprehensive firm-level database provided by Tokyo Shoko Research (TSR), one of Japan's largest credit investigation companies.[6] This database contains rich information on firm characteristics, including location, founding year, number of employees, and sales, as well

[6] Databases from credit investigation companies provide detailed longitudinal firm-level data—including financial information, managerial attributes, and interfirm relationships—over extended time periods, making them well-suited for studying firm dynamics in Japan. In addition to TSR, which is used in this study, Teikoku Data Bank (TDB) is another major credit investigation company that provides a similar database. Several prior studies on Japanese start-ups have drawn on these databases (e.g., Kato and Honjo, 2015; Coad and Kato, 2021; Kato et al., 2022; Honjo et al., 2025).

as detailed information on firm representatives, such as name, education, gender, and age. A key advantage of this dataset is that it allows us to track firm dynamics longitudinally from the time of establishment. In addition, we merge these firm-level data with patent information obtained from the Institute of Intellectual Property (IIP), enabling us to construct measures of firms' innovative activities.

Figure 1 presents the number of firms selected under the J-Startup program by year and category. The number of selected firms varies considerably over time, with an initial cohort of 92 firms in 2018 and subsequent waves of varying size. The program includes different categories (e.g., Local, Normal, and Impact), with the largest intake observed in 2023, when 140 firms were selected. This variation reflects the evolving scope and scale of the program over time.

Table 1 reports descriptive statistics on firm age (measured as years since establishment) and firm size (measured by number of employees). While the program targets start-ups, the data reveal substantial heterogeneity in firm characteristics. The average firm age is approximately six years, but the maximum reaches up to 57 years, indicating that relatively mature firms are also included in the program. Similarly, although the average firm size is modest, the maximum number of employees exceeds 600, suggesting that some relatively large firms are selected. These patterns imply that the J-Startup program does not exclusively target early-stage or small firms, but rather includes a broad range of firms with varying levels of maturity and scale.

Appendix Table A1 reports the distribution of firms across industries. The sample is concentrated in information and communications (36.3%), manufacturing (25.8%), and professional services (21.2%), which together account for the majority of observations. Other sectors, such as agriculture, healthcare, and commerce, are represented to a much lesser extent, while several sectors (e.g., mining, construction, transportation, and public administration) have little to no representation. This distribution suggests that the J-Startup program primarily targets knowledge-intensive and technology-oriented sectors.

3.2 Matching procedure

To evaluate the causal effect of J-Startup program participation on firm outcomes, we construct a matched sample using propensity score matching (PSM), pairing each treated firm with observationally similar non-selected firms. Propensity scores are estimated via a logit model predicting the likelihood of program selection (*J-Startup*) based on pre-treatment firm characteristics, CEO attributes, innovation-related variables, and year and industry dummies.

At the firm level, we control for firm size in terms of employment (measured as the log of the number of employees in year $t-1$; *Employment*), previous employment growth (the log difference in employment between year t and $t-1$; *Previous emp growth*), and firm age (log of firm age in year $t-1$; *Firm age*).[7] These variables capture firm scale, recent growth dynamics, and stage of development, all of which are key determinants of both selection into the program and subsequent firm performance. In particular, firm size and prior growth proxy for underlying growth potential, while firm age reflects differences in resource constraints and the liability of newness. In addition, we control for firms' innovation capacity using a dummy for patent application activity in year $t-1$ (*Patent*) and the cumulative number of patent applications as of year $t-1$ (*Patent stock*), capturing both recent and accumulated technological capability. We further incorporate CEO-level characteristics, including gender (CEO gender) and age-group dummies for CEOs in their 20s, 30s, 50s, and 60s or above (*CEO age_20*, *CEO age_30*, *CEO age_50*, and *CEO age_60*, respectively; CEOs in their 40s serve as the reference category), along with educational attainment dummies for university degree holders, graduate degree holders, and those with missing educational information (*CEO univ*, *CEO grad*, and *CEO unknown*, respectively). These variables capture human capital and demographic attributes that may influence both the likelihood of selection and post-selection outcomes. Year and industry dummies are included to absorb time-specific shocks and sectoral heterogeneity. Table 2 provides definitions of all variables used in the analysis. Appendix Table A2 reports the correlation matrix of the variables used in the analysis.

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[7] We also estimated the propensity score model using sales-based measures of firm size (log of sales in year $t-1$) and previous growth (log difference in sales between year t and $t-1$) as alternatives to employment-based measures. The results were broadly consistent with those reported here and are available upon request.

The choice of these covariates is guided by the conditional independence assumption (CIA): conditional on observable characteristics, selection into the J-Startup program is plausibly independent of potential outcomes. By controlling for firm scale, growth trajectory, stage of development, innovation capacity, and managerial characteristics—factors that jointly shape both selection and performance—we aim to mitigate observable selection bias and approximate a credible counterfactual.

For each treated firm, we identify up to ten nearest control candidates based on the estimated propensity score and retain candidate matches within a caliper of 0.05 in absolute propensity score differences. From these candidates, the single nearest control firm is selected for each treated observation, resulting in one-to-one matched pairs. Matching is performed at the pre-treatment year, and the resulting pairs are fixed across all subsequent outcome periods. This approach ensures that the matched sample remains balanced on pre-treatment characteristics throughout the analysis, avoiding the re-matching that would otherwise occur when outcome availability varies across variables and time periods.

To verify the quality of matching, we conduct balance tests comparing the distribution of pre-treatment covariates between treated and matched control firms. The results, reported in Appendix Table A3, confirm that the matched sample achieves adequate covariate balance across the full set of covariates. Since matched pairs are fixed at the pre-treatment year ($t-1$), missing values in outcome variables are not imputed; instead, observations are dropped when either the treated firm or its matched control has missing values for the relevant outcome variable at a given event time. This results in variation in the number of matched pairs across outcome variables and event times, as reported in the ATT tables.

Table 3 reports the logit estimates of program selection. Selection into the J-Startup program is positively associated with firm size, prior employment growth, and prior patenting activity, and negatively associated with firm age. These results indicate that the program disproportionately targets younger, larger, and more innovation-active firms. Regarding CEO characteristics, firms led by younger and more highly educated CEOs are more likely to be selected, whereas older age categories are negatively associated with selection. Overall, the selection process appears to favor firms with stronger observable growth and innovation potential, underscoring the importance of addressing selection bias in the estimation of program effects.

3.3 Estimation strategy

We examine three primary outcome variables: employment growth (*Emp growth*), sales growth (*Sales growth*), and productivity growth (*Prod growth*), each defined as the log difference between year t+k (k = 1–6) and the pre-treatment year t−1. In addition, we construct high-growth firm dummies for each outcome (*H_emp growth*, *H_sales growth*, and *H_prod growth*), defined as dummy variables equal to one if the average annual growth rate up to year t+k exceeds 20%. We estimate the average treatment effect on the treated (ATT) for each outcome and event time. ATT is estimated by comparing each treated firm to its closest matched control with non-missing values for the relevant outcome variable at each event time. Our identification strategy relies on the assumption that, conditional on the included covariates, selection into the program is as good as random. Under this assumption, PSM allows us to recover the causal effect of program participation on firm outcomes by comparing treated firms to a counterfactual group with similar observable characteristics.

To examine heterogeneity in program effects, we also estimate OLS regressions using the difference between treated firms and their closest matched controls as the dependent variable. This matched-pair difference specification is consistent with the design underlying the ATT estimates in the baseline model. Interaction terms between the treatment indicator and firm age and size are introduced to test H2a and H2b. For binary and count outcomes, we additionally assess robustness using fixed-effects logit and fixed-effects Poisson models estimated on stacked factual-counterfactual panels constructed from treated firms and their matched controls.

To explore the mechanisms through which program participation affects firm growth, we estimate ATT for a set of intermediate outcomes that proxy for the two mediating channels identified in Section 2. For the financing channel, we examine capital increase, defined as the log difference in paid-in capital relative to the pre-treatment year. For the network expansion channel, we examine two variables: shareholder increase, defined as the log difference in the number of shareholder firms relative to the pre-treatment year, which captures the expansion of investor relationships and the associated improvement in financing capacity; and customer expansion, defined as the log difference in the number of trading partner firms relative to the pre-treatment year, which captures the development of commercial business relationships. This measure captures not only firms reported as customers by the firm itself, but also firms that report the firm as a supplier in their own records. If program participation operates through the financing channel, we would expect positive ATT estimates for capital increase. Similarly, positive ATT estimates for shareholder increase and customer expansion would provide evidence in favor of the network expansion channel. This approach allows us to identify which channels are operative and to rule out those that are not, providing direct empirical evidence on the mechanisms underlying program effectiveness.

4. Results

4.1 Baseline results

Table 4 reports the ATT estimates for employment growth, sales growth, and productivity growth over event time *t* to *t*+6. All estimates are based on the matched sample described in Section 3. Program participation has no statistically significant effect on employment growth at the time of selection, but the effect becomes statistically significant at the 1% level from *t*+1 onward, and remains positive and statistically significant at least at the 10% level through *t*+6. The magnitude of the effect increases over time, suggesting that the benefits of program participation accumulate gradually. For sales growth, the ATT is positive and statistically significant at the 5% level at *t*, and remains positive and statistically significant at various levels through *t*+1 and *t*+6. Similar to employment growth, the magnitude of the effect also increases over time. Productivity growth shows a positive and statistically significant effect at the 10% level at *t*, but the effects are not statistically significant at subsequent periods. Overall, these results provide support for H1, indicating that J-Startup participation positively affects firm growth, particularly in employment and sales.

Table 5 reports the ATT estimates for high-growth firm dummies. Program participation significantly increases the likelihood of achieving high employment growth, with effects statistically significant at the 1% level from *t* through *t*+6, with the exception of *t*+6 where the effect remains statistically significant at the 5% level. Similarly, the likelihood of achieving high sales growth is significantly higher for treated firms, with effects statistically significant at the 1% level from *t* through *t*+5. For high productivity growth, the effects are positive and statistically significant at the 1% level at *t*, at the 5% level at *t*+1 and *t*+2, at the 10% level at *t*+3, and the 1% level at t+4, but become statistically insignificant at t+5 and t+6. Taken together, these results confirm that J-Startup participation not only improves average growth performance but also increases the likelihood of generating high-growth firms across multiple dimensions. Figure 3 presents the ATT estimates for employment growth, sales growth, and productivity growth graphically over event time, illustrating the gradual accumulation of treatment effects particularly for employment and sales growth.

4.2 Heterogeneity analysis

Table 6 reports OLS estimates of the moderating role of firm age. The estimation pools observations across all event times from t to t+6, with event-time dummies included to account for differences across periods. The main effects—representing the estimated treatment effect for firms with average age—are positive and statistically significant for sales growth and productivity growth at t, and for employment growth from t+1 onward, consistent with the baseline ATT results. The interaction terms between event time and firm age are negative and statistically significant at the 5% level for sales growth at t+2, and for productivity growth at t+2 through t+4. For high-growth dummies, the interaction terms are negative and statistically significant for productivity growth at t+1 through t+5 (except for t+2). These findings suggest that older firms tend to benefit less from program participation in terms of productivity growth, providing partial support for H2a. However, the moderating role of firm age is not consistently observed across all outcome variables, particularly for employment growth, where the interaction terms are not statistically significant.

Table 7 reports OLS estimates of the moderating role of firm size. The estimation pools observations across all event times from t to t+6, with event-time dummies included to account for differences across periods. The main effects are positive and statistically significant for employment growth from t+1 through t+5, and for sales growth at t+4 and t+5. The interaction terms between event time and firm size are negative and statistically significant at the 10% level for sales growth and productivity growth at t+5. For high productivity growth, the interaction term is negative and statistically significant at the 5% level at t+6. These results provide limited support for H2b, suggesting that larger firms tend to benefit somewhat less from program participation in terms of sales and productivity growth at longer time horizons. However, the moderating role of firm size is not consistently observed across all outcomes and periods, indicating that the evidence on firm size remains inconclusive overall.

4.3 Mechanism analysis

Table 8 reports the ATT estimates for the three mediating variables. To construct the matched sample for the mechanism analysis, a separate propensity score matching procedure is conducted using the same set of covariates as the baseline matching, with the following modifications: previous employment growth is excluded, and pre-treatment levels of paid-in capital, the number of trading partners, the number of shareholder firms, the number of joint patent applicants, sales, and labor productivity (all measured in logarithms in year $t-1$) are additionally included as covariates to improve balance on pre-treatment characteristics relevant to each mediating variable. Balance tests confirm that the matched sample achieves adequate covariate balance across the full set of covariates, although the detailed results are not reported for brevity.

For the financing channel, capital increase shows positive and statistically significant effects at the 1% level at t and $t+1$, and at the 5% level at $t+2$, but the effects are not statistically significant from $t+3$ onward. For the network expansion channel, shareholder increase shows positive and statistically significant effects at the 1% level at t through $t+1$ and $t+3$ through $t+4$, and at the 5% level at $t+2$ and $t+5$, suggesting a sustained expansion of investor relationships. Notably, shareholder increase captures both the broadening of the investor base and the associated improvement in financing capacity—two aspects that are inherently intertwined in the context of equity financing. Customer expansion shows no statistically significant effect at t, but becomes statistically significant at the 10% level at $t+1$, at the 5% level at $t+2$ through $t+5$, and at the 1% level at $t+6$, indicating a gradually strengthening effect on commercial network expansion. These results suggest that program participation enhances both financing capacity and network expansion, with the financing channel operating primarily in the short term and the network expansion channel becoming more pronounced over longer time horizons.

Tables 9 and 10 report OLS estimates of the association between mediating variables and firm growth outcomes. To examine whether mediating variables are associated with firm growth within matched pairs, the dependent variable is defined as the difference in the outcome between the treated firm and its matched control (Y_treated − Y_control), and the independent variable is defined as the corresponding difference in the mediating variable (X_treated − X_control). For capital increase, the association with employment growth is positive and statistically significant at the 10% level at *t*+1 and *t*+2, and at the 1% level from *t*+3 through *t*+6. The association with sales growth is positive and statistically significant at the 10% level at *t* and at the 5% level at *t*+2 and *t*+3. The association with productivity growth is positive and statistically significant at the 10% level at *t*, although it is not significant at subsequent periods. These results suggest that capital increase is positively associated with firm growth, particularly employment growth, consistent with a financing channel through which program participation translates into firm growth.

For shareholder increase, the association with employment growth is positive and statistically significant at the 1% level at *t*, but is not statistically significant at subsequent periods, and the association with sales and productivity growth is generally not statistically significant. This suggests that while program participation successfully expands the investor base, the growth benefits of this network expansion are limited and concentrated in the short term. For customer expansion, the association with sales growth is positive and statistically significant at the 1% level at *t*+3, but is not consistently statistically significant across other periods or outcomes.

Table 10 shows that capital increase is positively associated with high employment growth at the 5% level at *t*+1, at the 1% or 5% level from *t*+2 through *t*+6, and with high sales growth at the 1% level at *t*+2. Shareholder increase is positively associated with high employment growth and high sales growth at the 5% level at *t*, but the associations are not statistically significant at subsequent periods. Customer expansion shows no consistent statistically significant association with high-growth firm creation.

Taken together, these results suggest that the financing channel—particularly through capital increase—plays the most consistent and sustained role in linking program participation to firm growth, providing support for H3a. While program participation also expands investor and customer networks, the direct associations between these network variables and firm growth outcomes remain limited, providing only partial support for H3b.

5. Discussion

5.1 Summary of findings

This study examines the causal effects of participation in the J-Startup program on firm growth, heterogeneity in these effects across firm characteristics, and the mechanisms through which program participation translates into growth. Three main findings emerge from the analysis. First, program participation significantly enhances firm growth, particularly in employment and sales, and substantially increases the likelihood of generating high-growth firms. These findings are consistent with a broader body of evidence suggesting that selective public support programs confer measurable performance advantages on participating firms (Lerner, 1999; Hallen et al., 2020; Gonzalez-Uribe and Reyes, 2021).

Second, the effects of program participation are heterogeneous across firm characteristics. The moderating role of firm age is most evident for firm growth, where older firms tend to benefit less. The evidence on firm size is less consistent, suggesting that the relationship between firm size and policy effectiveness is more nuanced than previously assumed.

Third, the mechanism analysis reveals that program participation enhances both financing capacity and network expansion, but these channels differ in their associations with firm growth. The financing channel—particularly through capital increase—emerges as the most consistent mechanism linking program participation to firm growth. Network expansion through investor and customer relationships, while significant in its own right, shows limited direct association with firm growth outcomes.

5.2 Academic implications

The findings of this study contribute to several strands of the entrepreneurship and innovation policy literature. First, the results provide direct empirical support for the certification hypothesis and extend its theoretical scope. Prior studies have documented certification effects primarily in the context of discrete financial support programs such as the SBIR (Lerner, 1999; Howell, 2017), where the credibility of the signal is closely tied to the provision of financial resources. The present findings suggest that certification effects can operate independently of direct financial transfers: selection into a comprehensive public acceleration program—

where the signal derives from the rigor of the screening process rather than the financial value of the award—is sufficient to generate measurable growth advantages. This implies that the credibility of the selection process itself, rather than the resources attached to it, may be the primary driver of certification effects, with important implications for how such effects are theorized and measured.

Second, the heterogeneity analysis contributes to the literature on the moderating role of firm characteristics in policy effectiveness (Grilli et al., 2023; Chapman and Hottenrott, 2024). The finding that younger firms benefit more from program participation—particularly in terms of productivity growth—is consistent with the liability of newness argument (Stinchcombe, 1965). Importantly, however, the inconclusive evidence on firm size suggests that information asymmetries, rather than resource constraints per se, may be the more critical moderating factor: it is the absence of a track record, rather than firm scale, that determines how much a firm stands to gain from government certification. This distinction has theoretical implications for how heterogeneity in policy effectiveness is conceptualized, suggesting that future research should more carefully separate the roles of informational and resource-based constraints in moderating program effects.

Third, the mechanism analysis contributes to the theoretical understanding of the channels through which public support translates into firm growth. The finding that the financing channel—particularly through capital increase—is the most consistent mediating pathway suggests that certification operates primarily by enhancing financial credibility in the eyes of investors, rather than by directly expanding commercial networks. This points to a hierarchy of certification effects: financial credibility is established rapidly and translates directly into growth, while network expansion, though real, operates more slowly and indirectly. This temporal hierarchy has not been previously theorized in the certification literature and represents a novel contribution to understanding how government-backed signals propagate through entrepreneurial ecosystems. The limited direct association between network expansion and firm growth further suggests that network relationships may be a necessary but not sufficient condition for growth, requiring complementary resources—such as financial capital—to be activated. Moreover, the gradual strengthening of customer expansion effects over longer time horizons points to the possibility that network-based growth mechanisms operate with a substantial time lag. This suggests that studies with shorter observation windows may systematically underestimate the role of network expansion as a growth channel, and that future research should adopt longer-term panel data to more fully capture the temporal dynamics of certification-induced network effects.

5.3 Practical implications

The findings carry several implications for different stakeholders. For policymakers, the positive and sustained effects of J-Startup participation on employment and sales growth, as well as on the likelihood of generating high-growth firms, suggest that selective public acceleration programs can be effective instruments for fostering start-up growth. At the same time, the heterogeneity analysis points to a potential mismatch between selection criteria and policy effectiveness. While the program tends to select larger and younger firms, the moderating role analysis suggests that younger firms benefit more from participation in certain dimensions. This implies that policymakers may wish to place greater emphasis on firm age as a selection criterion, ensuring that the program reaches firms at earlier stages of development where the marginal impact of certification is greatest. Furthermore, the mechanism analysis suggests that the financing channel is the most effective pathway through which program effects operate, implying that policy design should prioritize interventions that strengthen firms' access to equity financing, such as facilitating connections between selected firms and investors.

Beyond these design considerations, the findings offer concrete lessons for how the J-Startup program itself—and similar initiatives elsewhere—can be improved and evaluated going forward. First, the evidence that younger firms benefit most from participation suggests that the program's selection criteria should be periodically reviewed and recalibrated to ensure alignment with program effectiveness rather than firm visibility or prior success. Second, the finding that capital increase is the most consistent channel linking program participation to firm growth implies that program administrators should actively strengthen the investor-matching component of the support ecosystem, for instance by expanding the pool of participating investors and facilitating more structured follow-on financing opportunities for selected firms. Third, the limited evidence for network expansion as a direct growth channel in the short term does not necessarily imply that networking components are ineffective; rather, it suggests that their benefits may materialize over longer time horizons. Program administrators should therefore consider extending the duration of networking support and maintaining long-term relationships between selected firms and their corporate partners, rather than limiting engagement to the formal program period. Finally, the results underscore the value of rigorous quantitative evaluation as an integral part of program management. Regular impact assessments of this kind can provide program administrators with actionable feedback on which aspects of support are most effective, enabling evidence-based refinement of program design over time.

For start-ups at earlier stages of development—where information asymmetries and resource constraints are most severe—program participation can generate significant growth benefits, as the certification effect of selection can substitute for the track record they lack. Start-ups should therefore actively leverage program participation as a signal to potential investors and seek to translate this certification advantage into concrete equity financing opportunities, rather than treating program participation solely as a networking or mentoring experience.

For investors, selection into competitive public acceleration programs such as J-Startup provides actionable information about firm quality that may not be readily available through other screening mechanisms. The positive and sustained growth effects documented in this study suggest that program selection can serve as a reliable leading indicator of firm growth potential. Investors may therefore find it beneficial to systematically monitor the cohorts of firms selected into competitive public acceleration programs as a source of investment opportunities, particularly given the rigorous expert-based screening process that underlies program selection.

5.4 Limitations and future research avenues

Several limitations of this study should be acknowledged. First, the identification strategy relies on the conditional independence assumption, which requires that, conditional on the observed covariates, selection into the J-Startup program is independent of potential outcomes. While we control for a rich set of pre-treatment firm and CEO characteristics, the possibility of selection on unobservable characteristics cannot be ruled out. Future research could address this limitation by exploiting quasi-experimental variation in program eligibility, such as regression discontinuity designs based on selection scores, if such data become available through collaboration with program administrators.

Second, the mechanism analysis is based on reduced-form ATT estimates for intermediate outcomes and OLS estimates of the association between mediating variables and firm growth. While this approach allows us to identify which channels are operative and to rule out those that are not, it does not provide a formal decomposition of the total treatment effect into direct and indirect components. Future research could employ causal mediation analysis to provide a more rigorous assessment of the relative importance of each channel.

Third, the analysis is limited to firms that applied to and were selected into the J-Startup program, and the control group consists of observationally similar non-selected firms drawn from the TSR database. The generalizability of the findings to other public acceleration programs or other national contexts may be limited. Future research could examine whether similar effects are observed in other countries or program contexts, and whether the relative importance of financing and network expansion channels varies across institutional settings.

Fourth, the sample size decreases substantially over longer event time horizons due to attrition and missing data, which may affect the precision and reliability of the estimates at $t+5$ and $t+6$. Future research with longer panel data would allow for a more robust assessment of the long-term effects of program participation.

Fifth, while the results demonstrate that J-Startup participation generates positive effects on firm growth, this study does not assess whether these effects are commensurate with the costs of the program. The observed growth effects reflect outcomes for the selected firms, but it remains unclear whether a different selection process would have generated larger aggregate gains. Moreover, the analysis does not account for the opportunity costs of public resources devoted to the program, nor does it address potential deadweight losses arising from the possibility that some selected firms would have grown even in the absence of support (Kösters, 2010). A comprehensive cost-benefit analysis, which would require data on program costs and a broader counterfactual framework (Biancalani et al., 2022), lies beyond the scope of this study but represents an important avenue for future research.

6. Conclusions

This study evaluates the causal effects of participation in the J-Startup program, Japan’s flagship public acceleration initiative, on firm growth. Using propensity score matching, we find that program participation generates significant and sustained improvements in employment and sales growth, and substantially increases the likelihood of generating high-growth firms. These effects are most pronounced for younger firms, while the evidence on firm size remains inconclusive. Regarding mechanisms, capital increase emerges as the most consistent channel linking program participation to firm growth, consistent with a certification-induced improvement in access to equity financing, while network expansion shows limited direct association with firm growth outcomes in the short term.

Taken together, the findings highlight the potential of selective public acceleration programs as certification mechanisms that reduce information asymmetries and facilitate access to external resources. They also point to a potential mismatch between selection criteria and policy effectiveness, underscoring the importance of targeting firms at earlier stages of development. These insights carry direct implications for the design of public support programs, not only in Japan but also in other countries where selective acceleration initiatives are increasingly used as instruments of entrepreneurship policy.

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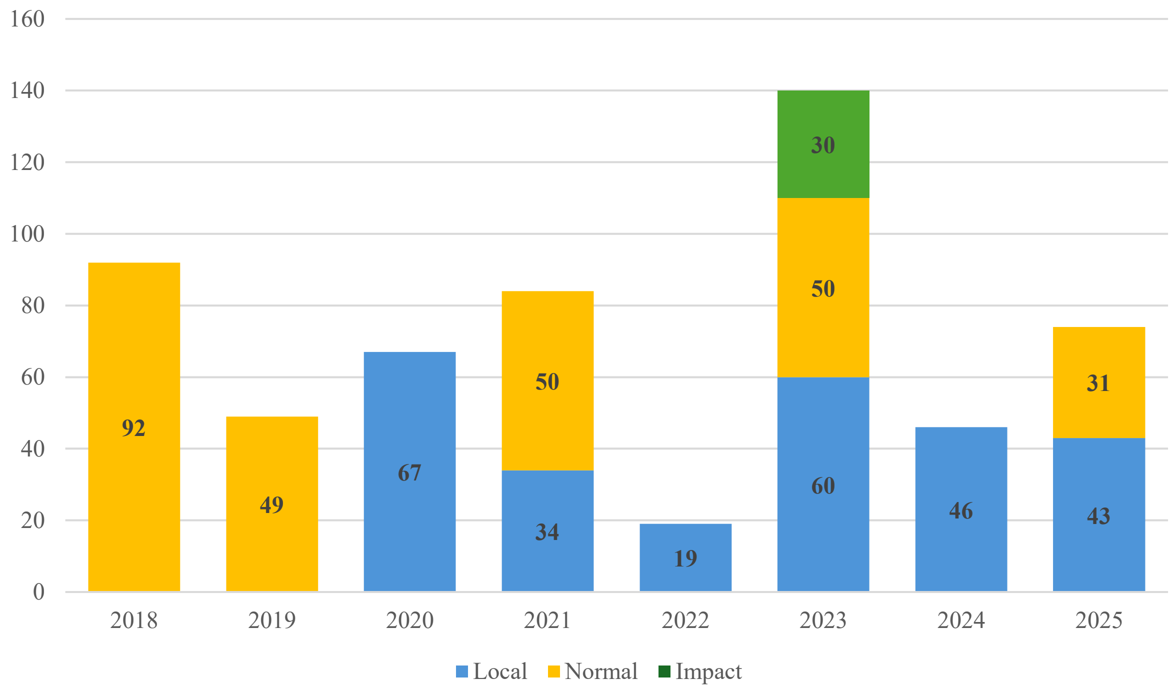


Figure 1. Number of firms awarded by the J-Startup program by the type.

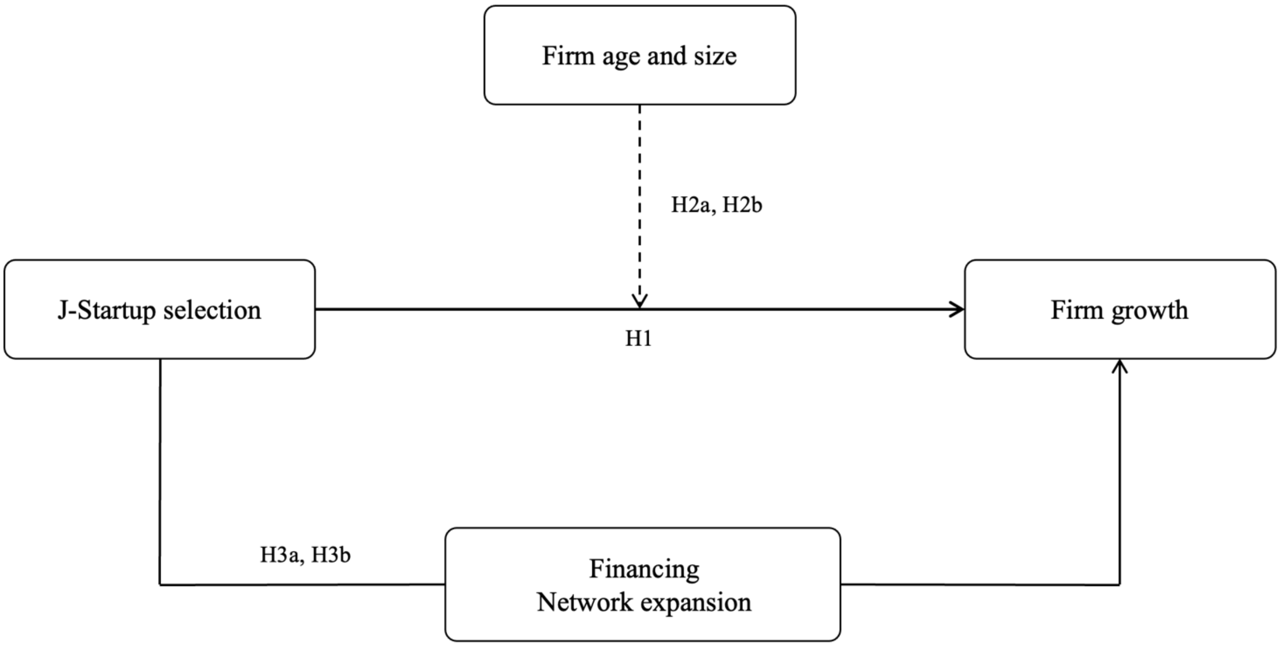
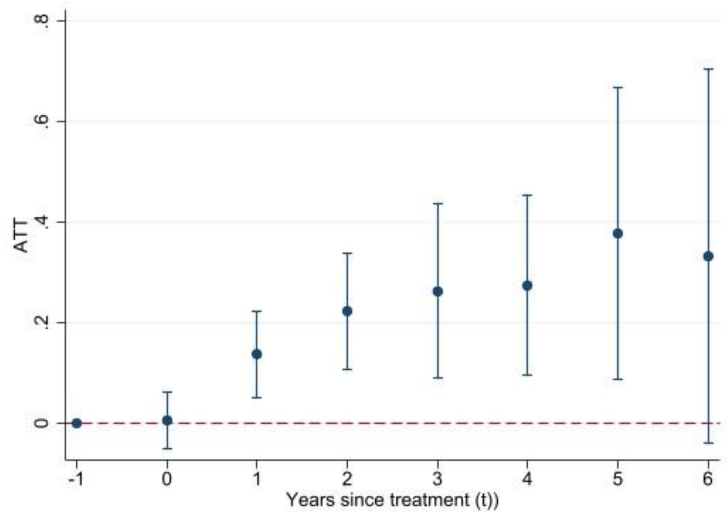
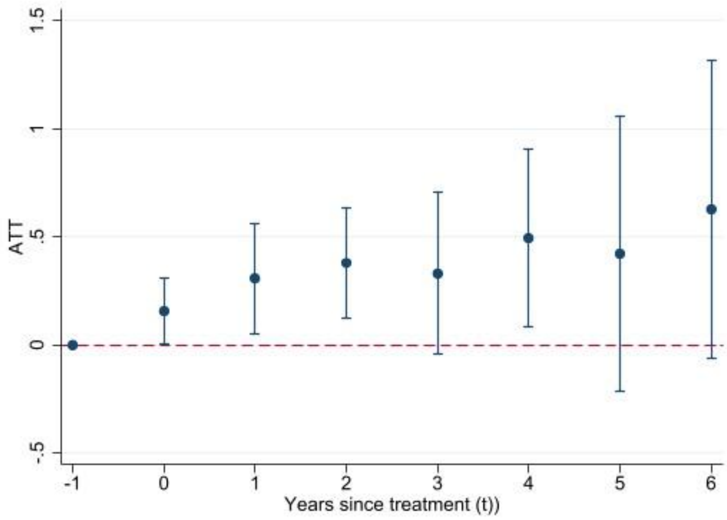


Figure 2. Analytical framework.

(a) Employment growth



(b) Sales growth



(c) Productivity growth

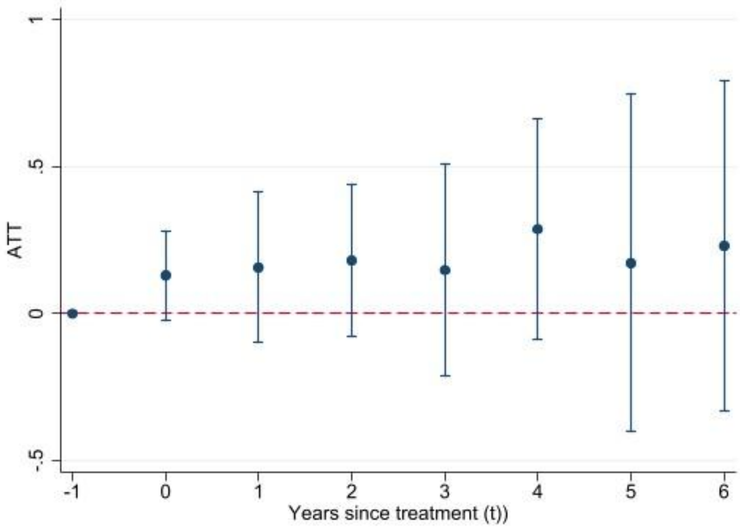


Figure 3. Average treatment effects on the treated over time.

Table 1. Firm characteristics for J-Startup firms.

(a) Firm age

Year	N	Mean	S.D.	Min	p50	Max
2018	92	6.1	3.7	1.0	5.0	18.0
2019	49	4.7	2.8	1.0	4.0	12.0
2020	67	4.6	3.3	1.0	4.0	14.0
2021	79	6.3	4.1	1.0	5.0	20.0
2022	19	4.9	3.4	1.0	4.0	11.0
2023	109	6.4	6.6	0.0	5.0	51.0
2024	46	7.8	8.9	0.0	6.0	57.0
2025	69	6.0	4.6	0.0	5.0	23.0
Total	530	6.0	5.1	0.0	5.0	57.0

(b) Firm size

Year	N	Mean	S.D.	Min	p50	Max
2018	59	55.8	91.8	2.0	30.0	652.0
2019	29	43.7	80.5	1.0	16.0	420.0
2020	36	18.0	15.9	1.0	10.5	70.0
2021	59	51.4	62.7	2.0	30.0	237.0
2022	9	24.8	28.2	4.0	10.0	80.0
2023	66	29.4	39.3	1.0	15.5	184.0
2024	32	28.2	43.9	1.0	14.5	180.0
2025	49	32.9	35.2	1.0	20.0	156.0
Total	339	38.1	59.3	1.0	19.0	652.0

Table 2. Definition of variables.

Variable	Definition
(Outcome variable)	
Emp growth	Log difference in the number of employees between years $t+k$ (k = 1–6) and $t-1$.
Sales growth	Log difference in sales between years $t+k$ (k = 1–6) and $t-1$.
Prod growth	Log difference in sales per employee between years $t+k$ (k = 1–6) and $t-1$.
H_emp growth	Dummy variable equal to one if the average annual growth rate of employment up to year $t+k$ (k = 1–6) exceeds 20%.
H_sales growth	Dummy variable equal to one if the average annual growth rate of sales up to year $t+k$ (k = 1–6) exceeds 20%.
H_prod growth	Dummy variable equal to one if the average annual growth rate of sales per employee up to year $t+k$ (k = 1–6) exceeds 20%.
(Treatment variable)	
J-Startup	Dummy variable equal to one if the firm was selected into the J-Startup program in year t, 0 otherwise.
(Covariates used for matching)	
Employment	Log of the number of employees in year $t-1$.
Previous emp growth	Log difference in the number of employees between year t and $t-1$.
Firm age	Log of firm age in year $t-1$.
Patent	Dummy variable indicating whether the firm filed at least one patent application in year $t-1$.
Patent stock	Cumulative number of patent applications as of year $t-1$.
CEO gender	Dummy variable indicating whether the representative (in year $t-1$) is female.
CEO age_20	Dummy variable for representative in their 20s (year $t-1$).
CEO age_30	Dummy variable for representative in their 30s (year $t-1$).
CEO age_50	Dummy variable for representative in their 50s (year $t-1$).
CEO age_60	Dummy variable for representative aged 60 or above (year $t-1$).
CEO univ	Dummy variable indicating that the representative holds a bachelor's degree (year $t-1$).
CEO grad	Dummy variable indicating that the representative holds a graduate degree (year $t-1$).
CEO unknown	Dummy variable indicating missing information on the representative's education (year $t-1$).
Year dummies	Dummy variables for each year.
Industry dummies	Dummy variables for each industry.
(Mediator variable)	
Capital increase	Log difference in paid-in capital between year t and the pre-treatment year.
Shareholder increase	Log difference in the number of shareholder firms between year t and the pre-treatment year.
Customer expansion	Log difference in the number of trading partner firms between year t and the pre-treatment year. Includes firms reported as customers by the firm itself as well as firms that report the firm as a supplier in their own records.

Table 3. Logit regressions for the determinants of the J-startup selection (*J-Startup*).

Variable	Coefficient
Employment	0.451***
	[0.042]
Previous emp growth	1.456***
	[0.121]
Firm age	-1.692***
	[0.050]
Patent experience	2.585***
	[0.172]
Previous patent stock	-0.001
	[0.001]
CEO gender	0.303
	[0.260]
CEO age_20	1.267***
	[0.413]
CEO age _30	0.530***
	[0.190]
CEO age _50	-0.985***
	[0.210]
CEO age _60	-1.831***
	[0.271]
CEO univ	1.192***
	[0.203]
CEO grad	1.858***
	[0.259]
CEO unknown	-0.746***
	[0.211]
Constant term	-6.832***
	[0.558]
Year dummies	Yes
Industry dummies	Yes
Number of obs.	5,098,220
Number of clusters	884,174
Number of treated	270
Pseudo R^2	0.357
Log likelihood	-1881.6

Note. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Average treatment effect on the treated (ATT) based on one-to-one matching without imputation of missing values: growth rates.

(i) *Emp growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	528	0.222	0.216	0.006
t+1	434	0.425	0.288	0.137***
t+2	368	0.576	0.352	0.224***
t+3	270	0.693	0.430	0.263***
t+4	242	0.740	0.465	0.275***
t+5	160	0.908	0.530	0.378**
t+6	108	0.932	0.600	0.332*

(ii) *Sales growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	372	0.420	0.264	0.156**
t+1	324	0.690	0.384	0.307**
t+2	268	0.928	0.549	0.379***
t+3	194	1.081	0.750	0.330*
t+4	162	1.265	0.771	0.493**
t+5	100	1.488	1.067	0.422
t+6	72	1.605	0.977	0.627*

(iii) *Prod growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	372	0.165	0.036	0.129*
t+1	324	0.251	0.093	0.158
t+2	268	0.361	0.180	0.181
t+3	194	0.408	0.260	0.149
t+4	162	0.560	0.272	0.288
t+5	100	0.510	0.338	0.173
t+6	72	0.586	0.355	0.231

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 Average treatment effects on the treated (ATT) based on one-to-one matching without imputation of missing values: High growth dummies.

(i) *H_emp growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	528	0.405	0.303	0.102***
t+1	434	0.442	0.295	0.147***
t+2	368	0.446	0.277	0.168***
t+3	270	0.400	0.252	0.148***
t+4	242	0.339	0.198	0.140***
t+5	160	0.400	0.200	0.200***
t+6	108	0.333	0.167	0.167**

(ii) *H_sales growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	372	0.543	0.382	0.161***
t+1	324	0.506	0.302	0.204***
t+2	268	0.567	0.343	0.224***
t+3	194	0.577	0.392	0.186***
t+4	162	0.556	0.321	0.235***
t+5	100	0.620	0.360	0.260***
t+6	72	0.472	0.333	0.139

(iii) *H_prod growth*

Period	*N* (pairs)	Treated (J-Startup)	Control (matched)	ATT
t	372	0.387	0.210	0.177***
t+1	324	0.327	0.204	0.123**
t+2	268	0.313	0.187	0.127**
t+3	194	0.268	0.155	0.113*
t+4	162	0.272	0.099	0.173***
t+5	100	0.220	0.120	0.100
t+6	72	0.194	0.083	0.111

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Moderating role of firm age: OLS estimates.

Variable	(i) *Emp growth*	(ii) *Sales growth*	(iii) *Prod growth*	(iv) *H_emp growth*	(v) *H_sales growth*	(vi) *H_prod growth*
(Time since J-Startup selection)						
t	-0.029	0.218*	0.226*	0.071	0.095	0.211***
	[0.042]	[0.129]	[0.128]	[0.056]	[0.069]	[0.060]
t+1	0.110*	0.384*	0.253	0.153***	0.248***	0.201***
	[0.063]	[0.206]	[0.207]	[0.056]	[0.071]	[0.067]
t+2	0.191**	0.693***	0.506**	0.164***	0.273***	0.210**
	[0.086]	[0.219]	[0.221]	[0.062]	[0.077]	[0.086]
t+3	0.091	0.793*	0.779*	0.074	0.062	0.324***
	[0.172]	[0.442]	[0.425]	[0.116]	[0.133]	[0.122]
t+4	0.103	1.003*	0.948**	0.102	0.372***	0.345***
	[0.188]	[0.514]	[0.472]	[0.107]	[0.141]	[0.126]
t+5	0.292	0.538	0.416	0.215	0.236	0.319**
	[0.281]	[0.866]	[0.771]	[0.134]	[0.186]	[0.153]
t+6	0.049	0.884	0.923	0.095	0.228	0.168
	[0.405]	[0.942]	[0.780]	[0.162]	[0.217]	[0.168]
(Interaction terms)						
*t * Firm age*	0.005	-0.008	-0.012	0.004	0.008	-0.004
	[0.003]	[0.008]	[0.009]	[0.005]	[0.006]	[0.004]
t+1 * *Firm age*	0.004	-0.010	-0.012	-0.001	-0.005	-0.010**
	[0.004]	[0.014]	[0.014]	[0.005]	[0.005]	[0.005]
t+2 * *Firm age*	0.005	-0.043**	-0.044**	0.001	-0.007	-0.011
	[0.009]	[0.020]	[0.019]	[0.006]	[0.007]	[0.008]
t+3 * *Firm age*	0.026	-0.067	-0.091**	0.011	0.018	-0.031**
	[0.023]	[0.044]	[0.041]	[0.015]	[0.018]	[0.015]
t+4 * *Firm age*	0.027	-0.074	-0.096**	0.006	-0.020	-0.025*
	[0.023]	[0.052]	[0.047]	[0.014]	[0.017]	[0.013]
t+5 * *Firm age*	0.014	-0.017	-0.036	-0.002	0.004	-0.032*
	[0.039]	[0.087]	[0.077]	[0.018]	[0.021]	[0.019]
t+6 * *Firm age*	0.044	-0.036	-0.096	0.011	-0.012	-0.008
	[0.049]	[0.099]	[0.079]	[0.019]	[0.027]	[0.018]
N of observations	1,055	746	746	1,055	746	746
N of clusters	264	193	193	264	193	193
R^2	0.066	0.055	0.033	0.059	0.096	0.070
Adjusted R^2	0.053	0.037	0.015	0.046	0.079	0.053

Note. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Moderating role of firm size: OLS estimates.

Variable	(i) *Emp growth*	(ii) *Sales growth*	(iii) *Prod growth*	(iv) *H_emp growth*	(v) *H_sales growth*	(vi) *H_prod growth*
(Time since J-Startup selection)						
t	0.083	0.265	0.144	0.205**	0.026	0.026
	[0.077]	[0.240]	[0.241]	[0.093]	[0.121]	[0.117]
t+1	0.312**	0.430	0.069	0.196*	0.263*	0.164
	[0.126]	[0.355]	[0.345]	[0.106]	[0.145]	[0.132]
t+2	0.423***	0.418	-0.014	0.206*	0.122	0.027
	[0.157]	[0.322]	[0.333]	[0.120]	[0.163]	[0.160]
t+3	0.635**	0.529	-0.041	0.243	0.083	0.017
	[0.254]	[0.482]	[0.490]	[0.150]	[0.200]	[0.183]
t+4	0.607**	1.087**	0.399	0.297**	0.291	-0.046
	[0.257]	[0.520]	[0.487]	[0.140]	[0.221]	[0.180]
t+5	0.845**	1.804**	1.378*	0.352**	0.523**	0.231
	[0.404]	[0.782]	[0.776]	[0.172]	[0.245]	[0.241]
t+6	0.334	2.149	1.637	0.133	0.250	0.577**
	[0.486]	[1.365]	[1.201]	[0.188]	[0.341]	[0.223]
(Interaction terms)						
*t * Firm size*	-0.028	-0.039	-0.005	-0.037	0.048	0.054
	[0.025]	[0.072]	[0.070]	[0.032]	[0.041]	[0.037]
t+1 * *Firm size*	-0.064	-0.044	0.032	-0.018	-0.021	-0.014
	[0.041]	[0.109]	[0.103]	[0.036]	[0.049]	[0.045]
t+2 * *Firm size*	-0.071	-0.014	0.067	-0.014	0.035	0.034
	[0.049]	[0.104]	[0.097]	[0.042]	[0.054]	[0.049]
t+3 * *Firm size*	-0.130	-0.066	0.064	-0.033	0.035	0.032
	[0.080]	[0.145]	[0.138]	[0.051]	[0.065]	[0.058]
t+4 * *Firm size*	-0.113	-0.193	-0.036	-0.054	-0.018	0.071
	[0.081]	[0.155]	[0.138]	[0.049]	[0.069]	[0.052]
t+5 * *Firm size*	-0.169	-0.448*	-0.390*	-0.055	-0.085	-0.042
	[0.138]	[0.232]	[0.208]	[0.063]	[0.078]	[0.072]
t+6 * *Firm size*	-0.001	-0.463	-0.429	0.011	-0.034	-0.142**
	[0.165]	[0.400]	[0.309]	[0.064]	[0.103]	[0.064]
N of observations	1,055	746	746	1,055	746	746
N of clusters	264	193	193	264	193	193
R^2	0.074	0.059	0.024	0.061	0.095	0.065
Adjusted R^2	0.061	0.041	0.005	0.049	0.078	0.048

Note. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Average treatment effects on the treated (ATT): mechanism analysis.

(i) *Capital increase*

Period	N	Treated (J-Startup)	Control (matched)	ATT
t	418	0.396	-0.063	0.459***
t+1	356	0.448	-0.023	0.471***
t+2	296	0.332	-0.028	0.360**
t+3	218	0.349	0.019	0.329
t+4	194	0.202	0.023	0.179
t+5	130	0.227	0.093	0.134
t+6	90	0.219	-0.202	0.421

(ii) *Shareholder increase*

Period	N	Treated (J-Startup)	Control (matched)	ATT
t	200	0.242	0.053	0.189***
t+1	174	0.397	0.102	0.294***
t+2	150	0.444	0.154	0.291**
t+3	102	0.615	0.089	0.526***
t+4	96	0.634	0.164	0.470***
t+5	64	0.752	0.200	0.552**
t+6	48	0.391	0.148	0.244

(iii) *Customer expansion*

Period	N	Treated (J-Startup)	Control (matched)	ATT
t	178	0.106	0.030	0.076
t+1	144	0.214	0.023	0.191*
t+2	116	0.262	0.022	0.241**
t+3	92	0.393	0.063	0.330**
t+4	90	0.446	0.034	0.413**
t+5	50	0.564	-0.034	0.599**
t+6	36	0.780	-0.088	0.868***

Note. N indicates the total number of firms, including both treated firms and their matched controls. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Association between mediating variables and firm growth: Matched-pair difference OLS estimates.

(i) *Capital increase*

Period	*Emp growth*	*N*	R^2	*Sales growth*	*N*	R^2	*Prod growth*	*N*	R^2
t	-0.006	207	0.000	0.083*	147	0.020	0.083*	146	0.019
	[0.024]			[0.048]			[0.049]		
t+1	0.067*	177	0.021	0.090	129	0.019	0.021	128	0.001
	[0.035]			[0.058]			[0.057]		
t+2	0.076*	148	0.022	0.184***	102	0.078	0.096	101	0.025
	[0.042]			[0.064]			[0.061]		
t+3	0.157***	109	0.094	0.120**	76	0.051	-0.075	74	0.025
	[0.047]			[0.060]			[0.055]		
t+4	0.150***	97	0.085	0.0243	60	0.002	-0.075	60	0.020
	[0.050]			[0.079]			[0.069]		
t+5	0.187***	65	0.111	0.119	38	0.047	-0.009	38	0.000
	[0.067]			[0.090]			[0.078]		
t+6	0.217***	45	0.184	0.067	28	0.007	0.033	28	0.003
	[0.070]			[0.156]			[0.126]		

(ii) *Shareholder increase*

Period	*Emp growth*	*N*	R^2	*Sales growth*	*N*	R^2	*Prod growth*	*N*	R^2
t	0.214***	99	0.077	0.225	74	0.036	0.015	74	0.000
	[0.076]			[0.137]			[0.159]		
t+1	0.126	87	0.015	0.151	64	0.012	-0.018	64	0.000
	[0.112]			[0.176]			[0.174]		
t+2	0.119	75	0.012	0.124	54	0.008	-0.011	54	0.000
	[0.126]			[0.194]			[0.182]		
t+3	0.153	51	0.021	0.0194	38	0.000	-0.198	37	0.059
	[0.149]			[0.177]			[0.134]		
t+4	0.053	48	0.003	-0.173	31	0.023	-0.273	31	0.080
	[0.148]			[0.211]			[0.172]		
t+5	0.160	32	0.022	-0.185	22	0.027	-0.364*	22	0.147
	[0.193]			[0.248]			[0.196]		
t+6	-0.194	24	0.035	-0.409	17	0.044	-0.153	17	0.009
	[0.216]			[0.495]			[0.419]		

(iii) *Customer expansion*

Period	*Emp growth*	*N*	R^2	*Sales growth*	*N*	R^2	*Prod growth*	*N*	R^2
t	0.148	89	0.019	-0.170	73	0.010	-0.219	73	0.013
	[0.114]			[0.200]			[0.224]		
t+1	0.112	72	0.015	0.0561	63	0.002	-0.031	63	0.001
	[0.107]			[0.162]			[0.176]		
t+2	0.207	58	0.028	0.198	51	0.026	0.003	51	0.000
	[0.163]			[0.174]			[0.187]		
t+3	0.244	46	0.039	0.473***	40	0.165	0.114	39	0.012
	[0.184]			[0.173]			[0.172]		
t+4	0.105	45	0.017	0.0511	36	0.003	-0.0856	36	0.011
	[0.122]			[0.160]			[0.140]		
t+5	0.053	25	0.002	-0.154	21	0.027	-0.216	21	0.057
	[0.239]			[0.213]			[0.202]		
t+6	0.264	18	0.050	-0.232	15	0.040	-0.545*	15	0.209
	[0.288]			[0.316]			[0.295]		

Note. *N* indicates the number of pairs. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the within-pair difference in the outcome between the treated firm and its matched control (Y_treated − Y_control). The independent variable is the corresponding within-pair difference in the mediating variable (X_treated − X_control).

Table 10. Association between mediating variables and high-growth firm creation: Matched-pair difference OLS estimates.

(i) *Capital increase*

Period	*H_emp growth*	*N*	R^2	*H_sales growth*	*N*	R^2	*H_prod growth*	*N*	R^2
t	-0.010	207	0.001	0.032	147	0.004	0.028	146	0.003
	[0.027]			[0.039]			[0.039]		
t+1	0.058**	177	0.026	0.055	129	0.019	0.041	128	0.015
	[0.027]			[0.035]			[0.030]		
t+2	0.068***	148	0.047	0.118***	102	0.108	0.035	101	0.017
	[0.025]			[0.034]			[0.027]		
t+3	0.088***	109	0.095	0.038	76	0.019	-0.025	74	0.013
	[0.026]			[0.032]			[0.025]		
t+4	0.099***	97	0.157	0.027	60	0.009	-0.027	60	0.013
	[0.023]			[0.038]			[0.031]		
t+5	0.106***	65	0.159	0.066	38	0.068	-0.008	38	0.002
	[0.031]			[0.041]			[0.032]		
t+6	0.089**	45	0.144	-0.025	28	0.009	0.030	28	0.023
	[0.033]			[0.053]			[0.038]		

(ii) *Shareholder increase*

Period	*H_emp growth*	*N*	R^2	*H_sales growth*	*N*	R^2	*H_prod growth*	*N*	R^2
t	0.216**	99	0.054	0.240**	74	0.064	0.064	74	0.004
	[0.092]			[0.108]			[0.121]		
t+1	0.090	87	0.012	0.070	64	0.007	0.037	64	0.002
	[0.090]			[0.108]			[0.094]		
t+2	0.044	75	0.005	-0.077	54	0.012	-0.009	54	0.000
	[0.075]			[0.096]			[0.075]		
t+3	0.058	51	0.009	-0.128	38	0.053	-0.003	37	0.000
	[0.087]			[0.091]			[0.061]		
t+4	-0.028	48	0.003	-0.143	31	0.075	-0.007	31	0.000
	[0.082]			[0.093]			[0.080]		
t+5	0.128	32	0.056	-0.126	22	0.063	-0.129	22	0.104
	[0.096]			[0.109]			[0.085]		
t+6	-0.110	24	0.063	-0.379*	17	0.223	0.006	17	0.000
	[0.091]			[0.182]			[0.127]		

(iii) *Customer expansion*

Period	*H_emp growth*	*N*	R^2	*H_sales growth*	*N*	R^2	*H_prod growth*	*N*	R^2
t	0.161	89	0.016	-0.147	73	0.010	-0.080	73	0.003
	[0.134]			[0.170]			[0.178]		
t+1	0.040	72	0.002	-0.070	63	0.007	0.041	63	0.004
	[0.100]			[0.110]			[0.087]		
t+2	0.058	58	0.006	0.062	51	0.006	0.064	51	0.011
	[0.097]			[0.111]			[0.086]		
t+3	0.142	46	0.037	0.177	40	0.067	-0.063	39	0.018
	[0.109]			[0.107]			[0.075]		
t+4	0.025	45	0.003	-0.029	36	0.004	-0.075	36	0.041
	[0.073]			[0.083]			[0.062]		
t+5	0.106	25	0.036	-0.105	21	0.034	-0.138*	21	0.141
	[0.114]			[0.129]			[0.078]		
t+6	0.106	18	0.056	-0.086	15	0.014	-0.190	15	0.160
	[0.110]			[0.201]			[0.121]		

Note. *N* indicates the number of pairs. Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the within-pair difference in the outcome between the treated firm and its matched control (Y_treated − Y_control). The independent variable is the corresponding within-pair difference in the mediating variable (X_treated − X_control).

Appendix.

Table A1. Number of selected firms for the J-Startup program by sector.

Sector	N of obs.	(%)
A_Agriculture and Forestry	5	1.6%
B_Fisheries	3	1.0%
C_Mining	0	0.0%
D_Construction	0	0.0%
E_Manufacturing	79	25.8%
F_Electricity, Gas, and Utilities	1	0.3%
G_Information and Communications	111	36.3%
H_Transportation	0	0.0%
I_Commerce	26	8.5%
J_Finance and Insurance	2	0.7%
K_Real Estate	2	0.7%
L_Professional Services	65	21.2%
M_Accommodation and Food Services	2	0.7%
N_Living-Related and Personal Services	0	0.0%
O_Education	0	0.0%
P_Healthcare and Welfare	6	2.0%
Q_Compound Services	0	0.0%
R_Other Services	4	1.3%
S_Public Administration	0	0.0%
Total	306	100.0%

Table A2. Correlation matrix of variables for pre-matched sample (N: 5,098,220).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) *J-startup*	1.000													
(2) *Employment*	0.003	1.000												
(3) *Previous emp growth*	0.021	-0.024	1.000											
(4) *Firm age*	-0.031	0.163	-0.070	1.000										
(5) *Patent experience*	0.021	0.240	0.007	0.093	1.000									
(6) *Previous patent stock*	0.001	0.044	0.000	0.020	0.101	1.000								
(7) *CEO gender*	0.002	-0.056	-0.004	-0.005	-0.017	-0.005	1.000							
(8) *CEO age_20*	0.026	-0.012	0.011	-0.041	0.004	0.000	0.003	1.000						
(9) *CEO age_30*	0.029	-0.011	0.030	-0.096	0.007	-0.003	0.009	-0.004	1.000					
(10) *CEO age_50*	-0.002	0.017	-0.003	0.007	0.036	0.002	-0.008	-0.014	-0.074	1.000				
(11) *CEO age_60*	-0.010	-0.024	-0.025	0.132	0.019	-0.001	-0.024	-0.020	-0.103	-0.393	1.000			
(12) *CEO univ*	0.006	0.057	0.000	0.041	0.089	0.012	-0.037	0.005	0.048	0.127	0.218	1.000		
(13) *CEO grad*	0.017	0.015	0.016	-0.053	0.073	0.015	-0.006	0.006	0.035	0.016	-0.009	-0.118	1.000	
(14) *CEO unknown*	-0.008	-0.023	0.002	-0.057	-0.092	-0.005	0.050	-0.016	-0.071	-0.234	-0.361	-0.647	-0.088	1.000

Table A3. Covariate balance after matching for the baseline model.

	Treated (*N*:264)		Matched control (*N*: 264)			
Variable	Mean	S.D.	Mean	S.D.	Diff. Mean	*p*-value
Employment	2.774	1.176	2.631	1.513	0.143	0.198
Previous emp growth	0.222	0.385	0.216	0.437	0.006	0.838
Firm age	1.821	0.608	1.758	0.822	0.063	0.220
Patent	0.652	0.477	0.652	0.477	0.000	1.000
Patent stock	6.197	12.893	6.466	28.828	-0.269	0.889
CEO gender	0.068	0.253	0.076	0.265	-0.008	0.732
CEO age_20	0.027	0.161	0.027	0.161	0.000	1.000
CEO age_30	0.216	0.412	0.174	0.380	0.042	0.199
CEO age_50	0.129	0.336	0.152	0.359	-0.023	0.454
CEO age_60	0.068	0.253	0.068	0.253	0.000	1.000
CEO Edu_univ	0.580	0.495	0.606	0.490	-0.027	0.511
CEO Edu_grad	0.167	0.373	0.144	0.352	0.023	0.447
CEO Edu_unknown	0.311	0.464	0.292	0.455	0.019	0.626

Note. *N* means the number of observations. *p*-value indicates *p*-values from tests of mean differences between treated and matched control firms.