Supporting Entrepreneurs at the Local Level

IN FOCUS

The Effect of Accelerators and Mentors on Early-Stage Firms

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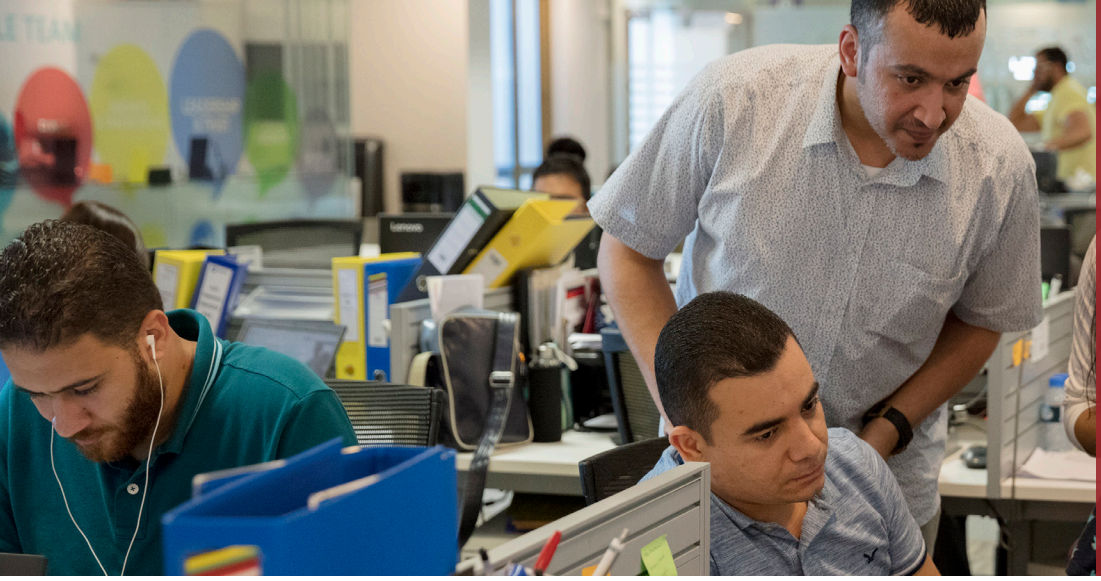

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Abstract

We investigate the association between entrepreneurship support programs and the likelihood of receiving funding for early-stage firms. We use a novel database of 2,887 early-stage technology companies from nine local ecosystems in eight countries that includes data about the founders' demographic characteristics, educational background, work experience, and entrepreneurial history; we also use data about the start-ups' history and evolution that follow their progress through support programs and early-stage funding. We isolate two support interventions—acceleration and mentorship—that the literature has found to have a larger effect on a firm's performance, and we test if such effect is supported from an ecosystem perspective. After accounting for variations in founder characteristics and business environment, we find a positive association between acceleration and mentorship by experienced founders and the likelihood of receiving funding, whereas other support programs, such as incubation, are negatively correlated with funding. We also find that some founders' characteristics, such as increased education and experience, have a positive correlation with funding.

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Introduction

Entrepreneurship and firm creation is an exciting topic for policy makers who are interested in economic development. Ample research documents the correlation of local entrepreneurship and economic growth (Delgado, Porter, and Stern 2010a, 2010b; Gennaiolo and others 2013; Glaeser and others 1992; Glaeser, Kerr, and Kerr 2012; Rosenthal and Strange 2003), and a large set of policies is applied to support entrepreneurship and to foster economic growth at local levels. Efforts to increase rates of entrepreneurship have ranged from long-term investments in human capital pipelines, available monetary capital, business-creation protocols, tax structures, or intellectual property laws to short-term support schemes for firms such as their providing hands-on training, partnership opportunities, seed funding, office space, or mentorship.

As technology-based start-ups have emerged as a global urban phenomenon (Florida 2013; Florida and King 2016), entrepreneurship support programs have become popular among investors, entrepreneurs, and policy makers. Those programs include accelerators (fixed-term cohort-based programs that last longer than two weeks and that provide mentorship, education, and funding to participating entrepreneurs),[1] incubators (office space and administrative support services provided for entrepreneurs), and other support schemes such as mentor-matching events, executive retreats, or entrepreneurial boot camps. The programs aim to support firm creation, primarily in their early stage. Because many such programs are focused on fast-growing technology-based ventures, one of their key objectives is to match start-ups with funding, thereby ensuring the resources that are needed to grow to the next stage.

The prevalence of those programs has generated a growing set of literature that focuses on specific accelerators and mentor-support programs. The studies find that both programs influence early-stage firm performance—where measures of performance are quantified metrics of funding, exit, or acquisition (Gonzalez-Uribe and Leatherbee 2018; Hallen, Cohen, and Bingham 2017; Hoffman and Radojevich-Kelley 2012; Roberts and others 2016; Winston Smith and Hannigan 2015; Yu 2016). Fewer studies, however, have attempted a broader analysis that looks beyond firm-level effect and focuses on the results of accelerators on the local economy. Fehder and Hochberg 2014 find that start-

[1] Cohen and Hochberg (2014) define accelerator programs as a "fixed-term, cohort-based program, including mentorship and educational components, that culminates in a public pitch event or demo-day." We largely follow this definition and take a flexible approach in terms of duration of such programs; moreover, we consider these programs from durations starting at two weeks, given the diversity on the different maturity of stages of the ecosystems where data were collected. There have been several studies about the characteristics of accelerators, their taxonomy, and their difference with incubators and other support programs. See Miller and Bound (2011); Dempwolf, Auer, and D'Ippiloto (2014); Hoffman and Radojevich-Kelley (2012); and Hochberg (2016) for examples of such studies.

up funding activity is exhibited in regions after an accelerator is established there. Bokhari and others (2018), who investigate the effect of accelerators (as urban entrepreneurial amenities) on early-stage firms' private equity performance, find evidence of correlation between start-up firm performance and accelerator program activities.

This paper takes the broader perspective and investigates the effect of support programs for the local entrepreneurial ecosystem. Instead of looking at a particular program or firm, we take the perspective of the entrepreneurial ecosystem and look across a large sample of firms in a region to analyze which type of support program (for example, accelerators, incubators, mentor matching, and entrepreneurial boot camps) is more effective for an early-stage firm's performance for the overall ecosystem. Because of our emphasis on the local context, we follow the definition by Audretsch and Belitski (2016) of the entrepreneurial ecosystem as "a dynamic community of inter-dependent actors (entrepreneurs, supplies, buyer, government, etc.) and system-level institutional informational and socioeconomic contexts." This analysis is possible because we use a novel data sample of early-stage technology firms that has been collected over nine ecosystems in eight countries through the Ecosystem Mapping Project of the Global Entrepreneurship Research Network (GERN). This database provides an overall perspective of relevant firms, support programs, and investors in those ecosystems.

To conduct our assessment, we isolate two support interventions—acceleration and mentorship—that the literature has found to have a larger effect on firm performance, and we test if such an effect is supported from the perspective of an ecosystem. Furthermore, we expand on the questions posed by the literature and probe whether acceleration is different from other types of support programs, such as incubation, and whether mentorship by experienced founders is different from mentorship by people without founding experience in relation to a firm's performance.

Our contribution to the existing literature is that first we analyze support programs from the perspective of local ecosystems while using a new dataset. Second, we conduct this analysis with data from nine different ecosystems across the world, thereby testing results over various country conditions and ecosystems' maturity stage. Finally, we analyze a larger body of support programs that are beyond accelerators.

The remainder of this paper is structured as follows: first, we describe the novel ecosystem-level database that we use; second, we present the methodology we apply for our analysis; third, we review the findings; and fourth, we explain conclusions

Data

Data from early-stage firms are challenging. Few relevant databases of start-ups are readily available. The fast-paced and multidimensional dynamics of start-up ecosystems—with new ventures constantly (a) being created, failing, and being closed and (b) being bought or transformed and thus changing names or purpose—make accurate measurement over time inherently difficult.

Some databases collect information about start-ups globally. The most complete databases are Pitchbook and CBInsights. Moreover, access to such databases is limited, and they are more representative of start-ups in the later stages of development and those that operate in China, the United States, and other developed countries. Other open databases lack accuracy or are limited to their affiliations. For instance, Crunchbase is a self-reported database with little or no curation; AngelList is constrained by the demand and supply of angel investment in this platform. None of those global databases, however, collect data at ecosystem level, nor do they provide a relevant dataset of firms that also depicts ecosystems of different stages of maturity, particularly those from developing countries.[2]

[2] Pitchbook (database), Pitchbook, Seattle, WA, https://pitchbook.com/; CBInsights (database), CBInsights, New York, https://www.cbinsights.com/; Crunchbase (database), Crunchbase, San Francisco, https://www.crunchbase.com/; AngelList (database), AngelList, https://angel.co/.

To combat this poor data availability, we developed a novel cross-section data sample of early-stage technology companies. This database collects data through a standard questionnaire from start-up founders at ecosystem level. Endeavor Insight (which is a research firm) or the World Bank conducted the questionnaire surveys, and they are part of the GERN's Ecosystem Mapping Project. The survey questionnaire details can be found in the Survey and Data Specifications section in this report.

Start-ups are defined as early-stage firms that are business ventures or social enterprises with a financial sustainability model—even if they are too young to make money. The firms use an innovative and technology-enabled approach to the product or service that the firms provide to ensure high growth and scalability. Those start-ups are primarily in the software, internet, and mobile application markets. Nongovernmental organizations, research projects, and nonprofits were excluded, but small and medium enterprises (SMEs) that were once start-ups but have already begun scaling up were included. All start-ups were founded in 2009 and later.

Our dataset includes 2,887 unique start-ups, 68 accelerators, 247 incubators and other support programs, 717 individual investors (known as angels), and 869 institutional investors (venture capital firms) gathered through surveys of 3,353 entrepreneurs in nine ecosystems: New York City (United States), Cairo (Arab Republic of Egypt), Medellín (Colombia), Bogotá (Colombia), Singapore, Santiago (Chile), Beirut (Lebanon), Dar es Salaam (Tanzania), and West Bank and Gaza between 2013 and 2017 (table 1).

Our database is different from databases of other early-stage firms in several aspects. First, our database provides a relevant sample of early-stage firms from the perspective of the local ecosystem. Second, the database provides data about founders' entrepreneurial characteristics and history, as well as about start-ups' history and evolution, including their progression through support programs and investment. Third, it provides data about early-stage firms in ecosystems that vary in maturity across geographies.

Our dataset includes seven variables of binary funding and four variables related to participation in support programs. In addition, we identify 11 binary and continuous variables related to the founder characteristics, the firm-level characteristics, and the regional business environments that are used as controls in our regressions. All binary variables are dummy variables that take on either a value of zero

Table 1. Survey Details

Ecosystem	Survey Start	Survey End	Survey Owner	Number of Responses
New York City	May 2013	November 2014	Endeavor Insight	643
Cairo	December 2014	March 2015	Endeavor Insight	227
Medellín	February 2015	September 2015	Endeavor Insight / World Bank	1,228[a]
Bogotá	February 2015	September 2015	Endeavor Insight / World Bank	1,228[a]
Singapore	March 2015	June 2015	Endeavor Insight	246
Santiago	April 2015	June 2015	Endeavor Insight	147
Beirut	February 2016	August 2016	World Bank	218
Dar es Salaam	July 2016	September 2016	World Bank	221
West Bank and Gaza	November 2016	February 2017	World Bank	423

[a] Survey administered by Endeavor Insight under a World Bank activity. Endeavor Insight collected 1,228 responses from Colombia. For this paper, the authors use only relevant data from Medellín and Bogotá.

or one. Although our data sample includes 2,887 unique start-ups, start-ups that operated in more than one region were counted more than once, thereby resulting in a maximum of 2,904 observations. Table 2 presents the definition of variables. Table 3 breaks out means for each variable by region.

Table 2. Definition of Variables

Variable	Category	Definition
Received funding (binary)[a]	Funding	Firm received angel or VC funding of any type, at any point during its existence, that was not provided as part of an acceleration or support program.
Received funding from cross-ecosystem investor (binary)	Funding	Firm received funding from an investor that has funded firms in more than one regional ecosystem in our dataset.
Received funding from more than 1 investor (binary)	Funding	Firm received funding from more than one investor.
Received funding for 2 consecutive years (binary)	Funding	Firm received funding for 2 years in a row at any point during its existence.
Received funding not from accelerator (binary)[a]	Funding	Firm received funding from an investor that was not follow-on funding from an accelerator it was accelerated by.
Received funding from angel (binary)	Funding	Firm received funding from a person, broadly interpreted as received funding from an angel investor.
Received funding from VC (binary)	Funding	Firm received funding from an organization, broadly interpreted as received funding from a VC firm.
Accelerated (binary)	Support programs	Firm participated in an accelerator program that was cohort based, that was longer than 2 weeks, and that provided funding to some or all participating entrepreneurs.
Participated in incubator or other support program (binary)	Support programs	Firm participated in an entrepreneurship support program of any time or format that did not fall within the definition of acceleration (definitional discretion left to respondent).
Mentored by founder in dataset (binary)[b]	Support programs	Founder of firm was mentored by founder of another firm in the dataset, although not necessarily in the same regional ecosystem.
Mentored by other (binary)[b]	Support programs	Founder of firm was mentored by someone who was not a founder in the dataset.
Average years of work experience per founder	Founder characteristics	Information derived by taking the difference of the firm founding date and each founder's earliest work experience start date, summing those figures and dividing by the number of founders.
Has at least 1 founder with past founding experience (binary)	Founder characteristics	Firm has at least 1 founder who had founded a firm before founding the current firm.
Has at least 1 founder with managerial experience (binary)	Founder characteristics	Firm has at least 1 founder who had previously worked as a manager, director, or C-level executive at a firm he or she did not found.
Has at least 1 founder with postgraduate degree (binary)	Founder characteristics	Firm has at least 1 founder who has received a professional, master's, or doctorate degree.
No technical degree (binary)	Founder characteristics	Firm has no founders who studied computer science, engineering, information technology, mathematics, statistics, science, or medicine.
No business degree (binary)	Founder characteristics	Firm has no founders who studied business or economics.

Average founder age	Founder characteristics	Information derived by summing founder ages and dividing by the number of founders.
All founders are female (binary)	Founder characteristics	Firm has only female founders.
Number of founders	Firm-level characteristics	Represents the number of founders associated with firm.
Years of existence	Firm-level characteristics	Represents the total number of years the firm has been operational.
Ease of Doing Business percentile[c]	Business environment	Represents conversion of the World Bank's Ease of Doing Business overall ranking to integer percentile.

Note: C-level = High-ranking officials of companies, including but not limited to Chief Executive Officer (CEO), Chief Financial Officer (CFO), Chief Information Officer (CIO), or Chief Operating Officer (COO; VC = venture capitalist.

a. For the "Received funding (binary)" variable, we include follow-on funding by the accelerator. If Firm X was accelerated by Accelerator Y, received $50,000 as part of the acceleration program, and later received $250,000 from the accelerator after the acceleration program ended, we count the $250,000 from Accelerator Y as an instance of received investment. For the "Received investment not from accelerator (binary)" variable, we do not include the $250,000 from Accelerator Y as an instance of received investment.

b. Ideally, we would be able to flag all mentors who were founders. However, because of the large number of mentors reported in the dataset across multiple regions, such identification was not possible to achieve accurately unless the mentors were founders in our dataset. Because the unit of data collection was the ecosystem, we took great care to identify founders in the critical mass of start-ups at the center of a region, and, as such, this variable can be interpreted to be the effect of mentorship by an influential founder central to the ecosystem.

c. We use a percentile transformation of the inverse of the 2017 Distance to Frontier metric from the World Bank Doing Business indicators (accessed March 2018), http://www.doingbusiness.org/. The "frontier" is the maximum aggregate Doing Business score across all countries. For our regressions, higher percentiles mean that a country is closer to the frontier. The Doing Business indicators rank regulatory practices such as starting a business, getting electricity, registering property, getting credit, protecting minority investors, paying taxes, enforcing contracts, resolving insolvency, dealing with construction permits, and trading across borders.

Methodology

We use a logit model to test the seven funding variables (dependent variables) against firm participation in support programs (acceleration, incubation, mentorship) and to account for variations in the founder characteristics (experience, education, demographics), the firm-level characteristics (number of founders, years of existence), and the regional business environment using seven regression specifications. Our choice of a logit model over a linear probability model is informed by our hypothesis that the true probabilities for funding can be extreme and that the effect of marginal interventions likely diminishes. Additionally, we choose the logit over the probit model for potential easy transformation of log-odds into odds ratios where necessary.

Our logit regression is represented in equation below. The left-hand side of equation is the logit transformation of the dependent variable, where p is the probability that each dependent variable (funding variables) is equal to one. Each X_n on the right-hand side of equation corresponds to an explanatory variable (nonfunding variables). We account for mean shifts in funding outcomes by using some specifications with regional and founding year fixed effects. Because of potential correlations between errors at the ecosystem level, we also clustered standard errors by region. We run a separate set of regressions for each of the seven outcome variables, and details on the specifications can be found in table 4.

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$$

There are some limitations to our approach. First, because our dataset is based on a survey, it is subject to sampling biases, survivorship biases, and errors inherent in self-reported datasets. Those biases are likely to inflate the likelihood of funding reported in the data. Second, findings may suffer from endogeneity caused by the unclear causal relationship between the inputs and unobserved characteristics of the firm, and there are omitted variables in the analysis.

Table 3. Means by Region

Variable	Beirut	Bogotá	Cairo	Dar es Salaam	Medellín	New York City	Santiago	Singapore	West Bank and Gaza
Funding (binary)	0.39	0.44	0.24	0.25	0.18	0.75	0.43	0.41	0.32
Funding from cross-ecosystem investor (binary)	0.01	0.13	0.08	0.02	0.13	0.15	0.07	0.16	0.04
Funding from more than 1 investor (binary)	0.08	0.02	0.08	0.01	0.05	0.51	0.11	0.26	0.02
Funding for 2 consecutive years (binary)	0.06	0.02	0.02	0.00	0.02	0.33	0.06	0.08	0.06
Funding not from accelerator (binary)	0.17	0.44	0.22	0.07	0.16	0.73	0.37	0.40	0.17
Funding from angel (binary)	0.10	0.40	0.17	0.06	0.11	0.34	0.09	0.30	0.14
Funding from VC (binary)	0.15	0.06	0.12	0.02	0.10	0.46	0.34	0.26	0.04
Accelerated (binary)	0.10	0.04	0.24	0.18	0.36	0.14	0.18	0.17	0.15
Participated in incubator or other support program (binary)	0.06	0.06	0.12	0.02	0.31	0.14	0.18	0.22	0.30
Mentored by founder in dataset (binary)	0.05	0.02	0.44	0.22	0.25	0.19	0.14	0.29	0.26
Mentored by other (binary)	0.24	0.10	0.49	0.43	0.44	0.19	0.21	0.32	0.59
Average years of work experience per founder	5.40	1.30	3.40	2.60	3.40	4.90	2.00	4.40	3.70
Has at least 1 founder with past founding experience (binary)	0.41	0.12	0.44	0.21	0.44	0.29	0.34	0.23	0.36
Has at least 1 founder with managerial experience (binary)	0.42	0.29	0.36	0.15	0.43	0.48	0.27	0.42	0.38
Has at least 1 founder with postgraduate degree (binary)	0.50	0.13	0.13	0.12	0.22	0.32	0.12	0.16	0.26
No technical degree (binary)	0.48	0.87	0.60	0.41	0.58	0.71	0.75	0.69	0.40
No business degree (binary)	0.71	0.87	0.81	0.82	0.67	0.69	0.86	0.73	0.68
Average founder age	30	28	29	24	29	31	30	30	28
All founders are female (binary)	0.08	0.04	0.02	0.10	0.05	0.07	0.00	0.08	0.15
Number of founders	1.80	1.40	2.10	1.70	2.00	2.00	1.60	1.80	1.80
Years of existence	2.90	2.80	2.10	2.10	2.70	2.50	1.90	2.50	2.30
Ease of Doing Business percentile	31	70	37	29	70	97	72	100	31

Note: VC = venture capitalist.

Table 4. Summary of Regression Specifications

	1	2	3	4	5	6	7
Accelerated (binary)	X	X	X	X	X	X	X
Participated in incubator or other support program (binary)	X	X	X	X	X	X	X
Mentored by founder in dataset (binary)		X	X	X	X	X	X
Mentored by other (binary)		X	X	X	X	X	X
Average years of work experience per founder			X	X	X	X	X
At least 1 founder with past founding experience (binary)			X	X	X	X	X
At least 1 founder with managerial experience (binary)			X	X	X	X	X
At least 1 founder with postgraduate degree (binary)				X	X	X	X
No technical degree (binary)				X	X	X	X
No business degree (binary)				X	X	X	X
Average founder age					X	X	X
All founders are female (binary)					X	X	X
Accelerated (binary) * participated in incubator or other support program (binary)						X	X
Accelerated (binary) * mentored by founder in dataset (binary)						X	X
Participated in incubator or other support program (binary)a mentored by founder in dataset (binary)						X	X
Accelerated (binary) * mentored by other (binary)						X	X
Participated in incubator or other support program (binary) * mentored by other (binary)						X	X
Number of founders	X	X	X	X	X	X	X
Years of existence	X	X	X	X	X	X	X
Ease of Doing Business percentile	X	X	X	X	X	X	
Surveyed by Endeavor Insight (binary)	X	X	X	X	X	X	
Regional dummies							X
Founding year dummies							X

Note: "X" = where calculations were conducted. Details of the outcomes of these regressions can be accessed at http://bit.ly/2wShoxl

For example, owing to lack of data availability, we do not consider the quality of the team beyond the founders or the quality of the business pitch. Whereas acceleration generally occurs before funding and it is likely reasonable to interpret this particular relationship as causal, the direction of the causal relationship between mentorship and funding and acceleration and mentorship is less clear and cannot be determined through this exercise. As such, we urge caution in interpreting the results, which we view as correlational and not causal.

Nevertheless, we think that the analysis of this dataset is a unique contribution to the study of entrepreneurship in light of the general difficulty of obtaining firm-level data from early-stage companies with the depth and breadth necessary to compare outcomes across multiple programs.

Findings

Our analysis finds multiple statistically significant correlations between the funding and support programs, the founder characteristics, the firm characteristics, and the regional business environment across a total of seven specifications for seven dependent variables.

Table 5 summarizes the average marginal effect of each explanatory variable on the likelihood of funding. The coefficient we present in each cell is the average of every marginal effect that is significant at the $p > 0.05$ level for that combination of dependent and independent variables. This approach means that each average marginal effect is the average of across up to seven specifications. We report the marginal effect for each variable only if it is significant at the $p > 0.05$ level for > = 50% of specifications it is entered in.

We find several strong correlations between acceleration, mentorship, and funding for start-ups, even after controlling for the founder characteristics, the firm characteristics, and the regional business environment.

First, we find a large positive marginal effect of acceleration on funding (ranging from 4.5 to 30.0 percentage points) but a negative effect for incubation and other nonacceleration support programs (ranging from –7.16 to –13.3 percentage points). This finding can be interpreted in multiple ways. First, it is possible that those negative effects are causal, although we cannot make this assertion within the limits of the current analysis. Second, it is also possible that this result is evidence that accelerators are simply better at screening for the best start-ups, thereby leaving less stellar start-ups to attend other support programs.

Second, there is a positive and significant correlation between mentorship by an experienced founder and funding (ranging from 5.0 to 8.6 percentage points), but we do not find a significant correlation for mentorship by mentors who were not known to be founders. This finding suggests that practical operational experience may be more important than technical knowledge, because mentors who are not founders but rather professors or corporate professionals can impart the latter but not the former.

Third, by dissecting the data further through interactions between acceleration and mentorship, we see that interactions take the sign of the mentorship variable, thus suggesting that the effects of mentorship may be more dominant. We find a positive interaction for firms that were both accelerated and mentored by an experienced founder (ranging from 8.9 to 10.4 percentage points), a negative interaction for firms that were accelerated and mentored by mentors not known to be founders (ranging from –7.2 to –10.4 percentage points), and a negative interaction for firms that participated in nonacceleration support programs and were mentored by mentors not known to be founders (approximately –3.9 percentage points). We did not find a significant interaction effect for firms that participated in nonacceleration support programs and were mentored by founders.

Fourth, the magnitude of the marginal effect of acceleration (ranging from 4.5 to 30.0 percentage points) is on average greater than that of mentorship by an experienced founder (ranging from 5.0 to 8.6 percentage points), indicating that acceleration may have more effect on funding. However, in the case of receiving funding from an angel investor, mentorship by an experienced founder has a greater marginal effect than acceleration, suggesting that angel investors may depend more heavily on personal networks for sourcing potential investments or that the angels themselves are more likely to be mentors.

In addition to such findings related to acceleration and mentorship, we also find statistically significant correlations for founder and firm characteristics.

First, we find that increased education and experience has a positive and significant correlation with funding. Teams with at least one postgraduate

Table 5. Summary of Marginal Effects

	Dependent Variables						
	Funding	Funding from Cross-ecosystem Investor	Funding from More than 1 Investor	Funding for 2 Consecutive Years	Funding not from Accelerator	Funding from Angel	Funding from V
Accelerated (binary)	0.181	0.045	0.136	0.103	0.101	0.071	0.300
Participated in incubator or other support program (binary)	–0.133		–0.071		–0.129		–0.082
Accelerated (binary) * participated in incubator or other support program (binary)							
Mentored by founder in dataset (binary)			0.074	0.050	0.062	0.086	0.072
Mentored by other (binary)							
Accelerated (binary) * mentored by founder in dataset (binary)	0.089				0.104		
Accelerated (binary) * mentored by other (binary)			–0.072				–0.104
Participated in incubator or other support program (binary) * mentored by founder in dataset (binary)		—					
Participated in incubator or other support program (binary) * mentored by other (binary)		–0.039					
Average years of work experience per founder				0.004			0.009
At least 1 founder with past founding experience (binary)				0.032			
At least 1 founder with managerial experience (binary)			0.044	0.051			
At least 1 founder with postgraduate degree (binary)	0.129		0.091	0.067	0.128		0.120
No technical degree (binary)			0.045	0.027	0.094		
No business degree (binary)							–0.044
Average founder age				–0.004			
All founders are female (binary)				0.036			
Number of founders	0.094	0.015	0.066	0.030	0.101	0.043	0.044
Years of existence	0.097	0.037	0.094	0.067	0.101	0.049	0.123
Ease of Doing Business percentile	0.010	0.001	0.010	0.006	0.010	0.004	0.007

degree have a positive correlation with funding (ranging from 6.7 to 12.9 percentage points). Similarly, teams with more senior experience are more likely to correlate with funding. We find the largest marginal effects for founding teams with previous managerial experience (ranging from 4.4 to 5.1 percentage points), followed by founding teams with previous founding experience (approximately 3.2 percentage points), and finally founders with any additional years of work experience (ranging from 0.4 to 0.9 percentage point per year).

We also find that each additional year of operation for the business correlates positively with funding (ranging from 3.7 to 12.3 percentage points per year). This finding is likely driven by a combination of effects, including the accumulation of experience by the team. Given the same likelihood of raising funding each year, additional years will also mean additional chances at a positive outcome, resulting in a higher cumulative effect. Additionally, founders are learning from attempts to secure funding, resulting in a higher likelihood of a positive outcome over the years. Finally, given the same firm quality, companies that have survived for a longer period may look more attractive to investors.

Second, we find positive and significant correlations between team expertise and demographics and funding. We detect a positive correlation between all-business founding teams without technical degrees and with funding (ranging from 2.7 to 9.4 percentage points) but a negative effect for all-technical founding teams without business degrees (approximately –4.4 percentage points). We also find a positive correlation between founding teams with only women and funding for two consecutive years (approximately 3.6 percentage points) and between founding teams with additional founders and funding (ranging from 1.5 to 10.1 percentage points per additional founder).

Finally, we find a small but significant effect of the regional business environment on successful funding outcomes (ranging from 0.1 to 1.0 percentage points for each percentile increase in the World Bank's Doing Business overall ranking).

Conclusion

This paper is one of the first to look across multiple support programs and to analyze the role of accelerators and mentors for funding of early-stage firms from the perspective of local ecosystems. On the one hand, our findings suggest that acceleration and mentorship by experienced founders likely do play a role in connecting early-stage technology companies to funding, both as independent and combined interventions. On the other hand, we find that the influence of other support programs such as incubators and mentorship by people who have not been founders may not have an effect. Although those findings do not provide clarity about the long-term effect on support programs beyond early-stage firms, this evidence suggests that those interventions do play some role in creating critical masses of funded start-ups.

Our findings about accelerators and mentorship are consistent with other studies about such topics and support existing evidence between accelerators and mentors and early-stage firm performance—understood as funding. Bokhari and others 2018 complement the findings by providing evidence of accelerators' correlation with cumulative funding and by suggesting that accelerators may also have a lasting effect over the long term.

Findings regarding the effect of higher education and increased experience for founders are consistent with survey results from Wadhwa and others 2009. Findings regarding the demographics of founders are also interesting in the context of existing literature. Robb and Coleman (2009) find that entrepreneurs' university coursework and job history reveal that they are likely to be jacks-of-all-trades rather than specialists, which is consistent with our finding that all-business founding teams have a funding advantage while a negative effect was found for all-technical founding teams. Furthermore, Robb and Coleman (2009) find that women are less likely to receive funding, which is the opposite of our findings.

However, we are unable to make further statements regarding causality or the mechanisms through which those correlations occur without additional research.

Are such results driven through a knowledge transfer effect, in which accelerators and mentors impart practical knowledge to entrepreneurs? Is it through a network effect, in which accelerators and mentors directly introduce promising entrepreneurs to valuable connections regardless of any knowledge transfer? Or is it through a filtering effect, in which accelerators and mentors are using rigorous acceptance criteria and selecting more successful start-ups regardless of the incremental added value of the intervention itself? Further research will be needed to analyze the causality of those presented correlations.

Finally, we are continuing to expand the number of ecosystems included in this dataset in the coming years in partnership with the GERN. As the number of regions covered reaches 20 to 30, we hope to be better able to distinguish effects between regions and to tease out interaction effects between regional macroeconomic trends and firm-level data about start-up creation.

Survey and Data Specifications

The standard questionnaire developed under the Global Entrepreneurship Research Network (GERN) Ecosystem Mapping Project includes the following categories of questions: (a) demographics and educational history (including vocational, boot camps, and certificate programs), (b) employment history, (c) founding history (serial entrepreneurship), (d) support programs history (for example, acceleration, incubation, and so forth), (e) connections with mentors and mentees, and (f) funding (angel and institutional).

Surveys followed a mixed distribution strategy that included telephone, email, and in-person surveys. Entrepreneurs filled out an online survey or were interviewed by Endeavor Insight, a survey firm, or a local partner. Technology start-ups are defined as for-profit business ventures that (a) have a financial model targeting high growth and (b) use an innovative and technology-enabled approach to the product or service that they provide to ensure scalability. So it could capture the whole technology start-up ecosystem, the definition of start-up was expanded beyond the phase in which such ventures are newly emerging, thereby encompassing also SMEs that were once start-ups and that have reached the scaling-up phase. This definition allowed us to collect data that described the evolution of technology start-ups over time.

To identify the initial universe of technology start-ups, we used multiple data sources, including databases from government, intermediaries (for example, accelerators), and founders (for example, venture capital firms). Additionally, data sources such as Crunchbase, AngelList, and LinkedIn were used to accumulate initial lists of founders and companies for outreach by contracted survey firms. As the survey developed, the universe of technology start-ups was expanded through a snowball effect following the connections reported by founders. To increase outreach of the survey, we partnered with multiple local intermediaries, founders, and public and private entrepreneurship support organizations in each ecosystem.

Nodes without location data and locations without geocode were passed to the Google Maps API to obtain standard location data wherever possible. This new dataset was de-duplicated using a process that marked similarities between names, email addresses, URLs, and dates. Entities that were determined to be likely duplicates were then merged, maintaining all existing data and privileging more recent data in the event of conflict. For this process, we used a combination of machine learning and manual methods. Education degrees and job titles provided by respondents were also classified into buckets using machine-learning methods. We then further reduced this cleaned dataset for analysis by focusing on start-ups that met our narrow definition. As such, the number of start-ups analyzed in this paper may not be an exact match to other papers written using the same datasets. The sample size was selected in relation to the size of the sector in the region, although the sample size in Santiago is likely somewhat low. The number of responses is not equal to the number of start-ups.

Details on each individual survey structure and collection methods can be found in Endeavor Insight (2014) for New York City; Endeavor Insight

and MC Egypt (2015) for Cairo; Endeavor Insight, FOMIN, and J. P. Morgan (2015) for Medellín; Endeavor Insight, MINTIC, and World Bank (2015) for Bogotá; Endeavor Insight and National University of Singapore (2015) for Singapore; Endeavor Insight, FOMIN, and J. P. Morgan (2016) for Santiago; World Bank (2017a) for Dar es Salaam; World Bank (2017b) for Beirut; and World Bank (2018) for West Bank and Gaza.

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