# STARTUPS IN AFRICA

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Abstract. High-growth startups are increasingly seen as a potential driver of innovation and structural transformation in Africa, yet systematic evidence on these firms remains scarce. We combine new large-scale experimental surveys and microdata to fill the evidence gap. First, in partnership with the World Bank's International Finance Corporation, we field a survey of startup founders in 51 African countries, with an embedded incentive-compatible experiment that elicits preferences over financing and investor attributes. Second, we assemble new global data on venture capital and private equity deals by linking deal-level investments to founders' work and education histories. We document three main findings. First, startups in Africa report severe financing constraints. Second, we show experimentally that entrepreneurs have a strong preference for equity rather than debt financing, and value investors with local presence and experience. Third, startup finance in Africa comes overwhelmingly from foreign investors and disproportionately flows to foreign and foreign-connected founders. We interpret these patterns through a model of startup financing across founder and investor origins, which we discipline through various tests on our data. We show how easing local equity financing frictions would expand startup formation, especially among local founders.

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## 1. Introduction

Young, high-growth, technology-enabled firms—or *startups*—are increasingly viewed as a potential engine of economic transformation in Africa. In cities such as Lagos, Nairobi, Cape Town, and Cairo, startups have attracted substantial venture and growth capital, built digital infrastructure, introduced new technologies, and expanded new business models in sectors ranging from payments to logistics to health. While these firms still account for a small share of total employment, they may matter disproportionately for long-run growth because they generate innovation, diffuse new technologies, and supply inputs and platforms that allow other firms to expand (Schumpeter, 1912; Kortum and Lerner, 2000; Schoar, 2010).

Despite the promise, the trajectory of Africa's startup ecosystem remains uncertain. After peaking in 2022, startup funding across the continent has declined sharply, as shown in Figure 1. The rapid rise and subsequent headwinds have sparked an active debate outside academia, centered on two related issues.[1] The first is whether the financing available to startups is well suited to the needs of high-growth firms in these markets. The second is whether the ecosystem is excessively reliant on foreign capital, a perceived concern frequently raised in anecdotal accounts, and whether such reliance creates distortions, increases exposure to global shocks, or channels funding toward the "wrong" firms.

Yet, there is incredibly limited systematic evidence on startups in Africa. Most of the development economics literature has focused on microenterprises and small and medium enterprises, leaving high-growth entrepreneurship in low-income settings comparatively understudied. As a result, several central questions remain open: who becomes an entrepreneur, what entrepreneurs seek from investors, how capital is allocated across firms, and how these forces shape the size and composition of the sector. This paper aims to fill the evidence gap by bringing to the table several new data sources.

First, in partnership with the International Finance Corporation (IFC)—the private sector arm of the World Bank Group—we field a new continent-wide survey of startup founders in 51 African countries. The survey combines detailed information on founders, firms, growth, and constraints with an embedded incentive-compatible experiment that elicits preferences over financing contracts and investor characteristics. The survey reached 10,285 target firms and yielded 4,444 respondents. Because there is no canonical sampling frame for startups in Africa, constructing the sample required building our own pipeline through IFC networks, startup support organizations, local accelerators and investors, and broader

[1]See, for example, the special reports by The Economist The capitalist revolution Africa needs (The Economist, January 2025) and Africa after aid is more resilient than you might think (The Economist, March 2026).

entrepreneurial networks across the continent. We aim to be representative of young (age <10) firms with at least 2 full-time employees that are looking to grow.

Second, we assemble a new dataset on more established startups, namely firms who have received venture capital and private equity investments between 2010 and 2024. The data combine the global commercial standard for such datasets (i.e., PitchBook) with new data from local data providers. We further combine these deal-level data with founders' work and education histories from LinkedIn, obtained from Revelio Labs, which we further validate through manual efforts. This established startup sample covers 9,064 deals and 5,801 unique companies.

Our analysis proceeds in three steps. First, we begin by documenting a set of facts about Africa's early stage startups and entrepreneurs from our IFC survey sample. Startups are highly concentrated in a few key urban startup "hubs." Entrepreneurs are on average 38 years old, nearly all have at least some college education, and slightly less than half have foreign education or work experience. The firms are small (11 full-time employees on average) but growing very rapidly, and the median respondent is seeking roughly $500,000 in external funding. Crucially, they are able to obtain only a small fraction of that amount. Our survey also reveals that access to finance is by far the most commonly reported constraint to growth, for both small and large firms and regardless of the specific funding source.

In the second part of the paper, we measure entrepreneurs' preferences over capital and investor attributes using an experimental design embedded in our IFC survey. Estimating these preferences is challenging because startups typically evaluate bundles of investor–investment pairs, where key attributes are jointly determined and highly correlated. To address this challenge, we co-designed with the IFC the "Connecting Africa's Entrepreneurs" study, which relies on our large-scale survey to also support startups in matching with potential investment partners.

In this setting, we implement a variation of the non-deceptive experimental design of Kessler, Low, and Sullivan (2019), adapted to the context of firm–investor matching as in Colonnelli, Li, and Liu (2024), where startups are invited to evaluate a series of potential investment opportunities. Specifically, we ask startups to rate profiles of potential investment offers that vary systematically along multiple randomized dimensions, including deal terms, investor characteristics, and team composition. This allows us to recover their preferences over key attributes in a controlled environment. The experiment is incentive-compatible: respondents are informed that their answers will be used to facilitate matching with real investment partners aligned with their stated preferences.

The results point to a clear and central finding: entrepreneurs display a strong preference for equity financing and a corresponding aversion to debt. This pattern holds across a wide range of firms, founders, and countries. Conditional on taking equity, entrepreneurs

are reluctant to give up control, as reflected in a strong aversion to board-seat requirements. Strikingly, we find that the source of capital has essentially no effect on preferences: entrepreneurs are largely indifferent to whether investors are foreign or domestic. They do strongly value investors with deep local knowledge, especially those with local teams, local experience, and strong local connections. By contrast, they place little value on non-financial support such as mentorship or training.

The preference for equity is economically large and pervasive, and larger in countries where venture markets are thinner. Even relatively favorable debt contracts are typically dominated by equity offers, indicating that the result is not driven by unusually costly debt. Qualitative survey responses point to a simple mechanism: early-stage firms in Africa place a very high value on cash flow and financial flexibility. Taken together, our findings suggest the demand for equity financing is both strong and largely unmet.

The second part of the paper turns to how startup finance is actually allocated. Here we document a stark disconnect between founders' stated preferences and realized financing patterns. While founders emphasize the importance of local investors, startup funding in Africa is overwhelmingly foreign. Over the years, about 80% of all venture capital and private equity deals in Africa involve at least one foreign investor. Moreover, the employees and in particular the founders of these funded startups are disproportionately likely to be foreign or have foreign education or work experience. The dominance of foreign financial and human capital is much stronger in Africa than in other developed or emerging markets.

Several patterns in the data indicate the foreign dominance of Africa's startup ecosystem matters. Using dyadic regressions of investor–startup matches, we show that foreign capital disproportionately flows to foreign or foreign-connected founders, consistent with matching frictions that favor shared geographic, educational, or professional ties. Indeed, we find no strong evidence that local entrepreneurs perform worse. While foreign-connected founders perform somewhat better along some dimensions unconditionally, these differences become modest once we condition on firm and deal characteristics. This pattern is more consistent with differential access to capital at the funding stage than with large differences in underlying entrepreneurial quality.

We then show that these financing patterns shape both startup formation and founder composition. Using variation in the supply of foreign capital in a shift-share empirical design, we find that startup activity responds strongly to changes in foreign funding conditions, with effects concentrated among foreign or foreign-connected founders. This implies that foreign and domestic capital are imperfect substitutes. As a result, the limited availability of local capital affects not only who finances startups, but also which entrepreneurs are able to start and scale firms in the first place.

To interpret these findings, in the third and final part of this paper we develop a simple organizing framework of a world economy with investors and entrepreneurs. Investors deploy capital across countries, while entrepreneurs differ both in where they operate and in their connections to different investor markets through prior education, work experience, or networks. For example, an entrepreneur in Kenya who previously studied in the United States may have easier access to U.S. investors.

We use the model to characterize the share of startups financed by foreign rather than local investors, and show that this depends on four forces: relative *capital wedges*, which capture in reduced form differences in the cost of capital and in frictions to its deployment; relative expected returns, which capture differences in the types of entrepreneurs matched with each source of capital and in their expected performance; relative preferences across capital sources; and the demand for different types of capital, which depends on the composition of entrepreneurs that reach the startup-financing stage—shaped by *entry wedges*—and on their differential access to investor markets.

We then bring the model to the data. We discipline substitution across capital sources by targeting the shift-share evidence on how startup activity in Africa responds to shocks to foreign capital supply, and we discipline differential access to investors by targeting the dyadic evidence that entrepreneurs are more likely to raise foreign capital from countries to which they are connected through prior education or work experience. We then invert the model to match the observed allocation of equity finance across investor origins and founder types. This allows us to recover the model's two central objects governing the composition of startup finance across countries: capital wedges and entry wedges. The estimates imply that Africa stands out on two dimensions: local equity is unusually expensive relative to foreign equity, and the mass of local entrepreneurs is comparatively low.

Next, we use the model to decompose the *sources of foreignness* in Africa's startup ecosystem. We ask what would happen if Africa faced the same capital wedges and founder composition (entry wedges) as Europe. In this counterfactual, the local investor share rises from about 25 percent to more than 50 percent, while the local founder share rises from about 30 percent to about 55 percent. A little more than half of this change is accounted for by the relative cost of local capital, about one third by the smaller mass of local entrepreneurs, and the remainder by complementarities between the two.

We then use the model to study what these frictions imply for the scale of startup activity. The same forces that make Africa's ecosystem unusually foreign also depress startup creation. Lowering local capital wedges, increasing the mass of local entrepreneurs, improving local entrepreneurs' access to foreign investors, or expanding local entrepreneurial human capital all generate economically large increases in startup activity. The model therefore

suggests that the foreignness observed in Africa is not merely compositional: it reflects underlying barriers that also constrain the number of startups that are created.

Finally, we use specific qualitative responses to our startup survey as an external consistency check on these mechanisms. We ask respondents directly why startup ecosystems in Africa are so foreign and show that their perceptions align strongly with the forces emphasized by our empirical and quantitative analysis.

Our paper primarily contributes to the literature on finance and entrepreneurship in developing countries. This literature has predominantly focused on micro-entrepreneurs, who are motivated by subsistence and are unlikely and uninterested in growing fast (De Mel, McKenzie, and Woodruff, 2010; Breza, Kaur, and Shamdasani, 2021; Bandiera, Elsayed, Heil, and Smurra, 2022; Bassi, Lee, Peter, Porzio, Sen, and Tugume, 2023). Recent influential work has led to a significant body of evidence on what works (or not) to spur the growth of these micro-enterprises.[2] Most of this work has primarily focused on randomized controlled trials (RCTs) testing the effects of various specific interventions, and results have been mixed.[3] Conducting RCTs on larger and high-growth firms is challenging. As a result, the evidence on these firms remains limited. Examples include Banerjee and Duflo (2014), who show that firms in India are severely financially constrained using a 1998 policy shock, and McKenzie (2017), who finds large effects of a national business plan competition in Nigeria providing firms with large ($50,000) grants. Because of the focus on micro-enterprises in traditional sectors, most work on the effects of access to finance for entrepreneurial growth have focused on debt, ubiquitous in micro-finance and characterized by small loans with inflexible terms. Several recent studies show the promise of going beyond simple debt instruments and towards larger, more flexible financial products as a way to jump-start firm growth (Field, Pande, Papp, and Rigol, 2013; Bryan, Karlan, and Osman, 2021; Battaglia, Gulesci, Madestam et al., 2023; Bari, Malik, Meki, and Quinn, 2024).

Our paper directly contributes to this body of work by shifting the focus to a new and understudied set of entrepreneurs in the poorest continent of the world. We do so by bringing to the table a new data and experimental infrastructure that allows us to provide some of the first evidence on the nature and constraints of high-potential entrepreneurs and high-growth firms. Doing so, we speak to a growing literature that highlights the key role of high-growth, innovation-led startups to economic growth (Botelho, Fehder, and Hochberg,

[2]See Woodruff (2018); Quinn and Woodruff (2019); Jayachandran (2021); McKenzie, Woodruff, Bjorvatn, Bruhn, Cai, Gonzalez-Uribe, Quinn, Sonobe, and Valdivia (2021) for comprehensive reviews of the large and growing body of work.

[3]While microfinance and business training have shown limited impacts on the growth of the average firm (De Mel, McKenzie, and Woodruff, 2008, 2012; Banerjee, Duflo, Glennerster, and Kinnan, 2015a; Banerjee, Karlan, and Zinman, 2015b), recent evidence shows promising results for specific sets of entrepreneurs (Anderson, Chandy, and Zia, 2018; Meager, 2019; Hussam, Rigol, and Roth, 2022) and for more intensive and individualized programs (Cai and Szeidl, 2018; Iacovone, Maloney, and McKenzie, 2022; Anderson and McKenzie, 2022).

2021). We uncover a stark preference for equity and a set of unique preferences displayed by young, highly educated entrepreneurs hungry for deeper pools of capital that fits local needs. In this regard, our study connects with a literature on entrepreneurial finance and development that remains exceptionally small, in part due to data limitations (Lerner and Schoar, 2005; Kaplan, Martel, and Stromberg, 2007; Colonnelli et al., 2024; Lerner, Liu, Moscona, and Yang, 2024; Colonnelli, Lerner, Cruz, and Pereira Lopez, 2025).

Our paper also naturally connects to a long-standing literature on finance and development (King and Levine, 1993; Rajan and Zingales, 1998; Levine, 1999; Wurgler, 2000; Levine, 2002; Buera, Kaboski, and Shin, 2011). Our main contribution is to shift the focus towards the importance of equity financing and venture capital, which has largely been ignored in the context of developing countries. The facts we establish on the dominance of foreign financial and human capital inputs for Africa's and other emerging markets' high-growth entrepreneurs are new within this literature. Relatedly, several of our new facts on global capital flows speak to a nascent and growing literature on international finance building new data to better understand patterns of global capital allocation (Maggiori, Neiman, and Schreger, 2020; Coppola, Maggiori, Neiman, and Schreger, 2021; Florez-Orrego, Maggiori, Schreger, Sun, and Tinda, 2023).

The rest of the paper proceeds as follows. Section 2 illustrates the data and the descriptive facts. Section 3 discusses the experimental setting and evidence on startup preferences. Section 4 documents the structure and allocation of startup financing in Africa. Section 5 introduces and estimates the model and uses it for counterfactual analysis. Section 6 concludes.

## 2. Data

Understanding the characteristics and preferences of high-potential entrepreneurs in Africa has long been constrained by the lack of data. To address this gap, we build two novel and complementary datasets. First, in partnership with the International Finance Corporation (IFC), the private-sector arm of the World Bank Group, we conduct a new large-scale survey "early-stage startups" across Africa that are young and actively seeking financing. Second, we assemble a new administrative dataset on "established startups" using venture capital and private equity records from both global and local commercial sources, supplemented with founder background information on education and work experience.

This section provides an overview of the main data sources used in the subsequent analysis. Section 2.1 describes the survey implementation, structure, and outreach strategy. Section 2.2 describes the construction of the administrative dataset. Section 2.3 presents descriptive and comparative analyses of the two datasets.

2.1. **Survey of Africa's Startups with the IFC.** We designed and conducted a large-scale survey to collect comprehensive insights on Africa's startups. Our goal was to obtain a broad and representative sample in order to understand the characteristics of startups, their key challenges in financing and firm growth, and their preferences for different investors and financing opportunities. We target high-potential startups that have been operating for fewer than ten years, employ at least two full-time workers (including founders), and are actively seeking external financing to expand their operations.

In order to achieve broad representativeness across regions and firm characteristics, we implemented a dual dissemination strategy in collaboration with the IFC. First, we identified and contacted an extensive network of more than twenty regional partners that are highly active in Africa's high-growth entrepreneurship ecosystem. These partners include accelerators, incubators, venture capital associations and advisory firms, business development consultancies, and entrepreneurship and university networks with deep connections to local startup communities across Africa. We asked these organizations to distribute the survey directly to startups within their networks. Second, we conducted targeted direct outreach to further expand coverage and improve representativeness. In this stage, we identified target firms through referrals from first-round participants and from various data sources on early-stage startups in Africa; the IFC then sent direct emails to the selected entrepreneurs.

We conducted two large-scale survey rounds: the first in Q4 of 2023, and the second in Q4 of 2025. We obtained a total of 10,285 target startups in 51 (out of 54) African countries, and obtained 3,121 respondents from the first round and 1,323 respondents from the second round. By combining the two survey rounds, we have a final sample of 4,444 respondents, with a response rate of about 40%.[4] Throughout the paper, we refer to this combined sample as the "early-stage startups," and use this pooled sample from the two survey rounds for our main analysis.[5]

The survey consists of two main components. The first collects descriptive information on founder characteristics, firm attributes, and perceived constraints in access to capital and firm growth. The second section embeds an incentive-compatible experimental design that allows us to elicit startups' revealed preferences over key attributes of investment opportunities and potential investment partners. Respondents had the option to do the survey in English, French, Portuguese, and Arabic. We solicited responses directly from the startup founders. To encourage truthful and engaged participation, we provided non-monetary incentives and implemented extensive quality checks to ensure data reliability. The experimental

[4]This response rate compares favorably to other large-scale surveys in similar settings (e.g., Da Rin and Phalippou, 2017; Bernstein, Lerner, and Mezzanotti, 2019; Zhang, 2020; Gornall and Strebulaev, 2025; Colonnelli et al., 2025). Surveys implemented through targeted partnerships with established personal and institutional networks have achieved similarly high response rates of 21–50% (e.g., Gompers, Kaplan, and Mukharlyamov, 2016; Gompers, Gornall, Kaplan, and Strebulaev, 2020; Colonnelli et al., 2024).

[5]We also show in the Appendix that our results are strongly consistent across survey rounds.

design is discussed in more detail in Section 3, while details on survey design, dissemination, data treatment and quality check can be found in Appendix A.2.

2.2. **New Data on Established Startups.** We define "established startups" as firms that raised venture capital or growth equity financing between 2010 and 2024. We construct this sample by combining global deal-level data from PitchBook with its Africa-focused counterparts, namely Briter Bridges and Africa: The Big Deal. This approach leverages PitchBook's broad global coverage while improving representativeness and depth through local sources. We then link these administrative records to LinkedIn-based workforce data from Revelio Labs, which allow us to recover founders' and employees' education and employment histories. Below, we describe these data sources and the construction of the combined dataset.

2.2.1. *PitchBook.* PitchBook is a leading venture capital (VC) and private equity (PE) database designed to provide comprehensive global coverage of startup financing transactions and is widely regarded as the industry gold standard for analyzing VC transactions and conducting international comparisons (Lerner et al., 2024; Colonnelli et al., 2025). The database includes detailed information on each company and its financing information. In addition to detailed company-level information, PitchBook also contains data on investors, capturing both Limited Partners (LPs, i.e., the providers of investment capital) and General Partners (GPs, i.e., those that invest the capital in the specific startups). Data are collected from a variety of sources, including direct contacts with investment funds and portfolio companies, as well as information from news articles, regulatory findings, and press releases. Detailed information on the characteristics, coverage, and data collection methodologies of PitchBook are outlined in Appendix A.3.1.

Our analysis leverages PitchBook's extensive data on VC and PE deals, and specifically we focus on accelerators/incubators, seed rounds, early-stage VC, late-stage VC, and PE growth and expansion. We exclude transactions related to grants, initial public offerings (IPOs), mergers and acquisitions (M&A), and private investments in public equity (PIPE). We restrict our analysis to investments made since 2010, as PitchBook's international coverage is highly robust from this period onwards. Applying these restrictions, we identify 6,293 deals in Africa between 2010 and 2024, involving 4,372 unique companies that received VCPE funding.

2.2.2. *Briter Bridges and Africa: The Big Deal.* There is no perfect dataset able to measure every single deal covering startups and VCPE deals everywhere around the world (Kaplan and Lerner, 2017). For example, it is plausible that PitchBook, a U.S.-based company, may have an overrepresentation of larger deals and deals made by investors from advanced economies, with more imperfect coverage of emerging markets. To address this potential issue, we augment the PitchBook data with information from two specialized Africa-focused

sources, Briter Bridges and Africa: The Big Deal. These sources are the leading providers of VC and PE deal data in Africa and leverage extensive on-the-ground networks to achieve near-universal coverage of local deals. By integrating data from these platforms, we enhance our coverage of smaller deals, early-stage investments, and transactions involving local investors that are less likely to be captured in international databases.

After augmenting the PitchBook data with information from Briter Bridges and Africa: The Big Deal, we identify 9,064 deals spanning from 2010 to 2024, involving 5,801 unique companies receiving VCPE capital in Africa. This represents a significant increase compared to using PitchBook alone.[6] Throughout this paper, we refer to startups in our augmented dataset from PitchBook, Briter Bridges, and Africa: The Big Deal as "established startups," and use this combined dataset for all primary analyses in this paper. In what follows, we refer to this merged dataset, PitchBook augmented with Briter Bridges and Africa: The Big Deal, as PitchBook+ (PB+). Additional information on the characteristics, coverage, and data combination methodologies of PitchBook, Briter Bridges, and Africa: The Big Deal is provided in Appendices A.3.1 and A.3.2.

While our primary focus is Africa, it is useful to place the African startup ecosystem in a global context and to assess how commercial venture databases capture startup activity across regions. To this end, we use PitchBook+ to construct a worldwide map of startup activity. Figure A1 plots the geographic distribution of startups recorded in PitchBook+ across developed markets, emerging markets, and Africa. The figure illustrates the strong concentration of VCPE-backed startup activity in a small number of global hubs in developed markets, alongside sizable clusters in large emerging-market ecosystems (e.g., China, Singapore, and Brazil). Within Africa, recorded activity is similarly concentrated in a limited set of major urban hubs, with much thinner coverage outside these centers, a pattern we revisit in detail in Section 2.3.

2.2.3. *LinkedIn Data from Revelio Labs.* We then match our sample of 5,801 unique African startups in PitchBook+ to the full Revelio Labs database. Revelio Labs provides access to more than 450 million publicly available employee and company LinkedIn profiles from over 700 million registered accounts (Amanzadeh, Kermani, and McQuade, 2024).[7] Revelio Labs standardizes LinkedIn data using advanced natural language processing techniques to create a structured dataset containing detailed information on roles, skills, and professional activities. In addition, Revelio Labs enriches its dataset by imputing gender, ethnicity, role, seniority, and estimated salary for each position. While Amanzadeh et al. (2024) note potential concerns about representativeness when using LinkedIn data—such as varying

[6]The additional deals captured through Briter Bridges and Africa: The Big Deal tend to be more recent, smaller in deal size, and more concentrated in the Finance/FinTech sector as well as in countries outside South Africa. Appendix Table A1 provides more details on these comparisons.

[7]See Revelio Labs - The entire workforce revealed, for additional details.

coverage across sectors, locations, and higher representation of college-educated and white-collar professionals—these concerns are less relevant for our analysis for two reasons. First, startups are predominantly managed by young, educated individuals with a strong digital presence. Second, as we discuss in greater detail below, we are able to effectively match a substantial percentage of our startup sample with LinkedIn profiles.

We use data from Revelio Labs current as of end of December 2024 and take several steps to further ensure data quality. We are bale to match 94.3% of firms in our data to Revelio Labs and LinkedIn records.

2.3. **Descriptive Analysis.** In this subsection, we present initial descriptive evidence on Africa's startups.

2.3.1. *Descriptive Analysis of Early-Stage Startups.* We begin assessing the representativeness of our survey sample along both geographic and industry dimensions. Figure 2 shows that the sample covers all African countries, with geographical density closely matching the spatial distribution of established startups who have already secured VCPE investment.[8] Table A3 further confirms this result by comparing the survey's country distribution to multiple benchmark distributions, all of which yield similar patterns. The survey sample is also broadly representative across industries: Panel C of Table 1 reports the industry composition of early-stage startups in our survey, while Panel A of Table 2 reports the corresponding distribution for established startups.[9] In both samples, Information Technology and Finance/FinTech are among the most prevalent sectors.[10]

We next use the survey to characterize founders and early-stage startups. Panel A of Table 1 reports founder characteristics. Founders are relatively young, with a mean age of 37.8 and a median of 37, and are highly educated: 95.5% report at least some college education, and 34.2% hold a graduate degree. Foreign exposure is common, with 42.6% reporting foreign education or work experience. Executive teams also display meaningful international diversity, with 20.9% of executives not born in Africa on average, though this share varies substantially across firms. Founders are predominantly male, and a large fraction report prior entrepreneurial experience.

Panel B of Table 1 summarizes firm characteristics. Startups are young, with a mean age of 4 years and a median of 3, and remain small in employment size, with a median of 6

[8]Appendix Figure A1 shows the distribution of established startups worldwide. Appendix Figure A2 illustrates the geographic distribution of our survey sample by two survey rounds.

[9]We also present word clouds of company descriptions for Established Startups in Africa, Emerging Markets, and Developed Markets in Appendix Figure A3.

[10]One notable difference is Agriculture/AgriTech, which accounts for a substantially larger share of early-stage startups in our survey than among established startups. We interpret this gap as reflecting a wedge between entrepreneurial demand and realized access to growth capital, rather than a representativeness concern: agricultural startups are disproportionately represented among capital-seeking early-stage firms but are comparatively underrepresented among firms that ultimately secure VCPE financing.

employees. Despite their small size, they exhibit rapid growth: 70.1% report being profitable, and revenue growth over the past three years is high on average, with half of firms growing at annual rates exceeding 100%. Founders retain substantial control rights, holding 70% of equity on average; this share exceeds 90% when co-founders are included.

As a final piece of our descriptive analysis, we present key qualitative survey evidence on the financial constraints faced by early-stage startups. Figure 3 summarizes early-stage startups' capital needs and realized financing outcomes, stratified by startup size measured by the number of full-time employees. Panel A shows the distribution of capital sought across firms of different sizes: larger startups tend to report larger funding needs, but even relatively small teams frequently seek substantial amounts. Overall, the typical respondent is actively seeking external capital—on average roughly $0.5 million—yet these needs translate only imperfectly into realized financing. Panel B reports the percentage of capital needs that firms successfully finance, again by startup size. The distribution is heavily concentrated at low success rates, and the mean fraction of capital secured is only about 25%, indicating that most firms finance only a minority of the capital they report needing. Taken together, the figure highlights that early-stage startups in Africa report being severely financially constrained.

Table 3 provides complementary survey evidence on where startups obtain funding and which obstacles they view as most binding. Panel A reports respondents' main source of funding over the past three years and divides the result by employment size bins. For the bulk of firms—especially smaller ones—financing is dominated by internal sources like personal savings/resources and family and friends. External finance becomes more salient only for the relatively small subset of larger startups: among firms with 21+ employees, the main source shifts toward angels/VCs and bank loans. Panel B then asks respondents to select the most binding obstacles preventing business growth. Access to finance is overwhelmingly the dominant constraint—78.2% overall—and remains highly salient even among the largest firms (71.2% for 21+ employees). This pattern reinforces the message from Figure 3 that early-stage startups see access to external finance as a key constraint.

2.3.2. *Descriptive Analysis of Established Startups.* We now turn to the Established Startup sample. Table 2 reports summary statistics for established startups and their VCPE financing, comparing Africa with Emerging Markets and Developed Markets. Panel A shows that, relative to other regions, Africa's startup sector is less concentrated in IT/SaaS/AI and more tilted toward Finance/FinTech and Agriculture/AgriTech. Panels B and C summarize firm and deal-level characteristics. Startups in Africa are comparable in size to other regions at the time of first financing, but deal sizes are substantially smaller. Consistent with underdeveloped late-stage equity markets, Africa's deal composition is also skewed toward earlier stages: Seed rounds account for 32.9% of deals (compared with 19.5% in Emerging Markets

and 29.8% in Developed Markets), while Later Stage VC remains relatively rare (11.0% in Africa versus 25–30% in Emerging and Developed Markets).

2.3.3. *Comparing Early-Stage and Established Startups.* The two datasets reveal both substantial overlap and important differences between Africa's startups seeking growth capital and those that ultimately obtain VCPE financing. In addition to the broad overlap in the set of industries represented in both samples, firms in the two datasets are not far apart in their lifecycle at the center of the distribution: the median early-stage startup is 3 years old and has 6 full-time employees, while the median established startup is also 3 years old and has 9 employees at the time of first financing. Founder gender composition is also similar across the two samples.

At the same time, the two samples differ along several important dimensions. First, early-stage startups are substantially smaller and younger than established startups at the time of their first deal, whether measured by age or employment. These differences likely help explain the pronounced gap in access to external finance between the two groups. Second, as we discuss further in Section 4, established startups are more likely to have founders with foreign experience. Table 4 shows that 69.1% of founders in the Established Startup sample have foreign experience. This difference may be important for understanding which firms are ultimately able to connect to external capital.

## 3. What Do Africa's Startups Want?

We have documented that startups place substantial value on access to capital, yet there is limited evidence on the specific type of capital they seek. To better understand these needs, we embedded an incentive-compatible experimental design in the IFC survey, allowing us to estimate high-growth entrepreneurs' preferences over key attributes of investment offers and potential investment partners.

The remainder of this section is structured as follows. Section 3.1 details the experimental design to evaluate startups' preferences for investors. Section 3.2 outlines the econometric specifications used to analyze our survey experiment and discusses the results.

3.1. **Experimental Design.** Our experimental design aims to identify the preferences of high-growth entrepreneurs over key attributes of investment deals and potential investment partners, including, among others, the form of capital (equity versus debt), the geographic origin of investors (local versus foreign), the provision of non-financial support, and the educational and professional backgrounds of investment teams. Estimating preferences in this setting is challenging for two reasons. First, in observational data, investment attributes are highly correlated, making it difficult to separately identify the value entrepreneurs place on individual attributes. For example, foreign investors are more likely to offer equity financing, larger ticket sizes, and access to professional networks, whereas local investors more often

provide debt, smaller investments, and shorter maturities. Second, investment opportunities are not randomly assigned: investment partners may selectively approach certain types of entrepreneurs, and entrepreneurs may tailor stated preferences to align with perceived investor expectations. As a result, observational data and standard qualitative survey questions are insufficient to recover entrepreneurs' underlying preferences.

Our experimental survey is designed to address these challenges by randomizing key characteristics of investment deals and partners while holding other characteristics fixed, and to isolate high-growth entrepreneurs' preferences for investment partners regardless of the likelihood of a match. Our design closely follows that of Colonnelli et al. (2024) and is broadly inspired by the nondeceptive incentivized resume rating design introduced by Kessler et al. (2019). In our context, we invite entrepreneurs from early-stage startups in Africa to report their interest in a set of 15 synthetic profiles of investment partners. We primarily focus on investors that are of significant interest to startups at this stage, namely venture capital investors and DFIs.[11] Importantly, this study involves no deception. While the profiles are designed to appear realistic, respondents are informed that the investment offerings are hypothetical.

To incentivize truthful and accurate responses, we explicitly inform respondents how their stated evaluations map into the benefits they may receive. Respondents are told that their evaluations of the synthetic profiles will be used to facilitate introductions to real investment partners that match their preferences.[12][13]

3.1.1. *Creating Investment Partner Profiles.* Respondents are shown 15 investor profiles, each containing concise textual descriptions highlighting the key characteristics of the investment partner. To construct the synthetic investment partner profiles, we first conducted a structured manual review of over 5,000 real investment partner profiles from a number of sources such as PitchBook.[14] Our analysis involved evaluating the structure and content within these profiles, identifying common elements, or "components," such as investment size, location, sector focus, investment performance, and team background, among others, as well as identifying the language commonly used to describe key investment attributes.

[11]In a subset of cases, we also present profiles of accelerators and incubators, depending on respondents' stated interest. In the second survey wave, we present only 10 synthetic profiles of potential investment partners and do not include accelerator or incubator options.

[12]Appendix Figure A4 presents the official advertisement and consent page for the first survey round, including a description of the survey and its key incentives.

[13]In the second round, due to time availability of the IFC staff, we changed the incentive to be slightly weaker. Respondents were offered (i) an internal Market Insights Report that benchmarks their stated preferences against those of startups with similar observable profiles and preference patterns, and (ii) exclusive group meetings with IFC consultants for a random sample of the respondents.

[14]To ensure the profiles were as realistic as possible, we compiled information on investment partners from various sources. We drew from the templates, language, and presentation styles found on leading platforms and databases, including PitchBook, VC4A, Crunchbase, Briter Bridges, and LinkedIn, among others.

Through this review, we then approximate the probability distribution of the key investment attributes presented in the hypothetical profiles.

We detail the profile components in Appendix Tables A4 (for venture capital investors) and A5 (for DFI investors). We then construct investment partner profiles by randomizing components based on pre-specified inclusion probabilities. To ensure that the profiles generated appear realistic, we conduct a detailed manual review of a random set of profiles. In Appendix Figure A5, we provide two examples of synthetic investor profiles.

3.1.2. *Rating Investment Partner Profiles.* To assess early-stage entrepreneurs' preferences for specific characteristics of investment deals and partners, we ask them to rate a randomly selected set of 15 synthetic investment partner profiles. Our main dependent variable is captured by the following question for profiles of investors:

(1) *"How interested would you be in receiving capital from this investor?"*

We employ a 7-point Likert scale to assess ratings, where 1 corresponds to "Somewhat interested" and 7 represents "Extremely interested."[15] This allows us to identify high-growth entrepreneurs' preferences towards characteristics of inframarginal investment partner profiles. Additionally, we provide the following instruction: "When thinking about your interest in receiving capital from the investment partner, assume that the investment partner is already interested in establishing an investment relationship with your organization–therefore, please only consider your views on the quality of the investment partner." This intends to isolate the early-stage entrepreneur's interest in the profiles from their perceived likelihood of receiving capital from the investment partner.[16]

3.2. **Estimating Preferences for Investors.** To measure the impact of each investment partner characteristic on startups' preferences, we estimate specifications of the following form:

$$y_{ij} = \beta_0 + \sum_{k=1}^{N} \beta_k \times Characteristics_{jk} + \alpha_i + \epsilon_{ij}, \tag{3.1}$$

[15]We set the lowest rating to correlate with "Somewhat interested" since we designed our filtering questions to ensure that respondents have some level of interest in all profiles presented to them.

[16]To further isolate entrepreneurs' genuine preferences, we ask an additional question designed to explicitly measure respondents' perceived likelihood of securing financing. Specifically, we ask the following question:

(2) *"How likely do you think it is that this investor would provide capital to you?"*

We measure responses on a scale of 1 to 7, where 1 is "Unlikely" and 7 is "Likely." On their own, these supplementary questions provide insights into entrepreneurs' perceptions concerning the likelihood of establishing a partnership with an investment partner. Before the respondent rates the investor profile, we also specify: "When thinking about whether the investment partner would provide capital to you, assume that you have already expressed interest in the investment partner–therefore, please only consider whether you think the investment partner is interested in providing capital to you." See Appendix Figure A6 for details about the profile rating instructions. Before rating profiles, respondents also watch a short instructional video; see Appendix Figure A7.

where $i$ indicates an early-stage entrepreneur who responds to the survey and $j$ indicates an investment partner profile evaluated by $i$. $y_{ij}$ is our main dependent variable, which represents the level of interest expressed by an entrepreneur in a given investment partner profile. The main parameters of interest are $\beta_k$, which measure the average level of interest given by the high-growth entrepreneurs. The parameters $\beta_k$ capture $N$ number of characteristics that we randomized in investment partner profiles. We include $\alpha_i$ in the specification to account for the variation in average ratings across different high-growth entrepreneurs, i.e., individual fixed effects. We use heteroscedasticity-consistent (robust) standard errors for statistical inferences (Abadie, Athey, Imbens, and Wooldridge, 2023). Appendix Table A6 summarizes the main variables used in the investor profiles. Each variable is represented by a binary indicator equal to 1 if a specific text component used to construct the given variable appears in an investment partner's profile, and 0 otherwise.

3.2.1. *Preferences for Different Investment Attributes.* We report our main experimental results on startups' preferences for investors in Figure 4. The figure includes all characteristics captured by the synthetic profiles presented to respondents, broadly categorized into three types: "deal" features (e.g., equity vs. debt, investment amounts, board seats requirement, and deal maturity), "investor" characteristics (e.g., whether the investor is foreign or local or DFI, investment focus, non-financial support), and "team" characteristics (e.g., whether the team is local or foreign, local v.s. foreign experience, top U.S. school graduates).[17]

We begin by showing that respondents' stated interest is driven primarily by *deal* terms, rather than by investor or team attributes. Figure 4 shows that respondents place substantial weight on financial terms—including equity stake, board-seat requirements, offer size, interest rate, and maturity—while assigning relatively little weight to many investor characteristics (e.g., regional or sector focus, DFI status, or past success) or team attributes (e.g., local teams or local experience). Appendix Figure A9 corroborates this pattern by showing that deal terms account for the majority of within-sample variation in stated interest, relative to investor and team attributes.

Most strikingly, we document a strong preference for *Equity* financing and a corresponding aversion to debt. Quantitatively, an equity offer is associated with a statistically significant coefficient of 0.678 on the 1–7 Likert scale, corresponding to an approximately 15% increase in average expressed interest. Figure 5 Panel A further examines how the preference for equity varies across 23 heterogeneity groups, defined by firm, founder, country,

[17]Appendix Figure A8 reports estimates separately by round and shows that the results are highly consistent across the two waves. Appendix Table A7 verifies the robustness of the results by reporting detailed estimated coefficients using a variety of model specifications. Appendix Table A8 further strengthens this robustness by reporting results using different weighting schemes to reweight the sample.

and region characteristics.[18] In every split, the estimated coefficient on equity remains positive. Conditional on equity financing, high-growth entrepreneurs display a strong aversion to relinquishing control. The coefficient on *Any Board Seat*—an indicator equal to one if the investor requires at least one board seat—is −0.358 on the Likert scale. In contrast, entrepreneurs place little to no value on *non-financial support*, such as mentorship or training.

We further find that the *source of capital*—including whether the investor is headquartered outside Africa or has a foreign team—has essentially no effect on stated preferences. Entrepreneurs are largely indifferent to internationally oriented attributes, including foreign teams, investors headquartered in developed markets (such as the United States or Europe) or emerging markets (such as China, the UAE, or Brazil), and teams with educational backgrounds from top U.S. institutions. Figure 5 Panel B further examines preferences regarding foreign investors across heterogeneity groups. Strikingly, the estimated effect remains small and statistically insignificant across all 23 splits by firm, founder, country, and region characteristics. These results indicate that, conditional on deal terms and other observable attributes, entrepreneurs do not attach additional value to foreign capital providers.

By contrast, we find a clear preference for investors with strong *local* knowledge and embeddedness. Startups favor investor teams with local members and local experience, particularly when investors' regional or sectoral focus aligns with the entrepreneur's firm. For example, the coefficient on investor teams with local members is 0.155 on the Likert scale and is statistically significant. Similarly, the coefficient on investors with local experience is 0.104 and is robust across specifications.

Taken together, these results show that high-growth entrepreneurs exhibit a strong preference for equity financing coupled with an aversion to loss of control, place little value on non-financial support, are broadly indifferent to the source of capital per se, and instead value "local" investors.

In addition to investor profiles, we conduct a similar experimental survey to estimate high-growth entrepreneurs' preferences for accelerators and incubators, which reveals broadly similar preference patterns. In particular, in the first round, for a subset of respondents expressing interest in accelerators, we present 10 investor profiles and 5 accelerator/incubator profiles.[19] As in the investor-profile exercise, we ask respondents to rate their interest in the synthetic profiles while isolating the perceived likelihood of receiving an offer. We report the experimental results on startups' preferences for accelerators and incubators in Appendix Figure A12.[20] We find that early-stage entrepreneurs display a strong preference for

[18]Appendix Figure A10 further examines the correlations among the firm and founder characteristics used to define the heterogeneity groups. These patterns are broadly consistent with the results in Figure 5 and align with standard intuition.

[19]Appendix Figure A11 provides examples of synthetic accelerator/incubator profiles. Appendix Table A9 summarizes the main variables used in the accelerator/incubator profiles.

[20]We also report detailed estimated coefficients in Appendix Table A10.

accelerators and incubators that offer grants, while showing a strong aversion to giving up control. They also exhibit a preference for foreign accelerators from both Developed Markets and Emerging Markets. These results further strengthen our main findings by showing that preferences for accelerators and incubators are largely consistent with the patterns observed for investors.

3.2.2. *Preferences for Equity vs. Debt.* To further examine the relative preference for debt versus equity, we study preference heterogeneity along two key price dimensions: the interest rate for debt and the required equity stake for equity. Figure 6 reports the results. In the baseline specification, we discretize interest rates and equity stakes into bins and use the highest interest rate (20%) as the baseline category, so that all coefficients are interpreted as relative preferences, holding other attributes fixed. Respondents respond strongly and monotonically to debt pricing, preferring cheaper debt, and display an analogous pattern for equity, favoring contracts that require smaller equity stakes. Strikingly, equity financing dominates debt across nearly the entire support: only the cheapest debt offers, with interest rates between 5–10%—levels implausibly low for startup borrowing—are preferred to the most dilutive equity offers requiring equity stakes above 30%. Outside this extreme case, all equity offers dominate all debt offers, indicating that the preference for equity financing is pervasive and not driven by unusually favorable contract terms.[21]

To better understand the drivers of high-growth entrepreneurs' financing preferences, we examine respondents' rationales for choosing between debt and equity. The choice typically involves a tradeoff: debt can provide tax benefits and preserve control but may reduce financial flexibility and entail limited investor involvement; equity can facilitate growth and risk-sharing but dilutes ownership and control. Early-stage startups, however, often face highly volatile cash flows or may be pre-revenue, which can make them reluctant to take on debt obligations. To further probe these mechanisms, we analyze responses to survey questions asking why respondents prefer debt and equity, respectively. We provide a detailed classification of these qualitative responses in Appendix Table A11. Panel A highlights "Keep ownership and operational independence" (54.3%) as a key reason entrepreneurs prefer debt, consistent with a strong desire to retain control. Conversely, Panel B shows that entrepreneurs most frequently cite "Cash flow and financial flexibility (no interest payments)" (48.4%) as the main reason for preferring equity, reflecting a central constraint for early-stage startups: the lack of stable cash flows to service interest obligations.

[21]Appendix Figure A13 reports estimates separately by survey round and shows that the results are highly consistent across waves. Appendix Figure A14 further addresses concerns related to perceived offer attractiveness and debt affordability, confirming that the results reflect underlying preferences rather than financial constraints.

3.2.3. *Preference for Equity: Country-Level Heterogeneity.* To further verify the validity of startups' preference for equity, we split African countries into four subregions—Northern, Southern, Eastern & Central, and Western Africa—and estimate our main experiment results separately. Appendix Figure A15 shows that the results are highly consistent across regions.

A complementary interpretation of entrepreneurs' strong preference for equity is that it reflects *unmet demand*. In many African markets, startups may want equity but face a limited local supply of growth equity, making the equity market thin—or, for many firms, effectively absent. To examine this channel, Figure 5 Panel A also reports heterogeneity in equity preferences across country characteristics. We find that the preference for *Equity* is especially strong in countries with both *High GDP per Capita*—defined as above the sample median—and *Low VCPE Development*—defined as below the sample-median VCPE-to-GDP ratio. Conditional on GDP per capita, a lower VCPE-to-GDP ratio captures a less developed local equity ecosystem, suggesting that entrepreneurs in these countries are more likely to be underserved along the equity margin.

This perspective delivers a first-order implication of our study: the observed *preference for equity* may partly reflect a revealed response to a *missing local equity market*. To situate Africa in a global context, Figure 7 plots several measures of VCPE activity against GDP per capita across countries worldwide. The figure reveals a positive relationship between income and local equity-market depth. This positive correlation becomes progressively stronger from Panel A to Panel C, suggesting that higher-income countries not only have more startups receiving financing, but also receives greater amounts of capital, and, in particular, invest even greater volumes of domestic capital. However, across all measures, African countries always cluster near the bottom of the distribution, displaying markedly low domestic VCPE activity per capita even conditional on income levels.

Overall, these patterns stand in tension with the policy emphasis in many settings on microfinance and other debt-based interventions. Our evidence instead suggests that (i) debt is often a poor match for high-growth startups, which typically lack collateral and face volatile, back-loaded cash flows, and (ii) equity is highly valued yet locally scarce in Africa. A natural implication is that expanding access to *local* growth equity—rather than scaling debt programs alone—may be pivotal for unlocking startup formation and financed growth.

## 4. Where is Venture Capital Coming from?

We showed in the previous section that African entrepreneurs place little weight on the origin of capital. At the same time, these preferences are observed in an ecosystem whose dominant narrative emphasizes the overwhelming role of foreign financing. This section examines the forces behind this pattern and resolves the apparent puzzle.

The remainder of the section is organized as follows. Section 4.1 documents the sources of startup financing and shows a clear dominance of foreign investors. Section 4.2 examines the allocation of capital, showing that funded founders in Africa are highly educated and disproportionately likely to possess foreign human capital through education and/or work experience abroad. Section 4.3 then investigates whether such foreign dominance matters.

4.1. **Where Does Capital Come From?** We next document a defining feature of Africa's startup ecosystem: its pronounced reliance on foreign financial capital. We define foreign capital as funding provided by investors—whether GPs or LPs—whose headquarters are located outside the African continent.[22] Panel A of Figure 8 plots the share of startup funding involving at least one foreign investor for Africa, Emerging Markets, and Developed Markets over the period 2010–2024. The figure reveals striking cross-regional differences in reliance on foreign capital. Startups in Africa consistently depend far more heavily on foreign investors, with the foreign-investor share typically ranging between 75% and 90% throughout the period. By contrast, the corresponding shares range from 30% to 55% in Emerging Markets and from 20% to 30% in Developed Markets.[23] Panel B of Figure 8 further illustrates this dependence by presenting, at the country level, the share of startup funding involving at least one foreign investor, plotted against GDP per capita. The figure displays a clear negative relationship between GDP per capita and reliance on foreign capital: countries with lower GDP per capita exhibit higher dependence on foreign investors for startup financing. African countries are heavily concentrated in the upper-left region of the figure, combining low income levels with exceptionally high shares of foreign participation, often exceeding 80%.

Having established the dominance of foreign capital in African startup financing, Figure 9 drills down into *where* that foreign capital comes from and how it is allocated within the continent. Panel A shows that inflows are overwhelmingly sourced from Northern America and Europe, with additional sizable contributions from DFIs and the Rest of the World. By contrast, capital originating from China, India, and Latin America is comparatively small. While African GPs contribute a non-trivial share, their aggregate footprint remains clearly secondary relative to U.S. and European sources, reinforcing that Africa's equity financing is largely intermediated through extra-continental investors.

[22]Investor location is determined using the headquarters of the investor's corresponding "parent company" as reported in PitchBook. For example, if an investor operates a local African office but is ultimately controlled by a parent firm headquartered in the United States, we classify the investor's country of origin as the United States.

[23]Appendix Figure A16 shows that these patterns are robust to a range of alternative measurement approaches, including allocating deal sizes equally across investors, defining foreignness based on the lead investor, imputing missing deal sizes, and weighting by investor size. Appendix Figure A17 further strengthens the robustness of these findings by comparing the result using PitchBook+ and PitchBook-only data in Panel F, along with comparisons of additional descriptive facts.

Panel B then decomposes these flows by destination subregions within Africa and highlights limited intra-African financial integration. Across Western, Eastern, Northern, and Southern Africa, the dominant inflows continue to come from Northern America and Europe, whereas cross-subregion flows originating from African GPs are relatively thin. In other words, locally originated capital appears largely segmented and concentrated within subregions, rather than being broadly reallocated across the continent.

We next move one step upstream and ask not only where the fund managers investing in Africa's entrepreneurs (GPs) are based, but also where their *capital providers* (LPs) are located. Figure A18 traces flows from LPs to GPs and ultimately to African startups, separately by African destination subregions. The upstream pool of capital financing African startups remain concentrated in a small set of extra-continental LP bases (most prominently Northern America and Europe), while locally sourced and locally intermediated capital remains limited. Additional patterns also emerge. DFIs appear as a salient upstream source of funds, consistent with their prominent role in channeling capital toward African markets.[24]

4.2. **Who Does Capital Flow To?** Having established that capital flowing into the African startup ecosystem is predominantly foreign, a natural follow-up question is whether the recipients of this capital, namely startup founders, are also foreign. We therefore examine who this capital flow to and document two salient features: Africa's startup founders tend to have high levels of educational attainment and strong links to foreign countries.

4.2.1. *College-Educated Founders.* We begin by documenting that entrepreneurs receiving VC and PE capital in Africa are highly educated. Figure 10 Panel A plots, at the country level, founders' average years of schooling against the national average from the Barro and Lee (2013) dataset. Two patterns are immediate. First, across all regions, founder education levels lie far above national averages. Second, this selection is particularly stark in Africa, where national average schooling is relatively low but funded founders' education clusters at levels comparable to those in Emerging and Developed Markets. In other words, even in low-education environments, the segment of founders that reaches the VCPE market is drawn from a thin, highly educated tail of the distribution.

Panel B shows that education is also tightly linked to the *scale* of the startup ecosystem. Countries with higher average schooling have substantially more established startups per capita, with the relationship holding across Africa, Emerging Markets, and Developed Markets. The gradient is economically large: moving from low-education to high-education countries is associated with an order-of-magnitude increase in startup density.

[24]As comparison, Appendix Figures A19 and A20 replicate the same flow decomposition for other destination regions, tracing capital from (i) GPs to companies and (ii) LPs to GPs to companies. The figures show that, outside Africa, startup financing is substantially more locally oriented rather than foreign dominated.

4.2.2. *Dominance of Foreign Human Capital.* Panel A of Table 4 summarizes the human-capital composition of founders in VCPE-backed startups by the firm's headquarters region. Column (3) reinforces the conclusion that entrepreneurs in Africa are highly educated, with a college attainment rate of 80.5%, comparable to that in other regions. The headline results, however, appear in Columns (4) and (5): founders exhibit strikingly high levels of *foreign human capital*. A striking 46.5% of founders have foreign educational experience and 57.8% have foreign professional experience—substantially higher than in Europe and North America—making Africa the region with the highest shares along both dimensions. When combined, Column (6) shows that a staggering 69.1% of founders in Africa have either foreign education or work experience.

The table also reveals some heterogeneity within Africa. Foreign education and professional experience shares are highest in Central Africa, followed by West Africa and East Africa. Northern Africa exhibits somewhat lower—but still elevated—levels, while Southern Africa stands out as the least foreign connected within the continent, yet still with foreign exposure rates of approximately 50%. Taken together, these patterns suggest that the prominence of foreign human capital among African founders is not driven by a single hub country, but rather reflects a broad-based feature across African subregions.

To make these foreign human-capital links more concrete, Appendix Figure A21 traces founders' typical cross-region trajectories, following individuals from the location of their last completed education, to their first job location, and then to their last job location (if different from the first job) prior to founding a startup. The figure highlights a common pipeline in which many African founders acquire education and early-career experience in Northern America or Europe, and subsequently return to Africa before founding their startups, consistent with a "brain circulation" pattern rather than purely local accumulation of entrepreneurial human capital.

We also find that foreign human capital is prevalent among startup employees. Panel B of Table 4 presents the human-capital composition of employees for the same sample of startups. Column (3) shows that 66.7% of employees are college educated, a higher share than in Europe and Latin America. Columns (4) and (5) show that 34.9% are foreign educated and 27.8% have foreign work experience—both considerably high relative to other regions worldwide. Taken together, these patterns suggest that foreign human capital is prevalent throughout African startups, but it is especially concentrated at the founder level.

4.3. **Does Foreign Dominance Matter?** Having shown that startup financing in Africa is dominated by foreign capital, we next ask whether the foreign character of the ecosystem matters. We show that it does in three ways. First, it shapes the selection of entrepreneurs who obtain financing. Second, this selection is consequential because some high-potential

local entrepreneurs may remain financially constrained and lack access to comparable networks. Third, these features have aggregate implications by affecting the overall level of startup activity and increasing its exposure to foreign shocks.

4.3.1. *Foreign Capital Shapes Who Get Financed Through Matching Frictions.* A natural hypothesis of the "foreign human capital" patterns is that foreign education and work experience may operate through *connections* that facilitate access to international investors. To test this mechanism directly, we adopt a dyadic design that links each founder in Africa to potential investor *countries*. For each founder $i$, investor-country $j$, and year $t$, we estimate variants of:

$$\begin{aligned} y_{ijt} =& \beta_1 \, \mathbf{1}_{j=\text{EduCountry}_i} + \beta_2 \, \mathbf{1}_{j=\text{ExpCountry}_i} + \beta_3 \log(\text{Distance}_{cj}) \\ &+ \alpha_{c(i)} + \gamma_j + \delta_t + \lambda_{\text{EduCountry}_i} + \kappa_{\text{ExpCountry}_i} + \varepsilon_{ijt}, \end{aligned} \tag{4.1}$$

where $y_{ijt}$ is either (i) an indicator equal to one if founder $i$ raises *any* VCPE funding from investor-country $j$ in year $t$, or (ii) the total amount of funding (in USD million) raised from investor-country $j$ in year $t$. The two key regressors are *Same Investor and Founder Edu Country* ($\mathbf{1}_{j=\text{EduCountry}_i}$) and *Same Investor and Founder Exp Country* ($\mathbf{1}_{j=\text{ExpCountry}_i}$), capturing whether the investor country coincides with the founder's education or professional-experience country prior to the first deal year, respectively. $\log(\text{Distance}_{cj})$ is the log geographic distance between the founder's company country $c(i)$ and investor-country $j$. The specification includes company-country fixed effects $\alpha_{c(i)}$, investor-country fixed effects $\gamma_j$, and year fixed effects $\delta_t$, founder education-country fixed effects $\lambda_{\text{EduCountry}_i}$ and founder experience-country fixed effects $\kappa_{\text{ExpCountry}_i}$, netting out broad differences across company locations, investor countries, and founders' background composition. The sample is restricted to all possible matching between Africa's founders with non-African investor origin countries.[25]

The estimates in Table 5 provide clear evidence that founder–investor connections predict cross-border capital flows on both the extensive and intensive margins. In Column (1), the coefficient on *Same Investor and Founder Edu Country* is 0.020, implying that the probability a founder raises any funding from investor-country $j$ in a given year is higher by 2.0 percentage points when $j$ matches the founder's education country. Relative to the mean deal probability of 3.3%, this corresponds to a roughly 60% increase in the likelihood of observing a deal. Column (4) shows that, in the same specification, the education-country match is also associated with an additional $3.03 million in annual funding from that investor country,

[25]In practice, Table 5 implements equation (4.1) in three variants: Columns (1) and (4) include the education-connection term and founder education-country fixed effects; Columns (2) and (5) include the experience-connection term and founder experience-country fixed effects; Columns (3) and (6) include both connection terms and both sets of founder-background fixed effects.

compared to a mean of about \$0.53 million. These effects are even larger for professional-experience ties. Matching the founder's work-experience country raises the probability of receiving any funding from that investor country by 7.6 percentage points, and is associated with \$4.36 million more in funding. When both connection measures are included jointly (Columns (3) and (6)), the experience match remains large and precisely estimated: the probability effect is 0.075 and the funding effect is \$3.94 million. By contrast, the education match becomes small and statistically indistinguishable from zero on the extensive margin, while remaining positive for amounts. This pattern is consistent with professional networks being the more salient channel for initiating cross-border matches, while education ties may still correlate with scale conditional on a match. Overall, Table 5 provides direct evidence that financial and human capital flow together. Such evidence on matching frictions implies that the foreign composition of capital shapes which entrepreneurs receive financing.

4.3.2. *No Evidence that Local Entrepreneurs Perform Worse.* The preceding evidence shows that VCPE financing in Africa disproportionately flows to founders with foreign human capital and, in particular, country-specific connections to foreign investors. One possibility is *selection on quality*: foreign (or foreign-connected) founders may run systematically better firms, so investors allocate capital efficiently toward higher-performing startups. An alternative is *selection on access*: foreign background primarily relaxes information and matching frictions, allowing internationally connected founders to obtain funding more easily even if their underlying performance potential is similar. Distinguishing these mechanisms matters for interpretation and welfare: if local founders perform comparably once funded, then the observed allocation of growth capital reflects frictions that distort who gains access to finance.

To test this, we compare ex post outcomes among African startups that receive VCPE financing by estimating cross-sectional regressions at the startup level of the form

$$y_i = \beta_1 \, \mathit{ForeignConnected}_i + \beta_2 \, \mathit{Foreign}_i + \Gamma' \mathbf{X}_i + \phi_{c(i)\times s(i)} + \eta_{\text{cohort}(i)} + \varepsilon_i, \tag{4.2}$$

where $y_i$ denotes an outcome measuring performance after the first recorded deal. Outcomes include binary exit indicators such as *Successful Exit* (IPO, M&A, buyout, or secondary transaction), *IPO*, *M&A*, and *Bankruptcy*, as well as continuous measures such as post-funding *Employment Growth*. $\mathit{Foreign}_i$ is an indicator equal to one if startup $i$ has at least one founder with foreign education or foreign work experience prior to the first deal year, and $\mathit{ForeignConnected}_i$ equals one if at least one founder's foreign education or work experience (prior to the first deal year) occurred in the same foreign country as a future foreign investor. $\mathbf{X}_i$ includes deal and firm controls (e.g., investor counts and subsequent-funding measures, and baseline employment where applicable). $\phi_{c\times s}$ are country–sector fixed effects, and $\eta_{\text{cohort}}$

are first-deal cohort fixed effects, so comparisons are made among startups operating in the same country and sector and entering the VCPE market in the same year.

Table 6 reports two sets of results. Columns (1)–(5) report unconditional performance estimates from a restricted version of (4.2) that excludes all controls, while columns (6)–(10) present conditional performance estimates from the full specification with the full set of controls. Unconditionally, foreign-connected founders perform somewhat better on some dimensions: they are 4.9% more likely to achieve a successful exit, 2.6% more likely to experience an M&A exit, and 7.6% less likely to go bankrupt. Across conditional performance outcomes, however, the coefficients on foreign background are small and statistically indistinguishable from zero. We find no evidence that foreign or foreign-connected startups are more likely to exit successfully, less likely to fail, or to experience faster post-funding employment growth. Conditional on accessing the VCPE market and receiving financing, local startups perform comparably to foreign and foreign-connected startups along standard exit and growth margins. This pattern suggests little evidence that local entrepreneurs are of systematically lower quality. As a result, the disproportionate allocation of capital to foreign-connected entrepreneurs may crowd out potentially high-quality local founders.

4.3.3. *Aggregate Implications.* We now show that the foreign dominance of capital has aggregate implications by employing a shift–share (Bartik) design that leverages plausibly exogenous sector-specific supply shocks from investor countries. Following the shift–share framework formalized in Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022), our identifying variation comes from investor country industry capital cycles—i.e., time variation in how much investors from country $o$ deploy in sector $s$ interacted with predetermined exposure shares of each African country–sector cell. Crucially, the shift is constructed at the investor-country-by-sector level, so that the instrument varies with fluctuations in investor countries' sectoral investment capacity and risk appetite rather than with contemporaneous conditions in African destination markets. By combining these external, investor-country sector shocks with pre-determined exposure weights, the design isolates changes in the availability of foreign VC and growth equity that are orthogonal to local demand shocks, allowing for a causal estimation.

To operationalize this idea, we implement a shift–share (Bartik) design at the sector–destination country–year level. Let $Y_{sd,t}$ denote startup activity in sector $s$ of destination country $d$ at time $t$, measured as the total VCPE deal size or count. Let $X_{sd,t}$ denote the endogenous foreign capital inflow received by $(s, d)$ at time $t$. We instrument $X_{sd,t}$ with an exposure-weighted sum of origin–sector supply shifts $Z_{sd,t}$. Define the pre-period exposure share of $(s, d)$ to investor origin $o$ as $share_{sd,o,t_0} = F_{sd,o,t_0} / \left(\sum_o F_{sd,o,t_0}\right)$, where $F_{sd,o,t_0}$ is the total capital supplied by investors from origin $o$ to destination country–sector cell $(s, d)$ in the base period $t_0$. We set base period as 2000-2014 and normalize shares to sum to one within

each $(s, d)$. Next, we construct the origin–sector shift $shift_{o,s,t} = \sum_{d' \neq d} F_{sd',o,t}$, which is a leave-one-out measure of how much capital investors from origin $o$ deploy in sector $s$ outside destination $d$ at time $t$. This shift captures time-varying conditions in the origin–sector pair $(o, s)$—e.g., sectoral fundraising cycles, risk appetite, and portfolio rebalancing by investors headquartered in $o$—while mechanically excluding flows into the focal destination $d$. Our Bartik instrument for $(s, d)$ at time $t$ is then

$$Z_{sd,t} \;=\; \sum_{o} share_{sd,o,t_0} \times \log\Big(shift_{o,s,t}\Big). \tag{4.3}$$

We estimate the following specification:

$$\log(Y_{sd,t}) \;=\; \beta\, Z_{sd,t} \;+\; \eta_t \;+\; \phi_{sd} \;+\; \varepsilon_{sd,t}, \tag{4.4}$$

where $\eta_t$ are year fixed effects and $\phi_{sd}$ are sector–destination fixed effects; standard errors are clustered at the $(s, d)$ level. The coefficient of primary interest is $\beta$, which measures how exogenous fluctuations in foreign funding availability translate into realized startup financing.

Table 7 provides the result that foreign capital supply is a binding constraint for entrepreneurial finance in Africa. Across all specifications, the coefficients are positive and statistically significant for both outcomes—total deal value and deal count—indicating that foreign capital supply shocks propagate directly into local startup activity. The estimated coefficient of 0.258 in Column (2) implies that a 10% increase in foreign capital availability predicts a 2.58% increase in African deal value. Taken together, these magnitudes are economically meaningful and consistent with limited substitutability: fluctuations in foreign capital supply translate into sizable changes in the amount of growth capital raised by startups in Africa.

Appendix Figure A22 further assesses the robustness of our Bartik results by varying the focal "leave-out" definition, modifying the fixed effect specification, changing the choice of base year used to construct exposure shares (2012, 2014, or 2016), or restricting the sample to the five largest startup ecosystems in our data (Kenya, Egypt, Nigeria, South Africa, and Uganda). Across both outcomes—log deal size (Panel A) and log deal count (Panel B)—the estimated coefficients remain predominantly positive and are typically statistically distinguishable from zero.

Appendix Table A12 studies heterogeneity in the Bartik effects by founders' *foreignness*. We split startup activity into two groups: financings received by startups founded by entrepreneurs with foreign education or professional experience ("Foreign"), versus financings received by startups founded by locally rooted entrepreneurs without such backgrounds ("Domestic"). The table then re-estimates the reduced-form relationship between foreign capital supply shocks and each group's deal activity, separately for log deal size and log deal

count. Although both groups' financing responds positively to foreign capital supply shocks, the response is systematically larger for the "Foreign" founder group. This differential sensitivity suggests that foreign capital supply shocks do not translate one-for-one into financing for all entrepreneurs: founders with foreign human capital appear better positioned to intermediate international capital cycles into realized funding, while local founders benefit less when foreign supply expands and are less connected to the marginal foreign inflows.

## 5. A Simple Model of Startups in Africa

We next develop a simple model to interpret the data, unpack the drivers of foreignness in Africa's startup ecosystem, and quantify how frictions in capital access affect both the composition and the number of startups. The model is intentionally parsimonious. It should be interpreted as an organizing framework—closer to an accounting device than to a fully structural theory of startup formation—that helps map the empirical evidence into a small number of economically meaningful objects.

We use the model for three purposes. First, we measure the wedges—in terms of the cost of capital and the mass of local entrepreneurs—that rationalize the empirical patterns in the data. Second, we decompose why startup activity in Africa is unusually foreign, both on the investor side and on the founder side. Third, we quantify how the measured wedges affect the aggregate number of startups and their composition, and hence how relaxing them changes startup activity. Throughout, several forces remain exogenous, so the counterfactuals should be interpreted as partial-equilibrium exercises that are informative about relative magnitudes rather than as full general-equilibrium predictions.

### 5.1. **Environment.**

We consider a world economy populated by investors and potential entrepreneurs. Investors are indexed by their country of origin, $x \in \mathbb{X}$. They do not move, but their capital is deployed from origin $x$ to startups located in destination $j$. Potential entrepreneurs are located in destination $j$ and are of different types, $k \in \mathbb{X}$, where type summarizes the entrepreneur's exposure to a region through prior education, work experience, or networks.[26]

*Investors.* Each country $x$ is populated by a large mass of atomistic investors. When investors from origin $x$ finance startups in destination $j$, they face an origin–destination specific capital wedge $r_{j,x}$. This reduced-form wedge captures both the opportunity cost of capital and any barriers to deploying funds in market $(j, x)$. There is free entry, so investors enter each market until expected returns equal this wedge.

*Entrepreneurs.* In each destination $j$, there is a mass $e_j^k$ of potential entrepreneurs of type $k$. We refer to this as an *entry wedge*, since it captures not only the mass of entrepreneurs of

[26]Using the same partition for investor origins and founder types is convenient because it allows us to map founder exposure directly into investor access.

each type, but also any barriers they face in becoming entrepreneurs and entering the pool of individuals able to seek financing to start a company. An entrepreneur of type $k$ draws project productivity $z_j^k \sim F_j^k(\cdot)$ and chooses whether to seek equity financing from investors based in any origin $x$ or to rely on a domestic outside option, which we interpret as debt.

In addition to productivity, founders differ along two dimensions. First, financing options differ in their deterministic utility component, denoted by $\bar{\tau}_{j,m}$ for $m \in \{d\} \cup \mathbb{X}$.[27] Second, founders differ in how effectively they can approach and match with investors from different origins, summarized by a connection term $\lambda_{j,x}^k$.[28]

*Markets.* Every entrepreneur can access a domestic debt market $d$, which serves as the outside option. If financed through debt, a type-$k$ entrepreneur with productivity $z$ obtains payoff

$$\Pi_{j,d}^k(z) = \bar{\tau}_{j,d}^k z.$$

For each pair $(j, x)$, there is a separate equity market in which investors from origin $x$ meet entrepreneurs in destination $j$. Let $s_{j,x}$ denote capital supply and $d_{j,x}$ denote effective demand in that market. The number of successful matches is given by the matching function

$$n_{j,x} = s_{j,x}^{\eta} d_{j,x}^{1-\eta}, \qquad \eta \in (0, 1).$$

Random matching implies that an entrepreneur searching in market $(j, x)$ is financed with probability $\frac{n_{j,x}}{d_{j,x}}$, while an investor supplying capital to that market is matched with probability $\frac{n_{j,x}}{s_{j,x}}$.

A financed entrepreneur produces output $z_j^k$, of which the investor receives share $\beta$ and the entrepreneur receives share $1 - \beta$.

5.2. **Equilibrium and Decomposition.** We now characterize the key equilibrium objects and present a set of simple lemmas that guide the analysis below. We focus on the number and composition of equity-financed startups, which are the key objects directly observed in our deal-level data.

[27] Notice that the utility component varies across investor origins, but not across founder types. This is consistent with the limited heterogeneity in preferences documented in Section 3.

[28] Throughout, the first subscript denotes entrepreneur location and the second denotes investor origin.

LEMMA **1.** *The equilibrium in each market $(j,x)$ satisfies*

$$\begin{aligned} s_{j,x} &= d_{j,x}\left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{1}{1-\eta}}, \\ d_{j,x} &= \sum_{k\in\mathbb{X}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k, \\ \mu_{j,x}^k &= \frac{\left(\bar{\tau}_{j,x}\lambda_{j,x}^k\left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}\right)^{\sigma}}{\sum_{c\in\mathbb{X}}\left(\bar{\tau}_{j,c}\lambda_{j,c}^k\left(\frac{s_{j,c}}{d_{j,c}}\right)^{\eta}\right)^{\sigma}+\left(\bar{\tau}_{j,d}^k\right)^{\sigma}}, \end{aligned}$$

*where*

$$E[z_{j,x}] = \frac{1}{d_{j,x}}\sum_{k\in\mathbb{X}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k \int z\, dF_j^k(z).$$

Lemma 1 summarizes the three main forces in the model. The supply of capital is pinned down by free entry: lower capital wedges, higher expected returns, or larger demand all raise the mass of investors active in market $(j,x)$. The demand equation shows that effective demand is the sum of entrepreneurs of each type, weighted both by their probability of searching in that market, $\mu_{j,x}^k$, and by how effectively they can approach investors from that origin, $\lambda_{j,x}^k$. Finally, the extreme-value structure yields a familiar expression for search probabilities. These depend on the attractiveness of each financing option (captured by preferences $\bar{\tau}$), on founders' ability to access each investor origin (captured by $\lambda$), and on market tightness (captured by $s_{j,x}/d_{j,x}$)—which determines the probability of actually obtaining financing conditional on searching there. The parameter $\sigma$ governs how sharply founders reallocate search across financing options when relative payoffs change.

The interaction of these forces determines startup formation in each destination $j$, as summarized in the next lemma.

LEMMA **2.** *The number of equity-financed startups in destination $j$ founded by type-$k$ entrepreneurs and financed by investors from origin $x$ is*

$$n_{j,x}^k = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k.$$

*Aggregating yields*

$$N_j = \sum_{x\in\mathbb{X}}\sum_{k\in\mathbb{X}} n_{j,x}^k = \sum_{x\in\mathbb{X}}\left[\left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}} \sum_{k\in\mathbb{X}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k\right].$$

Lemma 2 shows that both the total mass of startups and their composition depend jointly on the supply and demand for capital, and therefore on both the capital wedges and the entry wedges.

*Foreignness.* We next characterize the drivers of *foreignness*: the share of startups in a given destination financed by foreign rather than local investors, and the share of startups founded

by foreign rather than local entrepreneurs. For the next two lemmas, define

$$n_{j,x} \equiv \sum_k n^k_{j,x}, \qquad N^k_j \equiv \sum_x n^k_{j,x}.$$

We also define

$$\hat{\mu}^k_{j,x} \equiv \frac{\mu^k_{j,x}}{(\bar{\tau}_{j,x})^\sigma}, \qquad \hat{e}^k_{j,x} \equiv \hat{\mu}^k_{j,x} e^k_j.$$

The object $\hat{\mu}^k_{j,x}$ removes the direct preference shifter for investor origin $x$ from the search probability, while retaining the equilibrium denominator. It can therefore be interpreted as a taste-adjusted measure of search intensity. The object $\hat{e}^k_{j,x}$ is the corresponding *effective entrepreneur mass*: it combines the mass of type-$k$ entrepreneurs—that is, the entry wedge—with their taste-adjusted intensity of search toward investor origin $x$.

LEMMA **3.** *The ratio of foreign- to locally-financed startups in destination $j$ is*

$$\frac{n_{j,f}}{n_{j,\ell}} = \underbrace{\left(\frac{r_{j,\ell}}{r_{j,f}}\right)^{\frac{\eta}{1-\eta}}}_{\text{capital wedge}} \underbrace{\left(\frac{E[z_{j,f}]}{E[z_{j,\ell}]}\right)^{\frac{\eta}{1-\eta}}}_{\text{relative returns}} \underbrace{\left(\frac{\bar{\tau}_{j,f}}{\bar{\tau}_{j,\ell}}\right)^{\sigma}}_{\text{preferences}} \cdot \underbrace{\frac{\mathbb{E}_k[\lambda^k_{j,f}]\mathbb{E}_k[\hat{e}^k_{j,f}] + \mathrm{Cov}_k(\lambda^k_{j,f}, \hat{e}^k_{j,f})}{\mathbb{E}_k[\lambda^k_{j,\ell}]\mathbb{E}_k[\hat{e}^k_{j,\ell}] + \mathrm{Cov}_k(\lambda^k_{j,\ell}, \hat{e}^k_{j,\ell})}}_{\text{entry wedge and connections}}.$$

Lemma 3 decomposes foreign investor dominance into four objects: relative capital wedges, relative expected returns, relative preferences for foreign versus local equity, and a search-access-composition term. The last term depends on both the *entry wedge*—the mass of entrepreneurs of each type who enter the pool of potential founders—and on founders' connections to each investor origin. It can itself be decomposed into three parts: the average connectedness of founders to a given investor origin, the average effective entrepreneur mass searching in that market, and the covariance between the two. Foreign finance is therefore more prevalent not only when foreign capital is cheaper or offers higher expected returns, but also when the entrepreneurs who are more likely to enter and seek financing are precisely those who are better connected to foreign investors.

Lemma 3 characterizes foreignness on the financing side. We now turn to foreignness on the founder side. Towards this goal, we define

$$A_{j,x} \equiv \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}}, \qquad \omega^k_{j,x} \equiv (\bar{\tau}_{j,x})^\sigma \lambda^k_{j,x} \hat{\mu}^k_{j,x}.$$

The object $A_{j,x}$ is a reduced-form measure of capital supply from origin $x$ into destination $j$, while $\omega^k_{j,x}$ summarizes founder type-$k$'s effective access to investors from origin $x$, combining preferences, connectedness, and search intensity.

LEMMA **4.** *The ratio of startups in destination $j$ founded by foreign-type relative to local-type entrepreneurs is*

$$\frac{N_j^f}{N_j^\ell} = \underbrace{\frac{e_j^f}{e_j^\ell}}_{\text{entry wedge}} \cdot \underbrace{\frac{\mathbb{E}_x[A_{j,x}]\,\mathbb{E}_x[\omega_{j,x}^f] + \mathrm{Cov}_x(A_{j,x}, \omega_{j,x}^f)}{\mathbb{E}_x[A_{j,x}]\,\mathbb{E}_x[\omega_{j,x}^\ell] + \mathrm{Cov}_x(A_{j,x}, \omega_{j,x}^\ell)}}_{\text{access to capital}}.$$

Lemma 4 decomposes founder foreignness into two broad objects. The first is the relative mass of foreign and local entrepreneurs, which we interpret as the *entry wedge*: if fewer local entrepreneurs enter the pool of potential founders, then fewer startups will be founded by locals. The second is the relative weighted access to capital across investor origins. This access-to-capital term depends on the average capital available from the different investor origins (and therefore on the underlying *capital wedges*), on the average effective access of each founder type to those investor markets, and on the covariance between the two. Foreign founders therefore create relatively more startups when they are disproportionately connected to the investor origins where capital is cheapest.

5.3. **Bringing the Model to the Data.** We discipline the model with a parsimonious calibration. We set $\beta = 0.5$ and $\eta = 0.5$. We then impose three restrictions motivated by the empirical evidence. First, following the results in Section 3, we assume that entrepreneurs do not have differential tastes across the origins of equity financing—beyond an overall taste shifter for equity relative to debt. That is, among equity markets we set $\bar{\tau}_{j,x} = \bar{\tau}_j$ for all investor origins $x$. Second, following the results in Section 4.3.2, we assume that, conditional on receiving financing, differences across entrepreneurs operate primarily through access to capital rather than project quality. We therefore do not allow expected project quality to vary systematically across investor origins or founder types within destination $j$. Third, consistent with the empirical regressions of Section 4.3.1, we impose a diagonal connection structure: entrepreneurs enjoy a connection premium $\lambda$ when their exposure type matches investor origin.

Under these assumptions, the remaining free parameters are the substitution parameter $\sigma$ and the connection premium $\lambda$, while the latent entry wedges $\{e_j^k\}$ and origin–destination capital wedges $\{r_{j,x}\}$ are recovered to exactly match observed startup counts by investor origin and entrepreneur type. This is the sense in which the model recovers the two margins emphasized by Lemmas 3 and 4: the *capital wedge*, which governs the supply of capital into each market, and the *entry wedge*, which governs the mass of entrepreneurs of each type who reach the stage of seeking equity financing.

The empirical inputs for the calibration are two sets of moments. First, we construct $n_{j,x}$, the deal-size-weighted number of financed startups in destination $j$ backed by investors from origin $x$, using data from PitchBook, Africa: The Big Deal, and Briter Bridges over 2010–2024. Second, we construct $n_j^k$, the number of funded startups in destination $j$ founded

by entrepreneurs of type $k$, where type is assigned from education and work histories prior to startup founding using data from Revelio Labs. Conditional on $(\sigma, \lambda)$, the equilibrium system allows us to exactly pin down $\{e_j^k\}$ and $\{r_{j,x}\}$ region by region. We then choose $(\sigma, \lambda)$ to match two reduced-form moments from the data: the Bartik-style sensitivity of Africa's startup activity to shocks to foreign capital supply (see Table 7), and the dyadic tendency of entrepreneurs to raise capital from investor origins to which they are connected through prior education or work experience (see Table 5). These moments discipline, respectively, the elasticity of startup formation with respect to capital-supply conditions ($\sigma$) and the strength of connection-based access ($\lambda$). We find $\sigma = 3.01$ and $\lambda = 2.5$, meaning that entrepreneurs are 2.5 times more likely to match with an investors from the country to which they have been exposed.

Tables A13 and A14 show both the empirical targets and the results from the calibration. Table A13 compares observed capital flows $n_{j,x}$ to the solved wedge matrix $r_{j,x}$. Outside Africa, local investors tend to enjoy a clear home-market advantage: the wedge faced by local capital is low relative to that faced by foreign investors. Africa looks different. In several African regions, North American and European investors face wedges comparable to, or even lower than, those faced by local investors. The model therefore interprets foreign investor dominance in Africa as reflecting an unusually weak (or even negative) local-capital advantage.

Table A14 compares the observed composition of funded entrepreneurs $N_j^k$ to the latent entrepreneur masses $e_j^k$ that rationalize those shares in equilibrium. Here too Africa stands out. Relative to Europe and North America, African startup ecosystems feature a smaller mass of local entrepreneurs and a larger presence of entrepreneurs with foreign exposure. In the language of the model, this means that Africa displays a weaker *entry wedge* for local entrepreneurs: either there are fewer local individuals in the latent pool of potential founders, or local individuals face greater barriers to entering entrepreneurship and reaching the stage at which they seek startup finance. The model therefore points to two distinctive features of the African data: local equity is relatively scarce, and the latent pool of local entrepreneurs is relatively thin.

5.4. **Decomposing Foreignness.** We now use the model to decompose why startup ecosystems in Africa are unusually foreign, both on the investor side and on the entrepreneur side. Figure 11 reports the relevant counterfactuals.

Panel A studies the share of local investors. Guided by Lemma 3, we ask how this share changes when we alter the two margins that remain after the earlier empirical evidence has ruled out a leading role for preferences and project quality: capital wedges and entry wedges. In the first exercise, we lower the local capital wedge in Africa so that the ratio of the local wedge to the North American wedge matches the corresponding ratio in Europe. In the

second, we increase the latent mass of local entrepreneurs so that the local entrepreneur share matches that in Europe. In the third, we implement both changes simultaneously.

Both margins matter. In the baseline, the local investor share is 25.4%. Equalizing capital wedges raises it to 41.0%, equalizing the mass of local entrepreneurs raises it to 38.4%, and implementing both changes raises it to 56.0%. This maps directly into Lemma 3. Lowering the local capital wedge raises locally-financed startup activity through the first term in the decomposition, by making local capital cheaper relative to foreign capital. Increasing the mass of local entrepreneurs instead operates through the final term, the one capturing *entry wedges and connections*: a thicker pool of local entrepreneurs shifts effective demand toward the investor markets to which those entrepreneurs are more connected. Africa's foreign investor base is therefore jointly shaped by weak local capital supply and by the thinness of the local entrepreneur pool.

Panel B turns to the share of local entrepreneurs among funded startups. Here Lemma 4 provides the relevant decomposition. In the baseline, the local entrepreneur share is 30.9%. Equalizing capital wedges raises it to 39.7%, equalizing the mass of local entrepreneurs raises it to 46.8%, and implementing both changes raises it to 56.6%. The direct effect is the first term in Lemma 4, namely the relative *entry wedge*: increasing the mass of local entrepreneurs mechanically expands the pool of startups that can be founded by locals. But the second term also matters. When local capital becomes cheaper, equilibrium startup formation shifts toward investor markets that local entrepreneurs are better positioned to access, so that more of the latent local entrepreneur mass is translated into realized startups. Since the figure reports funded firms rather than latent entrepreneurs, this access-to-capital channel is quantitatively important.

Taken together, the two panels make a simple point. Africa is unusually foreign not because foreign investors are systematically preferred or because foreign-connected entrepreneurs are systematically better, but because local equity markets are weak and the pool of local entrepreneurs is relatively small. The model therefore interprets foreignness as the joint outcome of a supply-side distortion, captured by high local capital wedges, and a demand-side distortion, captured by low mass of local entrepreneur.

5.5. **Counterfactuals for Startup Activity.** The previous subsection focused on composition: who finances startups in Africa, and who creates them. We now turn to quantity and ask how many startups are created. Figure 12 reports the resulting counterfactual changes in startup activity. Consistent with Lemma 2, the counterfactuals operate through three margins: the supply of capital, via capital wedges; the mass of effective startup demand, via entry wedges; and the allocation of that demand across investor markets, via entrepreneurs' connections. In addition to the two counterfactuals already used in the foreignness decomposition, we also consider a connection counterfactual, in which local entrepreneurs in Africa are

allowed to have connection intensity $\lambda$ with investors from all origins, and a human-capital counterfactual, in which the latent mass of local entrepreneurs is recomputed after raising all African education groups to the schooling level of the high-education group. Appendix A.4.3 provides the details.

The first message is that the same frictions that generate foreignness also depress startup creation. Equalizing local capital wedges raises total startup activity by 13.3%. Equalizing the mass of local entrepreneurs raises it by 30.0%. Equalizing the connection structure of local entrepreneurs raises it by 18.6%, while the human-capital counterfactual raises it by 21.4%. These are economically large effects, implying that distortions in local capital supply, local entrepreneur entry, and access to investor markets all materially constrain startup creation in Africa.

Panel A decomposes these gains by entrepreneur type. Lower local capital wedges primarily benefit local entrepreneurs: locally-founded startups rise by 21.0%, while foreign-founded startups fall by 7.8%. Expanding the mass of local entrepreneurs raises locally-founded startups by 24.5% and foreign-founded startups by 5.5%. By contrast, improving the connection structure of local entrepreneurs generates a sharp reallocation across entrepreneur types: locally-founded startups fall by 18.7%, while foreign-founded startups rise by 37.3%. The human-capital counterfactual increases startup creation for both groups, raising locally-founded startups by 11.1% and foreign-founded startups by 10.3%.

Panel B decomposes the same counterfactuals by investor origin. Lower local capital wedges mainly expand locally-financed activity: locally-financed startups rise by 14.2%, while foreign-funded startups fall slightly, by 0.9%. Increasing the mass of local entrepreneurs raises locally-financed startups one-for-one, with essentially no change in foreign-funded startups. The same is true for the connection and human-capital counterfactuals, both of which operate almost entirely through the locally-financed margin.[29]

Taken together, the counterfactuals show that the forces identified in the foreignness decomposition are not merely compositional. Lower local capital wedges and stronger local entry both make the ecosystem less foreign and increase startup activity. Improvements in entrepreneur access to investors also raise startup creation, but through a different mechanism: they reallocate effective demand across entrepreneur types rather than primarily deepening local capital markets. More broadly, the model suggests that strengthening local equity markets, expanding the pool of local entrepreneurs, and reducing access frictions are all margins through which the startup ecosystem in Africa can grow.

[29]This reflects free entry on the investor side. Entrepreneurs do not compete for a fixed stock of capital: when effective demand rises in a market, investor entry expands capital supply rather than crowding out other entrepreneurs.

5.6. **Survey Evidence on Mechanisms.** In the second round of our survey, we asked respondents why the startup ecosystem in Africa is characterized by a high share of foreign investors and entrepreneurs. The goal was to assess whether entrepreneurs' own perceptions align with the mechanisms emphasized by our empirical and quantitative analysis.

Figure 13 shows that they do. On the investor side, respondents overwhelmingly point to forces that map naturally into capital wedges. Roughly half cite the limited availability of local capital, and another quarter cite the small number of local investors. By contrast, fewer than 10 percent point to stronger founder demand for foreign capital, consistent with our survey evidence that preference-based explanations are not first-order.

On the founder side, respondents primarily point to easier access to capital through networks and connections, and to investor bias. In the model, these forces operate through the parameter $\lambda$ and through entry wedges that limit the mass of local entrepreneurs. This is consistent with our large estimate for $\lambda$ and with the counterfactual finding that equalizing local entrepreneurs' access to foreign investors substantially raises the mass of local founders. It is also consistent with the effect of reducing capital wedges: because we estimate a large $\lambda$, an expansion in local capital disproportionately increases entry by local entrepreneurs. By contrast, explanations based on return differentials or easier screening receive much less support.

Overall, these responses provide an independent check that the model is capturing the mechanisms that market participants themselves see as central.

## 6. Conclusion

Understanding the role of high-growth startups and high-potential entrepreneurship is central to both policy and practice. Governments and development finance institutions around the world are committing substantial resources to support these firms, motivated by their potential to drive innovation, job creation, and structural transformation. Yet, despite this growing policy focus, there remains limited systematic evidence on how such startups operate in developing contexts and what constraints they face.

In this paper, we provide new large-scale evidence on high-growth entrepreneurship in Africa by combining experimental survey data with novel microdata on founders and investors. Using our unique survey of startup founders across 51 African countries, paired with an incentive-compatible experiment, we document that financing constraints remain a first-order barrier to firm growth. We show that entrepreneurs exhibit a strong preference for equity over debt financing and place substantial value on investors with local presence and contextual expertise. At the same time, we document that startup financing in Africa is overwhelmingly driven by foreign investors and disproportionately allocated to foreign and foreign-connected founders.

We interpret these findings through a framework that highlights frictions in local equity markets and asymmetries across founder and investor origins. Our results suggest that alleviating these frictions—particularly by expanding access to local equity capital—could significantly increase startup formation and growth, especially among local founders, with important implications for the design of policies aimed at fostering entrepreneurship and economic development.

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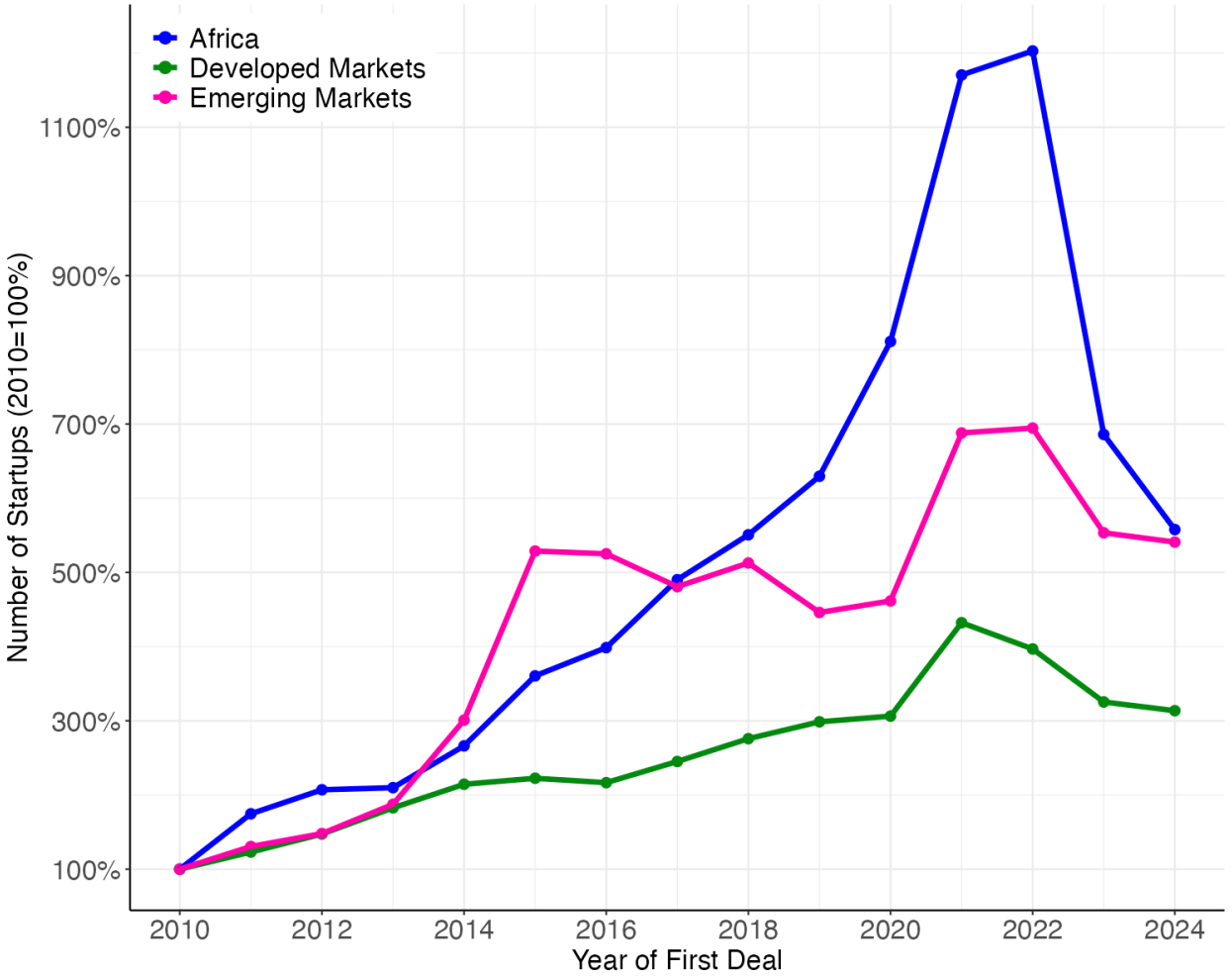



FIGURE 1. Number of New Startups

*Notes*: This figure displays the number of startups receiving their first recorded deal each year from 2010 to 2024 in Africa, Emerging Markets, and Developed Markets, using data derived from deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges, covering 5,801 companies in Africa, 65,821 in Emerging Markets, and 193,715 in Developed Markets. Developed Markets are identified based on classification criteria from MSCI, FTSE, and S&P.

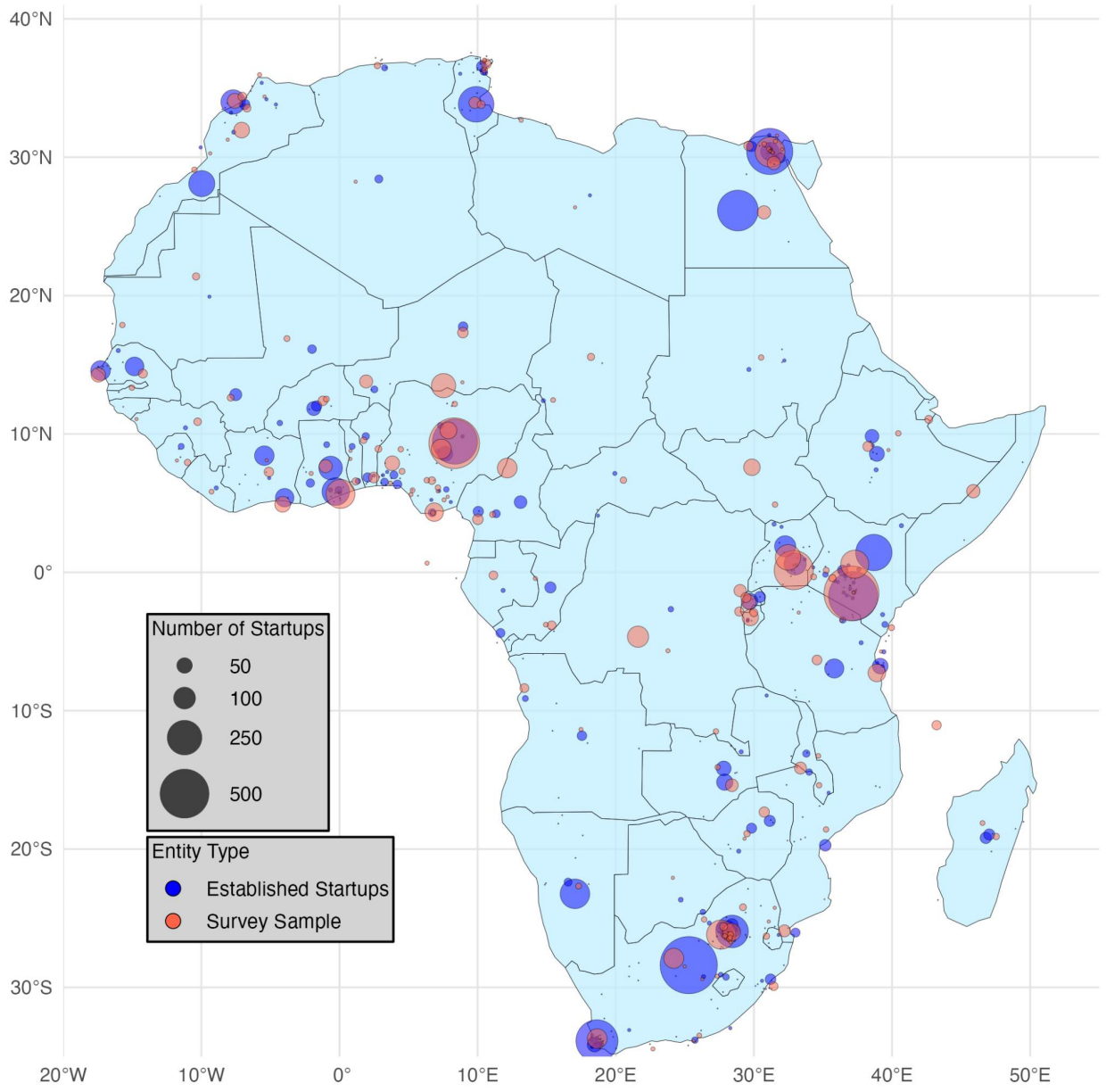
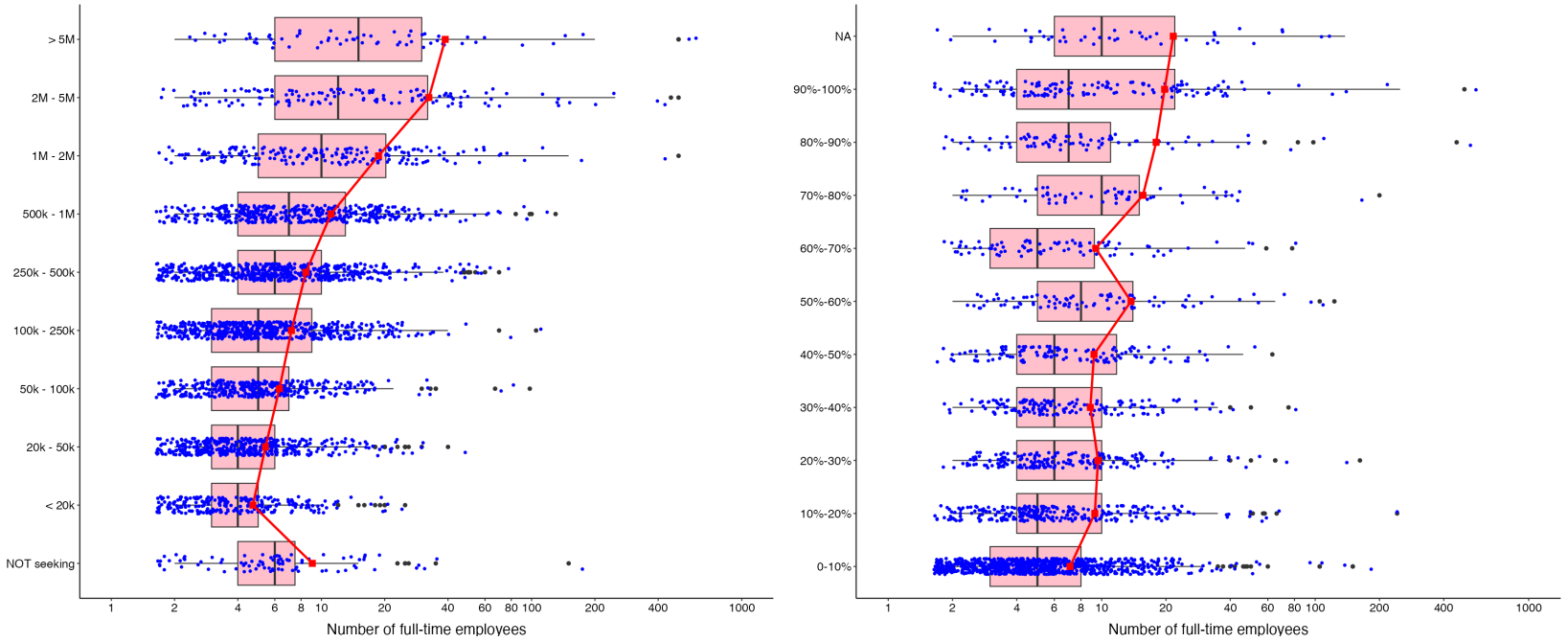



FIGURE 2. Geographical Distribution of Startups in Africa

*Notes*: This figure maps the geographic distribution of survey sample and established startups across African countries using their city information, with dot size proportional to the number of startups. When city information is unavailable, startups are plotted at the geographic center of their country. Established Startups are sourced from VCPE deal records in Pitchbook, Africa: The Big Deal and Briter Bridges in 2010-2024. The corresponding distributions for the two survey rounds separately are reported in Appendix Figure A2. A detailed comparison of the survey sample's country distribution with the representativeness benchmark is provided in Appendix Table A3.

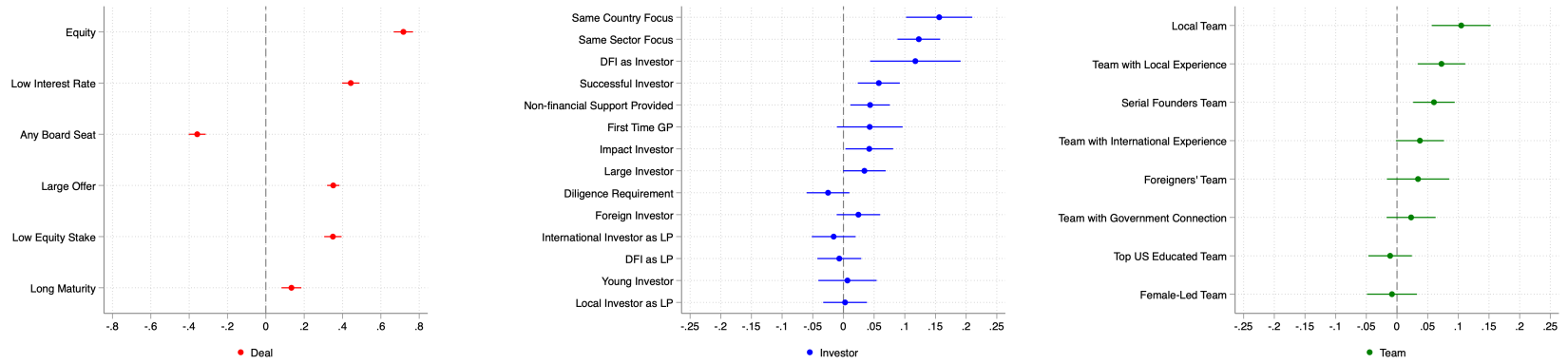



(A) Capital Sought by Startup Size

(B) Percentage of Capital Secured by Startup Size

FIGURE 3. Startups in Africa are Financially Constrained

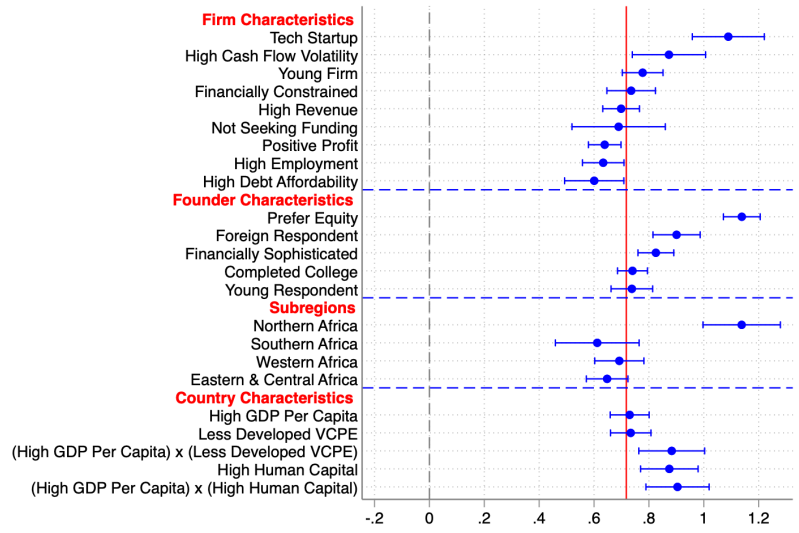
*Notes*: This figure plots survey respondents' capital needs and financing outcomes against firm size, measured by the number of full-time employees. Panel A presents the distribution of capital sought by startups, with the y-axis representing capital ranges and the x-axis representing the number of full-time employees. Panel B presents the percentage of capital needs successfully financed, with the y-axis displaying the percentage ranges and the x-axis representing the number of full-time employees. Each box plot displays the IQR of firm size distribution within each group, with blue dots indicating individual observations and a red line marking the mean.



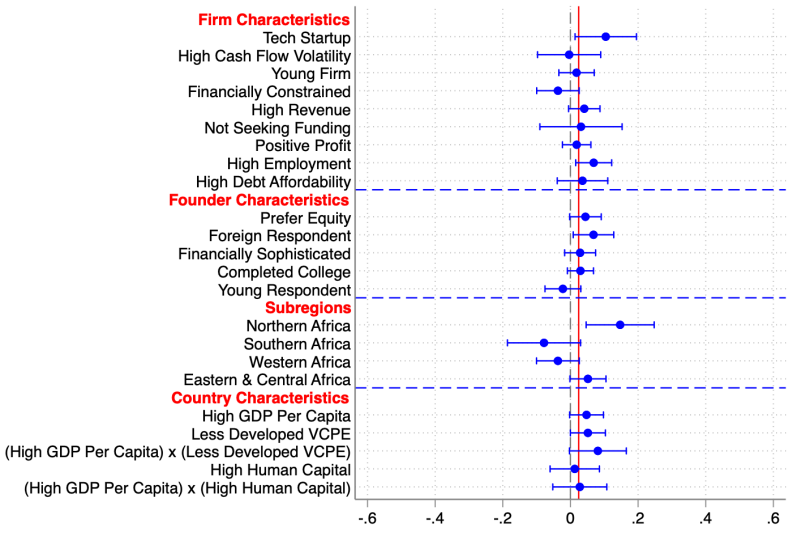

(A) "Deal" Characteristics (B) "Investor" Characteristics (C) "Team" Characteristics

FIGURE 4. Preferences for Investor and Financing Characteristics

*Notes*: This figure summarizes startups' preferences for different types of investment attributes featured in the synthetic investor and DFI profiles, as captured by $\beta_k$ in Equation 3.1. Panel A, B and C shows the preferences for "Deal", "Investor" and "Team" Characteristics, respectively. The figure also displays 95% confidence intervals for each investment attribute. Attributes are ordered from top to bottom by the absolute magnitude of their coefficients. The underlying coefficients presented in this figure are reported in Column (2) of Appendix Table A7. Appendix Tables A4 and A5 summarize the components and their inclusion probabilities used to generate the set of investment attributes in Table A6.



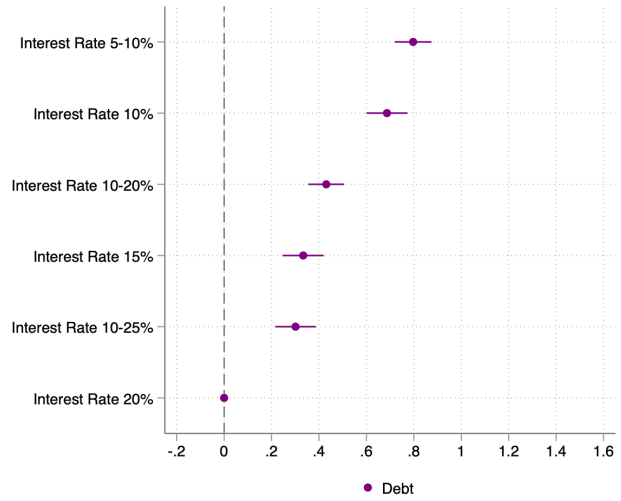

(A) Preference for Equity



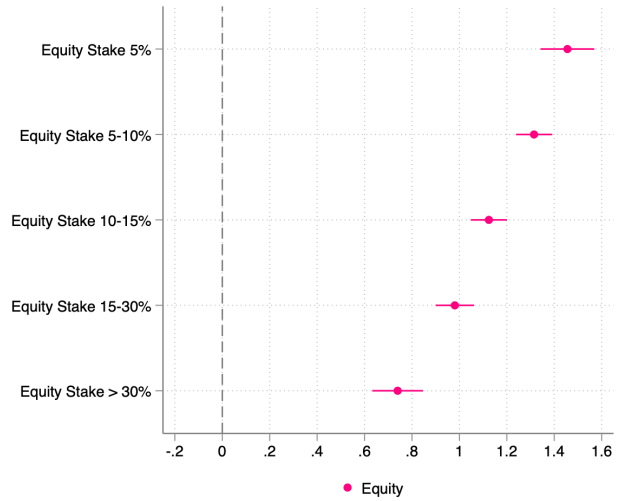

(B) Preference for Foreign Investor

FIGURE 5. Heterogeneity Analysis: Startup Preferences for Equity and Foreignness

*Notes*: This figure shows startups' preferences for two investment attributes—*"Equity"* and *"Foreign Investor"*—in the synthetic investor and DFI profiles, across different heterogeneity groups. Red vertical lines indicate the baseline coefficient estimated from the full sample. *"Tech Startup"* is defined as companies that appear technologically advanced, based on our manual classification procedure. *"High Cash Flow Volatility"* denotes firms indicating that forecasting their monthly cash flow is not easy. *"Young Firm"* refers to firms younger than the sample median (founded in or after 2021). *"Financially Constrained"* denotes firms for which the share of funding successfully secured in the past three years is below the sample median. *"High Revenue"* indicates firms with revenue above the sample median. *"Not Seeking Funding"* refers to respondents indicating that they are currently not seeking any external financing. *"Positive Profit"* includes firms reporting positive profits. *"High Employment"* denotes firms with employment size above the sample median. *"High Debt Affordability"* refers to firms reporting that the maximum interest rate they can afford to pay on a loan without harming their business exceeds 5%. *"Prefer Equity"* denotes respondents who self-report a preference for equity financing over debt financing. *"Foreign Respondent"* is defined as respondents with education or work experience outside Africa. *"Financially Sophisticated"* refers to respondents who correctly answer the following question: "Which of the following would you say is not a common source of equity funding? A. Venture capital; B. Bank loans; C. Angel investment." *"Completed College"* refers to respondents who have completed college education. *"Young Respondent"* refers to respondents with age below the sample median. Subregions are classified according to the UN geoscheme. *"High GDP Per Capita"* indicates that the respondent's country had GDP per capita in 2024 above the median of our sample. *"Less Developed VCPE"* indicates that the respondent's country had VCPE investment received in 2024 (from PitchBook+) as a share of GDP below the median of our sample. *"High Human Capital"* indicates that the respondent's country had an average of more than 8 years of schooling (corresponding to the 75th percentile of our sample) among the population aged 25–45. National average years of schooling are drawn from Barro and Lee (2013).




(A) Preference For Debt




(B) Preference For Equity

FIGURE 6. Heterogeneity Analysis: Startup Preferences for Debt vs. Equity

*Notes*: This figure shows the heterogeneity in preferences for debt and equity financing shown in the synthetic investor and DFI profiles. Panel A presents relative preferences for debt, split by different interest rates. Panel B presents relative preferences for equity, split by different equity stake requirement. We modified the specification of Equation 3.1 by replacing the indicator for *Equity*, *LowInterestRate* and *LowEquityStake* with six indicators for debt offers split by different *InterestRate*, and five indicators for equity offers split by different *EquityStake*. *InterestRate* denotes the annual interest rate associated with the debt offer in the synthetic profile, while *EquityStake* denotes the share of equity required in exchange for equity financing.



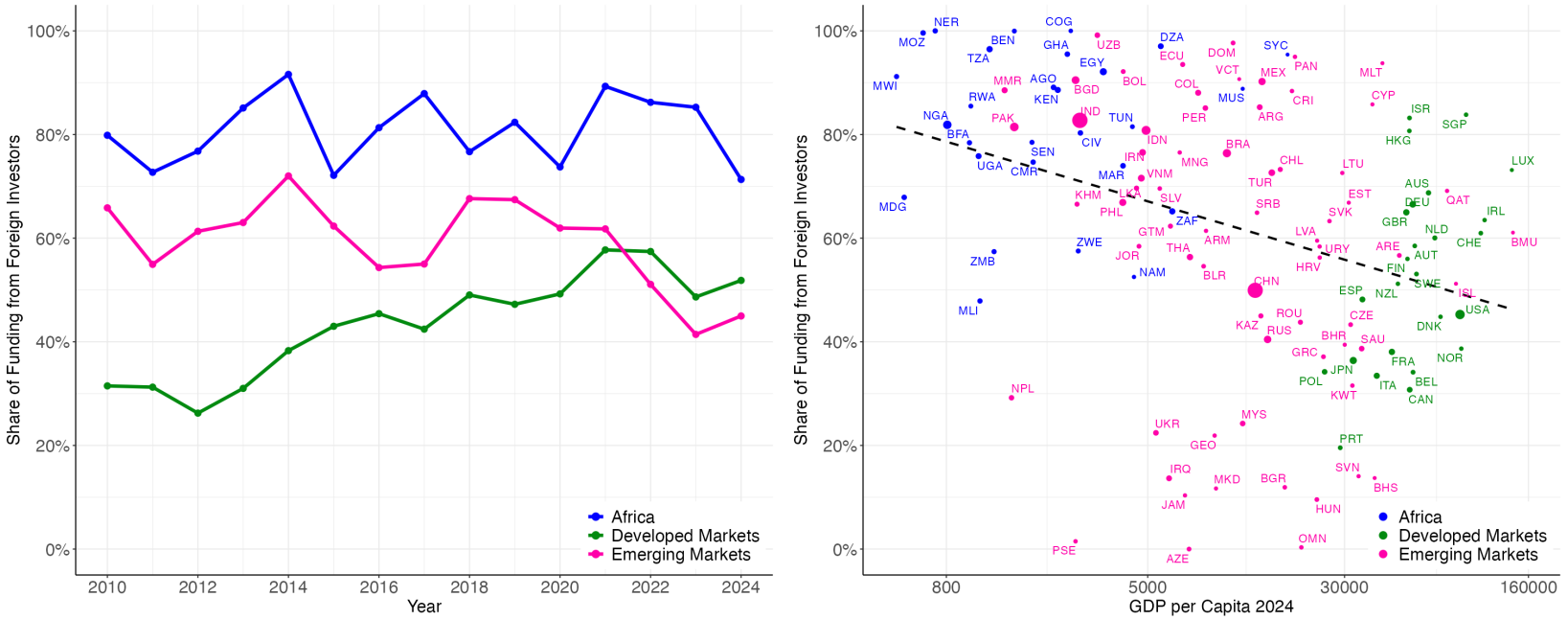

(A) Number of Financed Startups vs. GDP

(B) Amount of VCPE Investments by Startup Country vs. GDP

(C) Amount of VCPE Investments by Investor Country vs. GDP

FIGURE 7. Missing Local Equity Market in Africa

*Notes*: This figure plots several measures of VCPE activity against GDP per capita across countries in 2024, distinguishing among Africa, Emerging Markets, and Developed Markets. Panel A shows the number of financed startups per million people in each country over 2020–2024. Panel B shows the per capita USD value of VCPE deals received by startups in each country over 2020–2024. Panel C shows the per capita USD value of VCPE deals made by domestic investors in each country over 2020–2024. To ensure comparability, all three panels use the same scale on both axes. Marker size is proportional to country population in 2024. Developed Markets are identified based on classification criteria from MSCI, FTSE, and S&P. The data for VCPE deals are derived from PitchBook, Briter Bridges and Africa: The Big Deal, as discussed in Section 2.2. Both axes are log-transformed; the labels represent original values before log transformation.

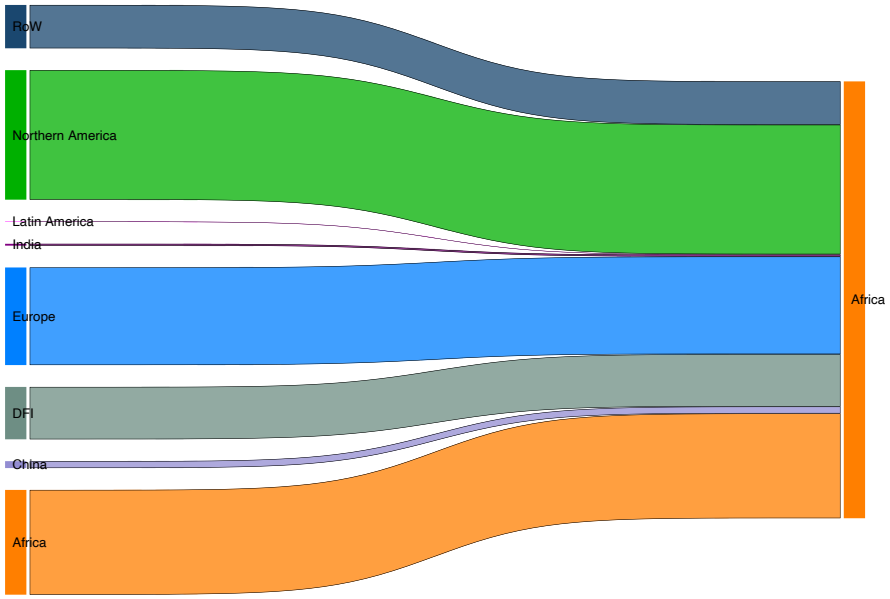



(A) Share of Funding from Foreign Investors

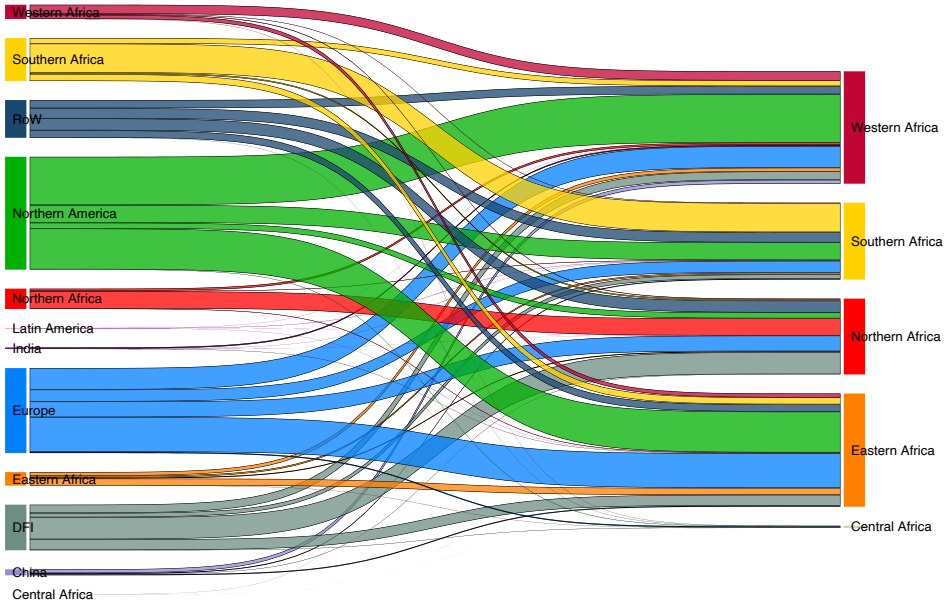
(B) Share of Funding from Foreign Investors vs. GDP

FIGURE 8. The Dominance of Foreign Capital

*Notes*: This figure shows the role of foreign capital in Africa, Emerging Markets, and Developed Markets. Panel A plots the annual share of funding from foreign investors across the three markets. Panel B shows the relationship between the share of funding involving at least one foreign investor from 2010 to 2024 and GDP per capita in 2024 for each country, with marker sizes reflect each country's population in 2024. The share of funding from foreign investors is defined as the proportion of total deal value that includes at least one investor from a foreign region. "Foreignness" is determined using seven major regions: Africa, Northern America, Europe, Latin America, China, India, and Rest of the World (RoW). Developed and Emerging Markets classifications follow criteria from MSCI, FTSE, and S&P. Data on venture capital and private equity (VCPE) deals are sourced from PitchBook, Briter Bridges and Africa: The Big Deal from 2010 to 2024, as described in Section 2.2. The y-axis in Panel B is log-transformed, but labels display the original values for easier interpretation.



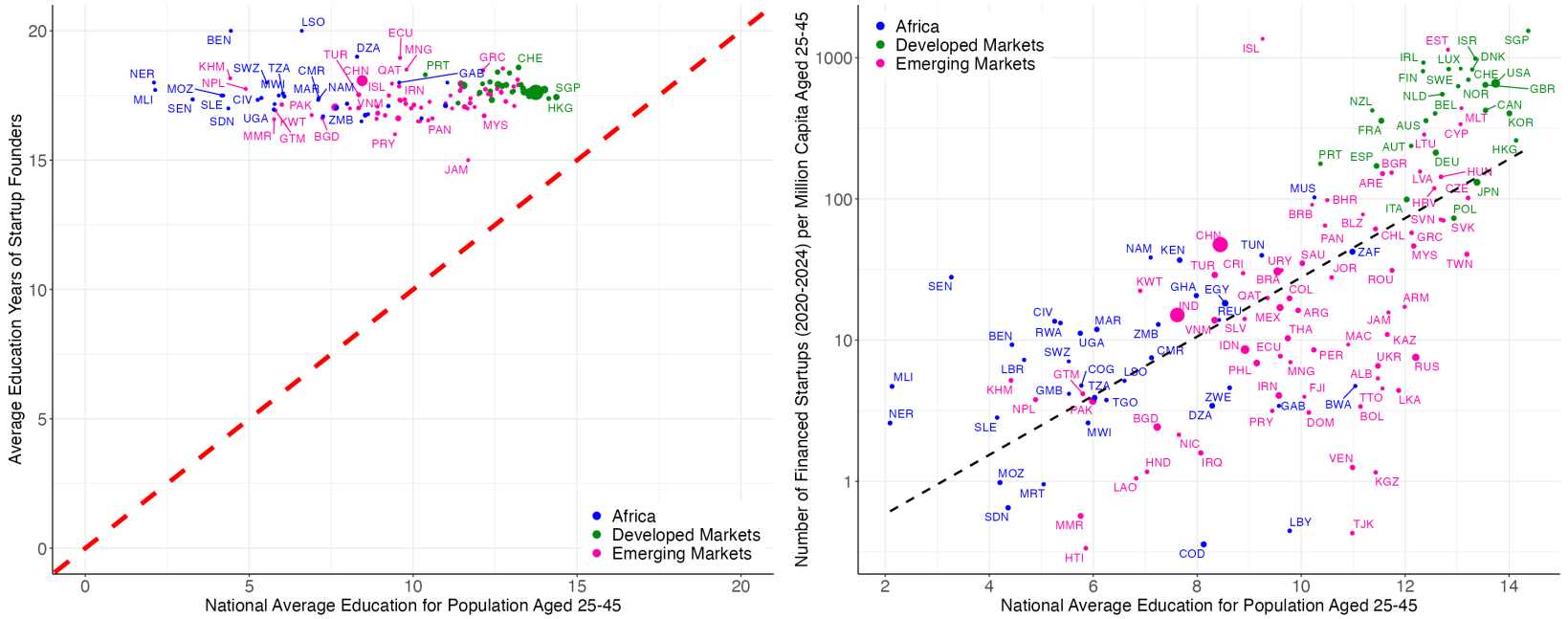

(A) By Region




(B) By Subregion

FIGURE 9. Who Finances Startups in Africa?

*Notes*: This figure shows the investment flows to Africa, showing the origins of capital from General Partners (GPs) to African startups using data sourced from PitchBook, Briter Bridges and Africa: The Big Deal from 2010 to 2024. The size of the flows represent the amount of funds in millions of USD. We exclude GP-company deal pairs when deal size or GP region is unknown, resulting in the exclusion of 31.0% of observations.

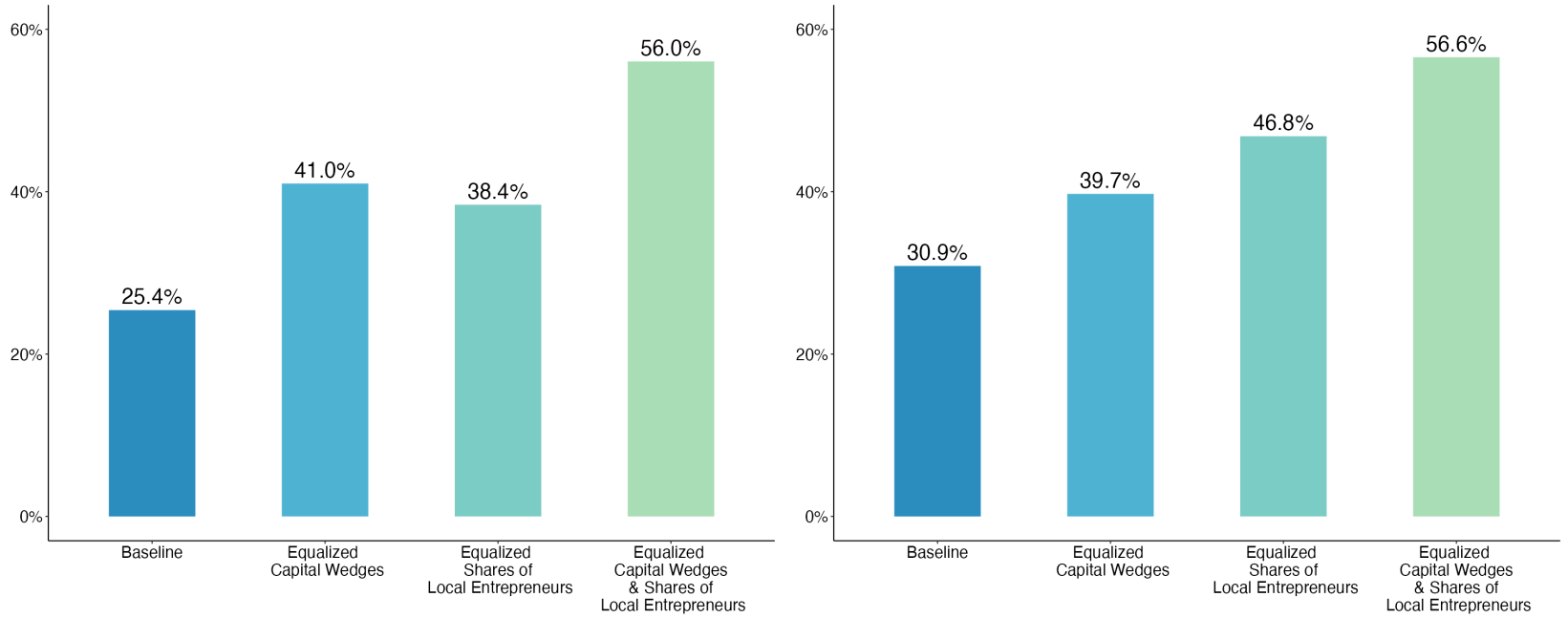



(A) Education: Startup Founders vs. National Average

(B) Number of Financed Startups vs. Average Education

FIGURE 10. Key Role for Higher Education

*Notes*: This figure illustrates the role of higher education in startup ecosystems across Africa, Emerging Markets, and Developed Markets. Panel A compares country-level average years of education between startup founders and the national population aged 25-45, with marker size proportional to the total number of established startups in each country. Panel B plots the number of financed startups per million people aged 25-45 over 2020–2024 against the national average years of education, with marker size proportional to population. National average education and population measures are drawn from Barro and Lee (2013), restricting the sample to individuals aged 25–45, the relevant age group for entrepreneurs. Data on venture capital and private equity (VCPE) deals are sourced from PitchBook, Briter Bridges and Africa: The Big Deal, supplemented with education records from Revelio Labs, as decribed in Section 2.2. Developed and Emerging Markets classifications follow criteria from MSCI, FTSE, and S&P. The y-axis in Panel B is log-transformed, but the labels represent the original values before log transformation to simplify interpretation.

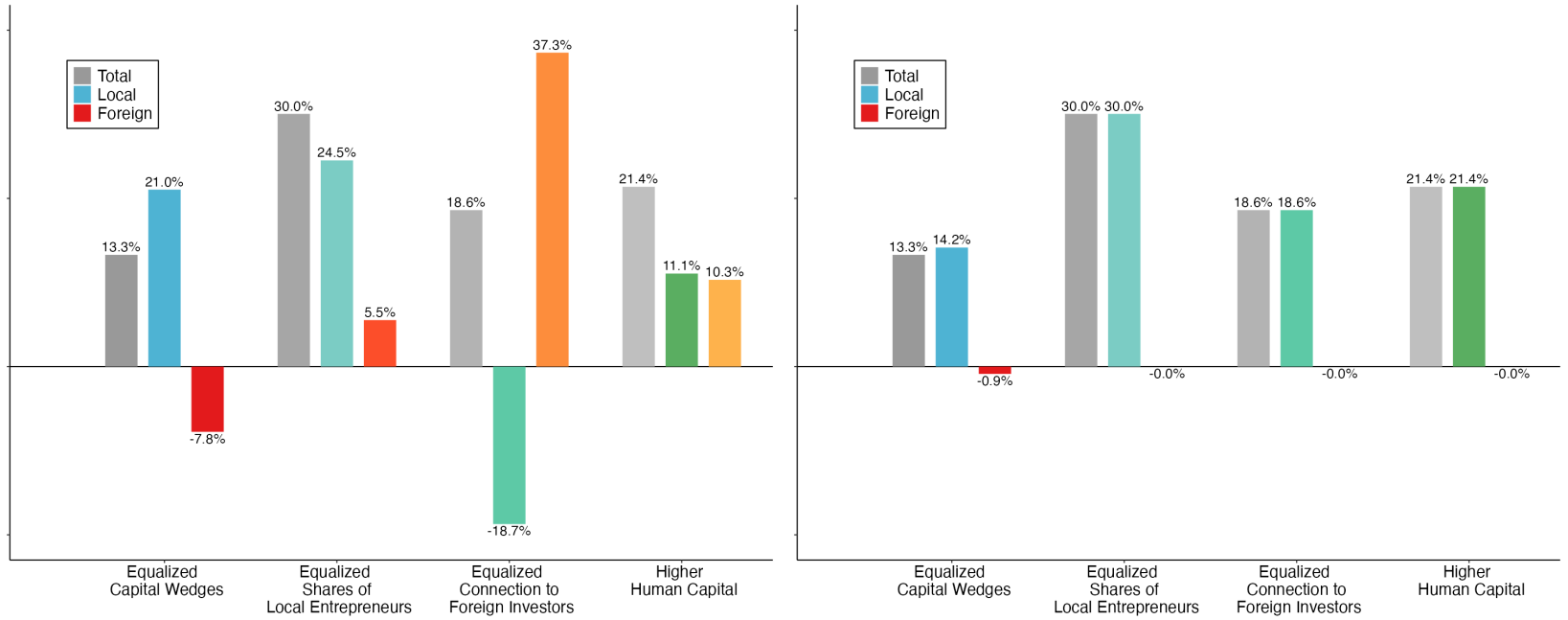



(A) Share of Local Investors

(B) Share of Local Entrepreneurs

FIGURE 11. Counterfactual Analysis on Foreignness

*Notes*: This figure reports counterfactual results for the shares of local investors and local entrepreneurs in Africa. "Baseline" uses the observed values in the data. "Equalized Capital Wedges" lowers the local capital wedge in Africa so that the ratio of the local investor wedge to the Northern America investor wedge matches the corresponding ratio in Europe. "Equalized Share of Local Entrepreneurs" raises the latent mass of local entrepreneurs so that their share matches that in Europe. "Equalized Capital Wedges & Shares of Local Entrepreneurs" combines these two counterfactual changes simultaneously. See Section 5.5 and Appendix A.4 for details on the model calibration and counterfactual setup.

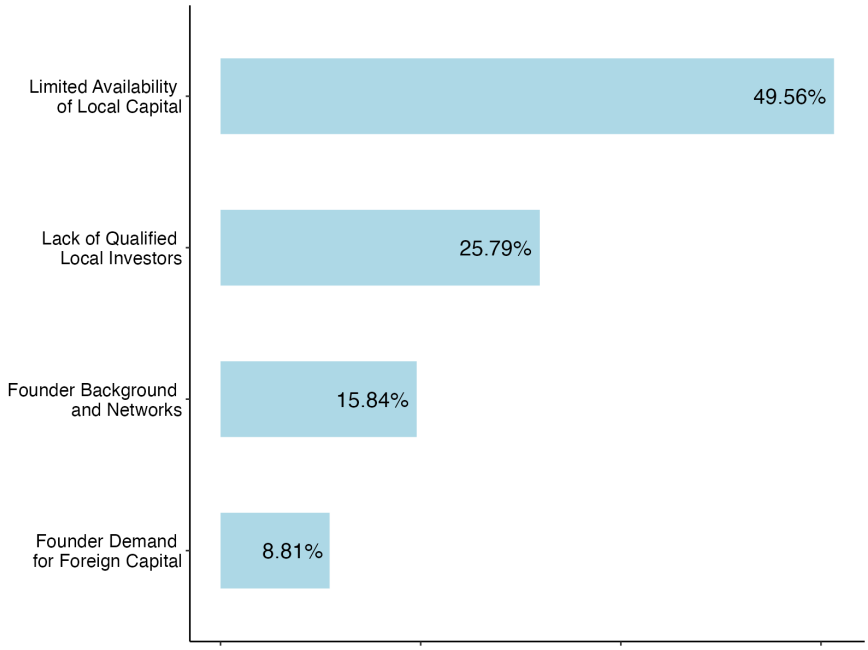



(A) By Investors' Region

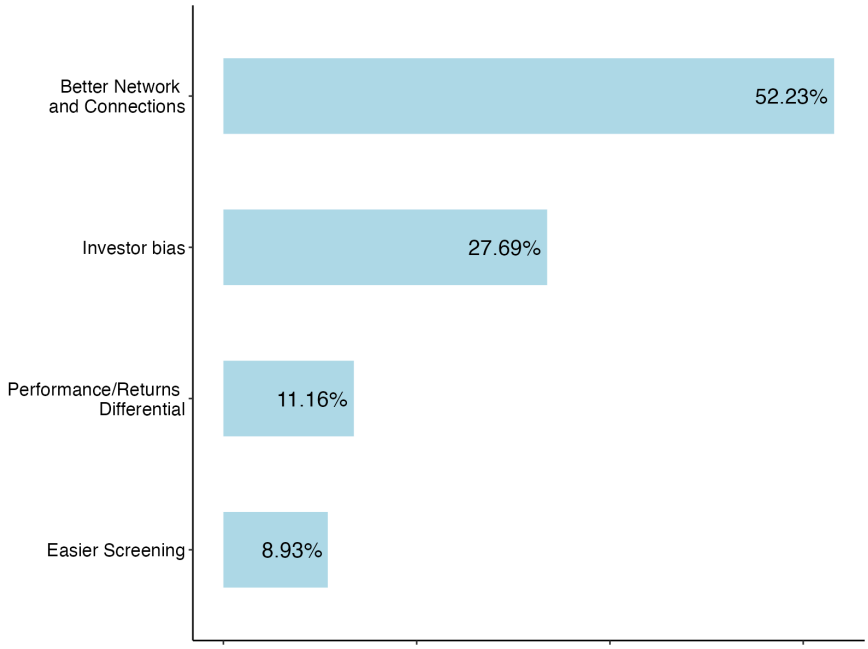
(B) By Entrepreneurs' Connection Type

FIGURE 12. Counterfactual Analysis on Startup Activity

*Notes*: This figure reports counterfactual results for the percentage change in the number of startups in Africa. Panel A decomposes the total change by investor origin, separating local and foreign investors, and Panel B decomposes it by entrepreneur type, separating local and foreign-connected entrepreneurs. All percentage changes are expressed relative to the observed total number of startups in Africa, including those for each subgroup, so that the changes for local and foreign types sum to the overall change. "Equalized Capital Wedges" lowers the local capital wedge in Africa so that the ratio of the local investor wedge to the Northern America investor wedge matches the corresponding ratio in Europe. "Equalized Share of Local Entrepreneurs" raises the latent mass of local entrepreneurs so that their share matches that in Europe. "Equalized Connection to Foreign Investors" raises the connection intensity between local entrepreneurs and foreign investors to the level of that between foreign-connected entrepreneurs and foreign investors. "Higher Human Capital" raises the latent mass of local entrepreneurs so that latent entrepreneur mass per capita matches that of the African country group with the highest average years of schooling. See Section 5.5 and Appendix A.4 for details on the model calibration and counterfactual setup.




(A) Why Foreign Capital?




(B) Why Foreign Founders?

FIGURE 13. Survey Result on Mechanisms for Foreignness

*Notes*: This figure reports responses to survey questions on the mechanisms underlying foreign dominance in African venture capital (VC) and private equity (PE) markets. Panel A presents respondents' views on the most important explanation for why approximately 80% of total VC and PE investment in Africa originates from foreign investors. Panel B presents respondents' views on the most important explanation for why around 50% of African startups receiving VC or PE funding have foreign founders or founders with strong foreign connections. Answer choices were displayed in randomized order. Both questions were optional and were included only in the second-round survey. The numbers of valid responses are 1,327 for Panel A and 1,210 for Panel B, corresponding to response rates of 93.5% and 91.5%, respectively.

TABLE 1. Descriptive Statistics of Early-Stage Startups

| (A) Founder Characteristics | Mean | SD | P10 | Median | P90 |
|---|---|---|---|---|---|
| Founder age | 37.8 | 8.9 | 28 | 37 | 50 |
| Share of founders who are males (%) | 71.3 | | | | |
| Share of founders with some college education (%) | 95.5 | | | | |
| Share of founders with graduate education (%) | 34.2 | | | | |
| Share of founders with foreign experience (%) | 42.6 | | | | |
| Percentage of executives not born in Africa (%) | 20.9 | 31.8 | 0 | 0 | 80 |
| Share of serial entrepreneurs (%) | 62.3 | | | | |
| **(B) Firm Characteristics** | **Mean** | **SD** | **P10** | **Median** | **P90** |
| Age of the company | 4 | 3.2 | 1 | 3 | 8 |
| Number of full-time employees | 11 | 16.8 | 2 | 6 | 22 |
| Share Profitable (%) | 70.1 | | | | |
| Percentage of equity share of main founder (%) | 70 | 28 | 30 | 70 | 100 |
| Percentage of equity share of co-founder(s) (%) | 23.3 | 24.5 | 0 | 20 | 51 |
| Revenue growth in the last three years (%) | 255.8 | 654.7 | -55.9 | 100 | 550 |
| **(C) Industry Distribution** | | | | **Early-Stage Startups (%)** | |
| Agriculture/AgriTech | | | | 26.22 | |
| Information Technology (IT/SaaS/AI) | | | | 9.88 | |
| Finance/FinTech | | | | 7.72 | |
| Education/EdTech | | | | 6.84 | |
| Retail/eCommerce | | | | 6.30 | |
| Health/BioTech | | | | 5.51 | |
| Energy/CleanTech | | | | 5.36 | |
| Manufacturing/Robotics | | | | 4.70 | |
| Media/Art/Entertainment | | | | 4.55 | |
| Transportation/Logistics/MobilityTech | | | | 4.03 | |
| Real Estate/Construction | | | | 3.96 | |
| Water/Sanitation/Waste Management | | | | 3.08 | |
| Hospitality/Smart Hospitality Solutions | | | | 2.99 | |
| Other | | | | 8.87 | |

*Notes*: This table presents descriptive statistics for the 4,444 early-stage startups surveyed as part of the "Connecting Africa's Entrepreneurs" study. All variables are self-reported by respondents. Panel A summarizes founder characteristics. Share of founders with some college education is the proportion of founders who have started or completed college or undergraduate education. Share of founders with graduate education is the percentage of founders who have started or completed graduate education (Masters, MBA, or PhD). Share of founders with foreign experience refers to the proportion of executive team members who have studied outside of Africa. Share of serial entrepreneurs represents the percentage of founders who have started at least one other business. Panel B summarizes firm attributes. Share of startups with revenue measures the percentage of firms that reported generating revenue in the previous fiscal year. All revenue data have been manually validated, as discussed in Appendix A.3.3. Percentage of equity share of main founder denotes the average equity ownership retained by the primary founder. Percentage of equity share of co-founder(s) reflects the combined equity stake held by co-founders, where applicable. Revenue growth over the past three years captures the percentage increase in revenue over the preceding three-year period, conditional on revenue being reported. Panel C presents the industry distribution of early-stage startups. The "Other" category includes startups operating in industries not explicitly listed.

## Table 2. Descriptive Statistics of Established Startups

| **(A) Industry** | **Africa** | **Emerging Markets** | **Developed Markets** |
|---|---|---|---|
| Information Technology (IT/SaaS/AI) | 22.9% | 36.8% | 39.2% |
| Finance/FinTech | 12.7% | 3.8% | 3.9% |
| Manufacturing/Robotics | 10.4% | 15.9% | 11.0% |
| Health/BioTech | 7.4% | 10.8% | 15.5% |
| Media/Art/Entertainment | 6.6% | 7.4% | 7.9% |
| Retail/eCommerce | 5.7% | 3.6% | 1.9% |
| Transportation/Logistics/MobilityTech | 5.7% | 4.6% | 2.8% |
| Energy/CleanTech | 5.5% | 2.7% | 3.5% |
| Agriculture/AgriTech | 5.4% | 1.0% | 0.8% |
| Education/EdTech | 3.9% | 2.7% | 1.4% |
| Real Estate/Construction | 2.9% | 2.1% | 2.0% |
| Hospitality/Smart Hospitality Solutions | 2.0% | 2.3% | 2.0% |
| Water/Sanitation/Waste Management | 1.4% | 0.4% | 0.5% |
| Other | 7.4% | 5.9% | 7.7% |

| **(B) Deal Types** | **Africa** | **Emerging Markets** | **Developed Markets** |
|---|---|---|---|
| Accelerator/Incubator | 3.7% | 0.4% | 0.8% |
| Seed Round | 32.9% | 19.5% | 29.8% |
| Early Stage VC | 33.3% | 44.2% | 31.1% |
| Later Stage VC | 11.0% | 29.0% | 27.3% |
| PE Growth/Expansion | 19.0% | 7.0% | 11.0% |

| **(C) Firm & Deal Characterisrics** | **Africa** | | | | | | **Emerging Markets** | | | | | | **Developed Markets** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | P10 | Median | P90 | Missing (%) | Mean | SD | P10 | Median | P90 | Missing (%) | Mean | SD | P10 | Median | P90 | Missing (%) |
| Age at the First Deal | 6.8 | 11.5 | 0.0 | 3.0 | 17.0 | 5.5 | 4.7 | 7.8 | 0.0 | 2.0 | 12.0 | 3.6 | 6.3 | 13.5 | 0.0 | 2.0 | 15.0 | 3.2 |
| Employment at the First Deal | 36.5 | 159.0 | 2.0 | 9.0 | 62.0 | 28.2 | 36.9 | 230.9 | 1.0 | 7.0 | 55.0 | 46.4 | 39.9 | 503.7 | 2.0 | 8.0 | 50.0 | 22.0 |
| Number of Founders | 4.0 | 5.9 | 1.0 | 3.0 | 8.0 | 36.2 | 4.3 | 7.9 | 1.0 | 3.0 | 8.0 | 58.0 | 5.1 | 10.9 | 1.0 | 3.0 | 10.0 | 26.0 |
| Share of Female Founders | 0.2 | 0.3 | 0.0 | 0.0 | 0.7 | 36.2 | 0.2 | 0.3 | 0.0 | 0.0 | 0.6 | 58.0 | 0.2 | 0.3 | 0.0 | 0.0 | 0.5 | 26.0 |
| Total Deal size per firm (in millions USD) | 12.4 | 39.8 | 0.1 | 1.0 | 25.0 | 40.0 | 15.0 | 49.3 | 0.0 | 0.5 | 30.3 | 40.1 | 15.0 | 45.7 | 0.0 | 1.3 | 31.5 | 29.5 |
| Total Deal count per firm | 1.6 | 1.3 | 1.0 | 1.0 | 3.0 | 0.0 | 1.9 | 1.4 | 1.0 | 1.0 | 4.0 | 0.0 | 1.8 | 1.3 | 1.0 | 1.0 | 4.0 | 0.0 |
| Deal Size (in millions USD) | 7.2 | 20.7 | 0.1 | 0.9 | 16.0 | 37.7 | 17.2 | 44.5 | 0.2 | 3.0 | 37.0 | 46.4 | 11.5 | 29.1 | 0.2 | 2.5 | 25.0 | 26.4 |
| # of Investor per Deal | 2.6 | 3.4 | 1.0 | 1.0 | 6.0 | 7.4 | 2.5 | 2.9 | 1.0 | 2.0 | 5.0 | 12.3 | 3.4 | 3.9 | 1.0 | 2.0 | 8.0 | 16.5 |

*Notes:* This table presents summary statistics on industry distribution, firm characteristics, and deal characteristics for Established Startups across Africa, Emerging Markets, and Developed Markets. Panel A reports the distribution of industries among established startups. Panel B reports the distribution of deal types. Panel C reports the distribution of firm and deal characteristics by region. Established Startups are defined as firms that received VCPE financing between 2010 and 2024, based on data from PitchBook, Africa: The Big Deal, and Briter Bridges, supplemented with founder and employee information from Revelio Labs, as described in Section 2.2. The sample covers 5,801 unique companies and 9,064 unique deals in Africa, 65,821 unique companies and 124,307 unique deals in Emerging Markets, and 193,715 unique companies and 356,315 unique deals in Developed Markets. Developed Markets are identified based on the classification standards of MSCI, FTSE, and S&P.

TABLE 3. Access to External Finance is a Key Constraint

(A) Main Source of Funding

| Main Source of the Funding | Share (%), Split by Number of Employees | | | | |
|---|---|---|---|---|---|
| | All (Avg=11) | 2-5 (Avg=4) | 6-10 (Avg=8) | 11-20 (Avg=15) | 21+ (Avg=48) |
| Personal savings/resources | 36.31 | 45.06 | 33.33 | 27.77 | 18.92 |
| Family and friends | 18.10 | 19.02 | 20.67 | 15.62 | 12.01 |
| Bank loans | 13.33 | 8.63 | 15.47 | 15.18 | 25.23 |
| Angel or VCs | 12.02 | 7.17 | 10.93 | 18.44 | 25.53 |
| Government funded or backed loans | 7.11 | 7.32 | 7.73 | 6.72 | 5.41 |
| Others (Grants, Crowdfunding, etc.) | 13.12 | 12.80 | 11.87 | 16.27 | 12.91 |
| Number of Respondents | 2911 | 1367 | 750 | 461 | 333 |

(B) Most Binding Obstacles Preventing Business Growth

| Most Binding Obstacles | Share (%), Split by Number of Employees | | | | |
|---|---|---|---|---|---|
| | All (Avg=11) | 2-5 (Avg=4) | 6-10 (Avg=8) | 11-20 (Avg=15) | 21+ (Avg=48) |
| Access to finance and funding sources | 78.19 | 78.74 | 79.98 | 78.28 | 71.18 |
| Access to markets | 33.06 | 34.95 | 33.15 | 30.00 | 28.17 |
| Access to good infrastructure | 27.30 | 28.31 | 28.44 | 26.72 | 20.65 |
| Lack of other qualified and skilled labor | 12.20 | 12.09 | 11.32 | 13.91 | 12.47 |
| Business regulations | 11.54 | 11.45 | 10.42 | 10.78 | 15.70 |
| Lack of qualified and skilled general managers | 8.38 | 6.60 | 8.15 | 9.84 | 15.27 |
| Lack of qualified and skilled financial managers | 6.47 | 5.63 | 7.16 | 7.50 | 7.31 |
| Other | 1.78 | 1.97 | 1.27 | 2.03 | 1.72 |
| Number of Respondents | 4392 | 2183 | 1104 | 640 | 465 |

*Notes*: This table shows early-stage startups' main source of funding and the most binding obstacles preventing business growth. Panel A summarizes the main source of funding, based on answers to the question: "What was the main source of the funding you have received in the last three years?" This question is shown only if the respondent indicated that they had sought funding in the past three years. Panel B summarizes the the most binding obstacles preventing business growth, based on answers to the multiple choice question: "What are the most binding obstacles preventing your business from growing?" Column (1) reports the share of respondents across each choices. Columns (2) to (5) reports the shares within 4 size groups split by number of employees, with the average number of employees in each group reported in parentheses. The numbers of respondents that answered each question are reported in the last row.

TABLE 4. Dominance of Foreign Human Capital

| Company HQ | (A) Characteristics of Founders | | | | | |
|---|---|---|---|---|---|---|
| | (1) % female | (2) % white | (3) % college | (4) % foreign edu | (5) % foreign exp | (6) % foreign edu or exp |
| **Africa** | 21.8 | 48.8 | 80.5 | 46.5 | 57.8 | 69.1 |
| N Africa | 16.3 | 81.0 | 77.8 | 39.2 | 54.0 | 63.9 |
| E Africa | 25.5 | 36.9 | 84.2 | 55.9 | 59.6 | 71.7 |
| C Africa | 21.6 | 43.2 | 77.7 | 63.5 | 73.9 | 85.8 |
| W Africa | 22.2 | 25.3 | 85.0 | 52.3 | 65.8 | 75.7 |
| S Africa | 22.4 | 58.0 | 74.7 | 35.7 | 49.2 | 59.6 |
| **Europe** | 20.8 | 87.2 | 72.5 | 21.3 | 31.8 | 40.2 |
| **NorthernAmerica** | 21.0 | 76.5 | 83.0 | 18.9 | 26.3 | 32.6 |
| **LatinAmerica** | 16.9 | 37.7 | 64.1 | 34.3 | 31.9 | 47.8 |
| **India** | 15.1 | 9.0 | 83.2 | 20.3 | 30.3 | 38.5 |
| **RoW** | 20.1 | 55.1 | 78.1 | 38.8 | 45.1 | 57.6 |

| Company HQ | (B) Characteristics of Current Employees | | | | | |
|---|---|---|---|---|---|---|
| | (1) % female | (2) % white | (3) % college | (4) % foreign edu | (5) % foreign exp | (6) % foreign edu or exp |
| **Africa** | 35.2 | 38.4 | 66.7 | 34.9 | 27.8 | 37.2 |
| N Africa | 30.1 | 75.3 | 64.6 | 33.6 | 31.2 | 40.1 |
| E Africa | 37.2 | 17.6 | 74.0 | 34.4 | 21.1 | 41.3 |
| C Africa | 37.5 | 33.5 | 64.2 | 39.8 | 39.1 | 48.7 |
| W Africa | 32.7 | 19.4 | 77.1 | 39.3 | 30.8 | 41.0 |
| S Africa | 41.2 | 34.5 | 52.3 | 31.3 | 26.3 | 34.9 |
| **Europe** | 40.3 | 77.2 | 64.2 | 36.6 | 39.3 | 44.6 |
| **NorthernAmerica** | 41.7 | 63.8 | 76.1 | 32.6 | 37.0 | 41.1 |
| **LatinAmerica** | 40.4 | 37.3 | 34.4 | 23.6 | 20.8 | 26.6 |
| **India** | 22.2 | 6.8 | 85.2 | 20.8 | 19.2 | 22.5 |
| **RoW** | 35.4 | 42.6 | 69.0 | 44.4 | 40.4 | 47.8 |

*Notes*: This table reports descriptive statistics for founders and current employees (including founders who remain employed by the firm) in established startups, using data from PitchBook, Briter Bridges, and Africa: The Big Deal for 2010–2024, merged with individual-level information from Revelio Labs. Panels (A) and (B) present summary statistics for founders and employees, respectively. Columns (1)–(6) report the shares of founders or employees who (1) are female; (2) are white, as defined in Appendix A.3.3; (3) have attained college-level education; (4) have foreign education experience; (5) have foreign work experience; and (6) have foreign education or work experience. The variables in columns (3)–(6) are constructed using founders' or employees' education and work experience measured prior to the startup's first recorded VCPE deal. "Foreignness" is determined using seven major regions: Africa, North America, Europe, Latin America, China, India, and the Rest of the World (RoW).

TABLE 5. The Role of Founders' Connections on Capital Flow

| | Prob. making 1+ deals | | | Total Funds (USD mln) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Same Investor and Founder Edu Country | 0.020*** | | 0.004 | 3.034*** | | 2.172*** |
| | (0.005) | | (0.005) | (0.376) | | (0.384) |
| Same Investor and Founder Exp Country | | 0.076*** | 0.075*** | | 4.361*** | 3.936*** |
| | | (0.005) | (0.005) | | (0.362) | (0.370) |
| Log(Distance Investor-Company) | -0.002 | -0.002 | -0.002 | -0.350** | -0.327** | -0.330** |
| | (0.002) | (0.002) | (0.002) | (0.122) | (0.122) | (0.122) |
| Observations | 176973 | 176971 | 176971 | 174786 | 174785 | 174785 |
| Mean Dep. Var. | 0.033 | 0.032 | 0.031 | 0.534 | 0.524 | 0.495 |
| Company Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Investor Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Founder Edu Country FE | Yes | | Yes | Yes | | Yes |
| Founder Exp Country FE | | Yes | Yes | | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table reports the effect of foreign connections on access to capital. Columns (1)–(3) estimate the effect of having a foreign connection—proxied by foreign education and/or work experience prior to receiving the first VCPE deal—on the probability of securing at least one deal, while Columns (4)–(6) estimate the effect on the total amount of funding received. Section 4.3.1 describes the empirical specification in detail. The underlying data consist of all possible founder–investor country pairs constructed from VCPE deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges during 2010–2024, supplemented with education and working experience data of founders obtained from Revelio Lab. The sample is restricted to potential matches between African founders and non-African investors. Robust standard errors are reported in parentheses. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

TABLE 6. Limited Outperformance by Foreign (Connected) Startups

| | Unconditional Performance | | | | | Conditional Performance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Successful Exit | (2) IPO | (3) M&A | (4) Bankruptcy | (5) Employment Growth | (6) Successful Exit | (7) IPO | (8) M&A | (9) Bankruptcy | (10) Employment Growth |
| Foreign Connected Startup | 0.049*** | 0.009 | 0.026** | -0.076*** | -7.162 | -0.026 | -0.002 | 0.006 | -0.004 | -6.844 |
| | (0.018) | (0.006) | (0.013) | (0.016) | (6.417) | (0.019) | (0.006) | (0.014) | (0.016) | (6.785) |
| Foreign Startup | -0.006 | -0.001 | 0.006 | -0.033** | 19.522 | -0.023 | -0.004 | 0.003 | 0.002 | 19.747 |
| | (0.015) | (0.004) | (0.010) | (0.015) | (23.404) | (0.015) | (0.004) | (0.010) | (0.014) | (23.465) |
| Unique Firms | 4188 | 4188 | 4188 | 4188 | 2345 | 4188 | 4188 | 4188 | 4188 | 2345 |
| Number of Events | 1094 | 55 | 324 | 830 | - | 1094 | 55 | 324 | 830 | - |
| Mean DV | 0.261 | 0.013 | 0.077 | 0.198 | 32.124 | 0.261 | 0.013 | 0.077 | 0.198 | 32.124 |
| Controls | No | No | No | No | No | Yes | Yes | Yes | Yes | Yes |
| Country-sector FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First-deal Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.285 | 0.083 | 0.116 | 0.099 | 0.198 | 0.323 | 0.125 | 0.135 | 0.174 | 0.198 |

*Notes*: This table compares startup performance across local startups, foreign startups, and foreign-connected startups. "Foreign Connected Startup" refers to those companies that have at least one founder whose education or work experience prior to the year of the first deal occurred in the same country as a future foreign investor. "Foreign Startup" refers to those companies that have at least one founder with foreign education or foreign work experience prior to the year of the first deal. Section 4.3.2 describes the empirical specification in detail. Columns (1)-(5) reports unconditional, Columns (6)-(10) report conditional performances. The underlying data consist of all established startups that have received VCPE financing in 2010-2024, as recorded in PitchBook, Africa: The Big Deal, and Briter Bridges, supplemented with education and working experience data of founders obtained from Revelio Lab. Robust standard errors are reported in parentheses. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

TABLE 7. Foreign Capital Supply Shocks Affect Startup Activity

| | Africa | | | |
|---|---|---|---|---|
| | Log Deal Size | | Log Deal Count | |
| | (1) | (2) | (3) | (4) |
| instrument (size) | 0.076*** | 0.258*** | | |
| | (0.024) | (0.065) | | |
| instrument (count) | | | 0.070*** | 0.423*** |
| | | | (0.018) | (0.086) |
| Constant | 0.783*** | 0.034 | 0.505*** | -0.358* |
| | (0.115) | (0.270) | (0.048) | (0.211) |
| Year FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | No | Yes | No |
| Sector FE | Yes | No | Yes | No |
| Country-Sector FE | No | Yes | No | Yes |
| N Country-Sector | 147 | 147 | 147 | 147 |
| Obs. | 1,470 | 1,470 | 1,470 | 1,470 |
| R-Squared | 0.477 | 0.613 | 0.658 | 0.767 |

*Notes*: This table reports the effects of foreign capital supply on local startup activity in Africa. Columns (1)–(2) use the total U.S. dollar value of VCPE deals as outcome measures, while Columns (3)–(4) use the total number of VCPE deals. The causal effects are estimated by proxying foreign capital supply shocks with Bartik-style shift–share instruments. Section 4.3.3 describes the empirical specification and the construction of the shift–share instruments in detail. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Online Appendix

## Appendix A.1. Additional Tables and Figures

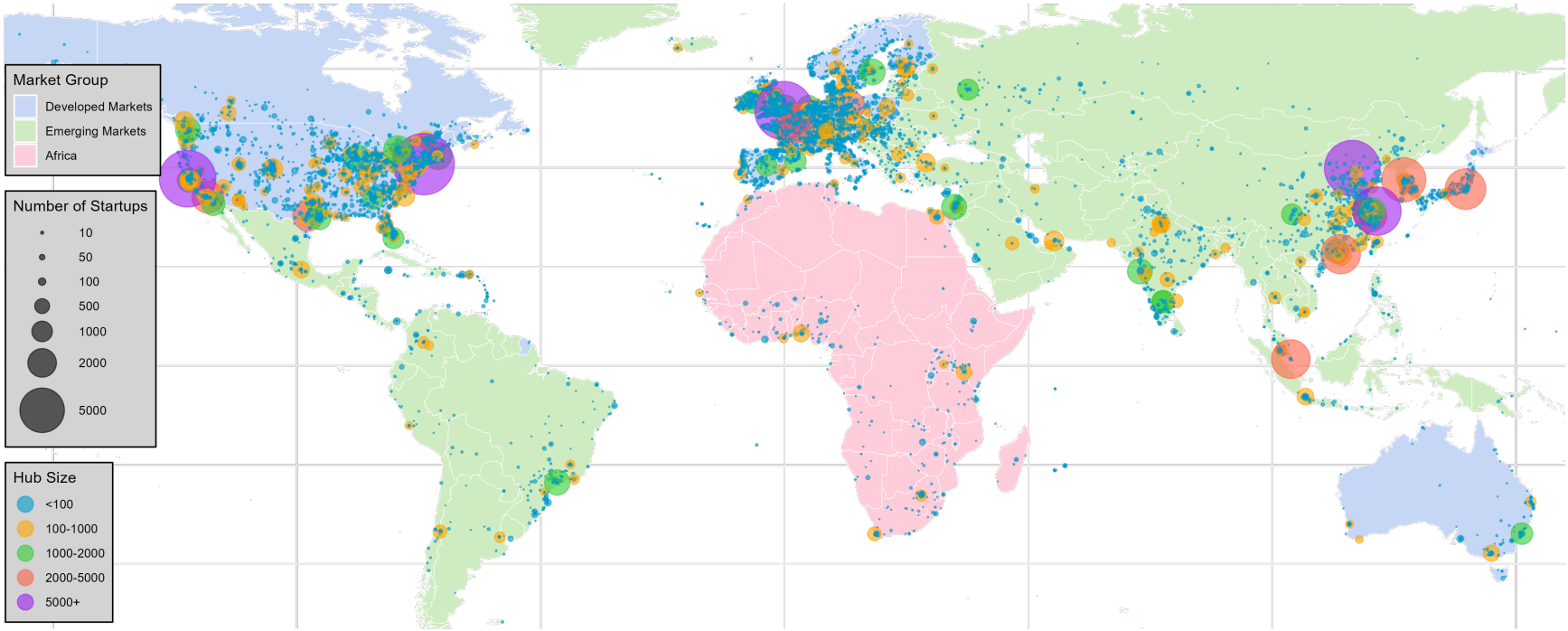



Figure A1. Global Startup Distribution

*Notes*: This figure displays the global distribution of startups that received at least one deal between 2010 and 2024 across various cities, using data derived from deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges, covering 5,801 companies in Africa, 65,821 in Emerging Markets, and 193,715 in Developed Markets. Developed Markets are identified based on classification criteria from MSCI, FTSE, and S&P. Each circle represents a city, and its size corresponds to the number of startups located in that city.

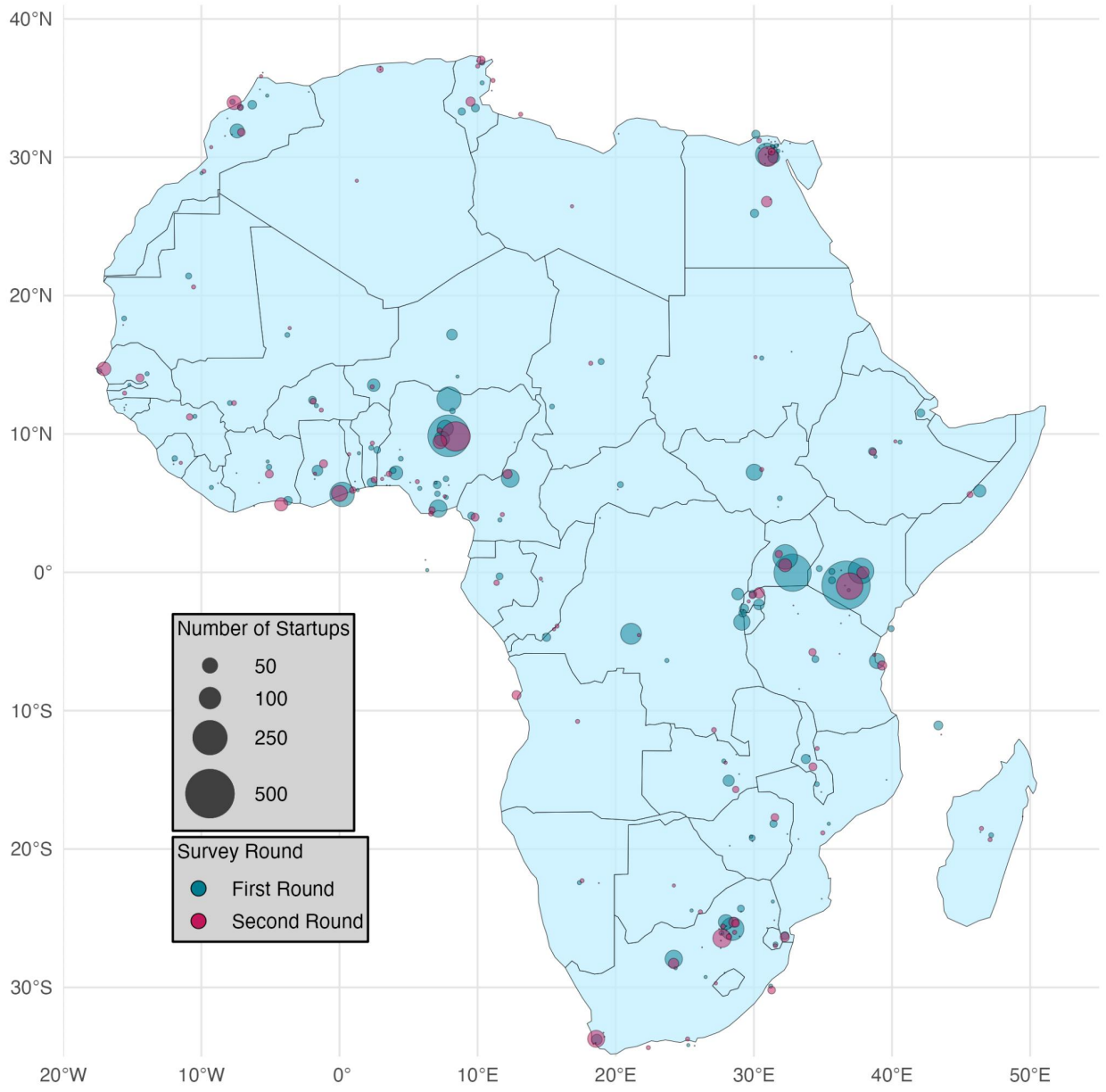



FIGURE A2. Geographical Distribution of Survey Samples by Survey Round

*Notes*: This figure presents the geographic distribution of survey respondents across African countries, shown separately for the two survey rounds. Dot sizes are proportional to the number of respondents in each country or city. For additional details on the survey design and the two survey rounds, see Section 3.1.




(A) Africa (B) Emerging Markets (C) Developed Markets

FIGURE A3. Startup Descriptions Around the World

*Notes:* This figure presents word clouds constructed from company descriptions of Established Startups sourced from PitchBook over the period 2010–2024. The sample includes 4,372 firms in Africa, 65,821 firms in Emerging Markets, and 193,715 firms in Developed Markets. Market classifications follow the criteria of MSCI, FTSE, and S&P. We remove common stop words and additional words that are unrelated to the company description.




(A) Official Advertisement at the IFC's Website

**Connecting Africa's Entrepreneurs: An IFC Study**

Dear Organization,

The **International Finance Corporation** (IFC), a member of **the World Bank Group**, has been a long-time promoter of growth of entrepreneurial ecosystems in Africa, by investing in and supporting companies, funds, accelerators/incubators, and other organizations.

The IFC is currently conducting a study to better understand and improve the matching process between entrepreneurs like you and investors/accelerators. The study is motivated by the difficulties many high-potential entrepreneurs face in obtaining capital and other support.

We have selected you as one of the ideal entrepreneurs we would like to participate in this exercise. To participate, we would like to kindly request your time in filling out this 30-minute survey. We know this is a big ask, but the survey is aimed to better understand your needs in an engaging way. In addition to asking for some information about your company, we will ask you to "rate" hypothetical profiles of potential partners. Based on your rating, we will use our extensive data on investors, ecosystem partners, and our contacts to introduce you to the partners that match your preferences. Please notice that some high-profiled investors, accelerators, and incubators that are interested in firms like yours have directly opted in to participate in this matching exercise.

Specifically, the **incentives for you** are:

1. The IFC will share your information with a selected group of 5-10 investors/accelerators/incubators and potentially make direct introductions whenever there is a mutual fit.
2. We will provide you with a list curated by the IFC list of top 50-100 recommended investment partners, together with a short report outlining why they are a particularly good match for you.
3. For some respondents (selected randomly among those who complete the survey), we will organize direct calls with IFC investment consultants (who will be instructed to help you match to the organizations matching your preferences).
4. For others (also selected randomly), we will organize meetings directly with IFC investment associates and partners to discuss potential investment opportunities in your company.

If you are **(a) the founder/manager** of a company (with at least 2 full-time employees) that started operations for less than 10 years and with main focus in Africa, **(b) looking for funding** to grow your company, and **(c) would like to participate in this match-making opportunity**, please complete our following survey.

The survey is available in English, French, and Portuguese.

If you would like to learn more about how this study can be helpful for you and your organization, please visit the IFC website for the project at https://www.ifc.org/en/events/2023/connecting-africas-entrepreneurs. Please contact a representative from the IFC at ifcsurveys@ifc.org if you have any questions or need additional information.

IFC International Finance Corporation WORLD BANK GROUP
*Creating Markets, Creating Opportunities*

(B) Script of Description and Incentives

FIGURE A4. The "Connecting Africa's Entrepreneurs" Experiment

*Notes*: This figure shows the official advertisement and the consent page of the "Connecting Africa's Entrepreneurs" study. Panel A is a screenshot of the official advertisement, describing the study's motivation and incentives for participating entrepreneurs and investment partners in the "Connecting Africa's Entrepreneurs" study. Panel B is the consent page, which displays the script shown to respondents describing the "Connecting Africa's Entrepreneurs" study, along with the incentives for participating in the study.

**AF-VC Fund**
Since 2000

**HQ Location** New York, USA
**Geographical Preferences** Africa

**Team**

| Charles Smith | Wala Odumegwu | Jacques Marino |
|---|---|---|
| Ex VC Fund | Ex Accenture<br>MBA, MIT Sloan | Ex Leading Venture Capital Firm |

**Team Strength**
- International investment perspective
- Team members have 12 years experience investing in Africa

**Offer**

| | |
|---|---|
| **Financing Type** | **Equity** |
| **Invesment Amount** | USD 1,750,000-2,000,000 |
| **Share Acquired** | 10% |

**Fund Characteristics**

| | |
|---|---|
| **Limited Partners** | Nedbank, Sovereign Wealth Funds, and Proparco - Agence Francaise de Developpement |
| **Targeted Sectors** | Generalist |

**Fund Performance**

| | |
|---|---|
| **Number of Previous Investments** | 37 |
| **Average Return on Investment** | History of returns are similar with industry's trend |

(A) Example 1

**AFR Founder Fund**

| | |
|---|---|
| **HQ Location** | Burkina Faso |
| **Geographical Preferences** | Burkina Faso, Niger, and Benin |

**Team**

| Tomilola Adeyemi | Moshe Onuoha | Sangu Jalloh |
|---|---|---|
| Ex Tech Startup's C-Suite<br>BS, Engineering | Ex Accenture | Ex Serial Startup Entrepreneur<br>BS, UChicago |

**Team Strength**
- International professional experience
- Female-led investment team
- Key people born and raised in Burkina Faso

**Offer**

| | |
|---|---|
| **Financing Type** | **Debt** |
| **Loan Amount** | USD 450,000-500,000 |
| **Interest Rate** | 5-10% |
| **Maturity** | Up to 10 years |

**Fund Characteristics**

| | |
|---|---|
| **AUM** | USD 20 Million |
| **Limited Partners** | High net worth individuals in Africa and Tesi - Finnish Industry Investment |
| **Number of Funds** | 3rd fund |
| **Targeted Sectors** | Water/Sanitation/Waste Management |
| **Diligence Requirements** | Audited financial books and high transparency required |

**Fund Performance**

| | |
|---|---|
| **Number of Previous Investments** | 20 |
| **Average Return on Investment** | Steady returns in line with market norms |

(B) Example 2

FIGURE A5. Example of Investor Profiles

*Notes*: This figure shows two examples of synthetic profiles of investors. Each component in the figure is randomly generated based on predefined (conditional) probability distributions. Different sections may also appear in varying colors randomly. For details, refer to Appendix A.2.

**Now come the investor profiles!**

You will be asked to rate investor profiles based on the following questions:

- **How interested would you be in receiving capital from this investor?**

  *When thinking about your interest in receiving capital from the investment partner, assume that the investment partner is already interested in establishing an investment relationship with your organization—therefore please only consider your views on the quality of the investment partner.*

- **How likely do you think it is that this investor would provide capital to you?**

  *When thinking about whether the investment partner would provide capital to you, assume that you have already expressed interest in the investment partner—therefore please only consider whether you think the investment partner is interested in providing capital to you.*

We will show a video that provides an example on how you should rate the profiles, right before you see hypothetical profiles of investment partners.

(A) Page 1

**To ensure that we can accurately interpret your preference from the ratings that you will kindly submit, it is extremely important that you do not rate all investor profiles equally.** If you do so, it implies that you are equally interested in all profiles, and our machine learning algorithm will not be able to effectively match you with the most suitable investors. You will not get more matches if you rate every profile highly.

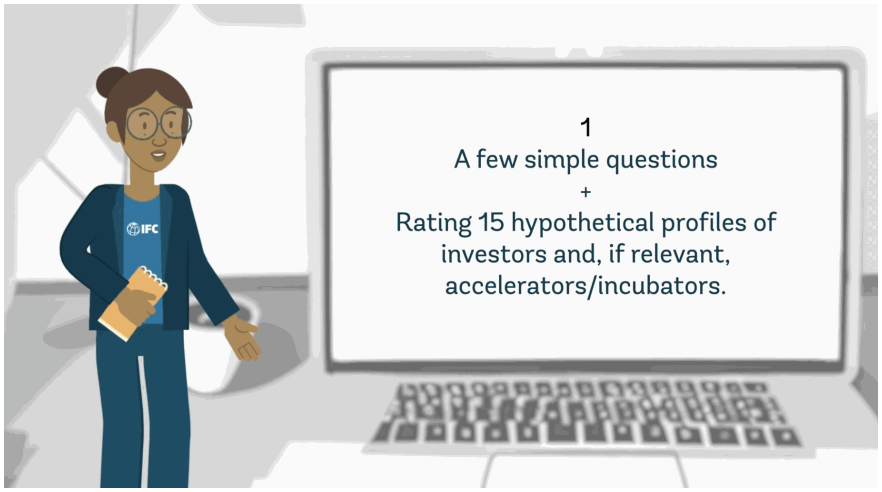
Given that we pre-selected **investor profiles that we believe are aligned with your sector and location**, **all investors** may appear intriguing to you. Therefore, we encourage you to use the **complete** 1-7 scale to indicate your **variation of interest across different investors**.

Please make sure to respond truthfully. As an additional incentive to this goal, we also analyze the data on investors' reciprocal interest towards organization like yours. **If you are able to predict potential investors' interest accurately (i.e., the likelihood rating question, which you will see right below the interest question), you will receive additional support from the IFC research team to match you with the right partners.**

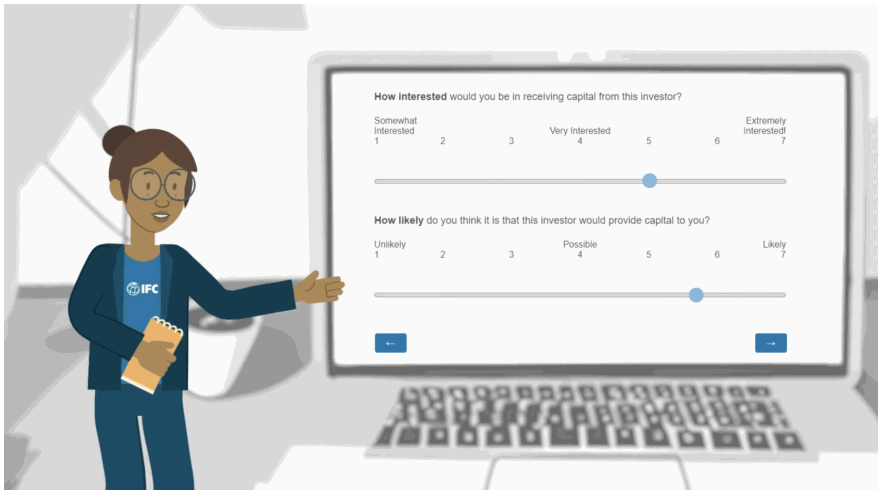
(B) Page 2

FIGURE A6. Script for Profile Rating Instructions

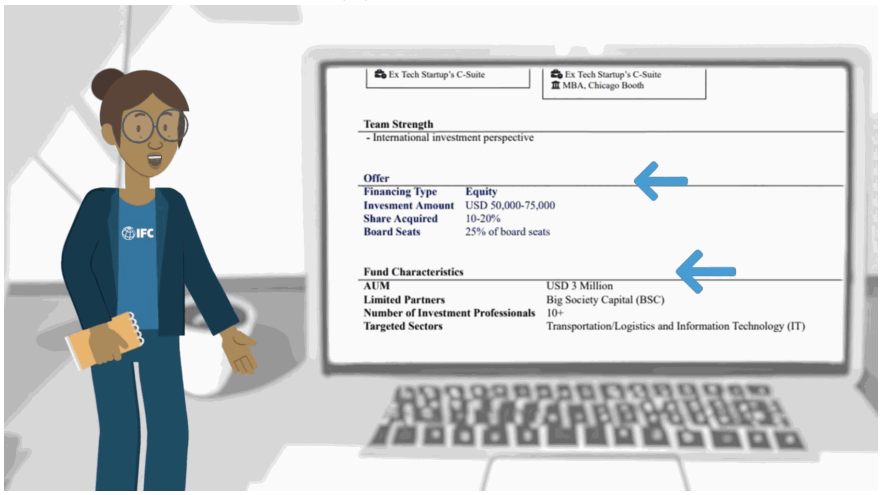
*Notes*: This figure displays screenshots of the survey pages shown to respondents that explain the instructions for rating profiles.




(A) Screenshot 1



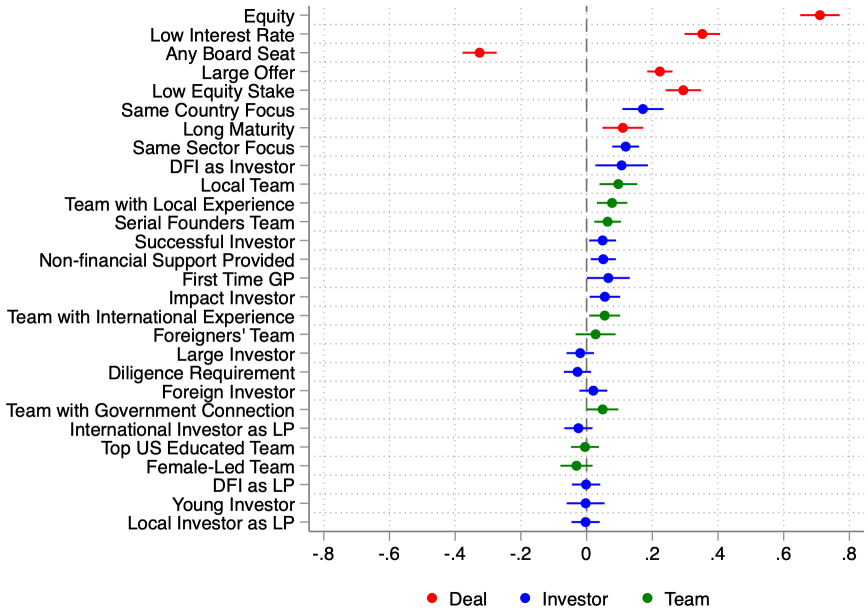

(B) Screenshot 2



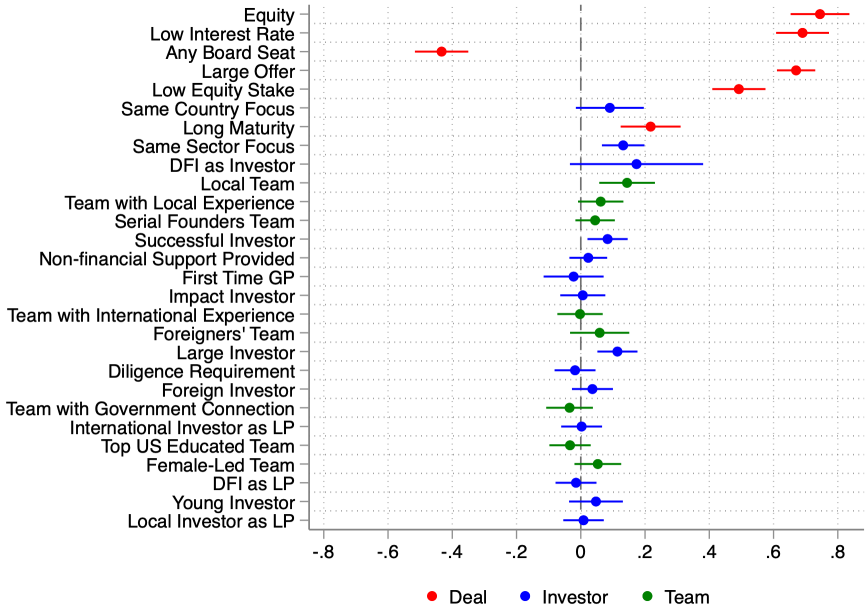

(C) Screenshot 3

FIGURE A7. Screenshots of Profile Rating Instruction Video

*Notes*: This figure shows screenshots from the instruction video guiding respondents on how to read and rate hypothetical investor profiles. The full video is available at https://www.youtube.com/watch?v=0BFK5n45_OA.




(A) First Round




(B) Second Round

FIGURE A8. Heterogeneity Analysis: Startup Preferences by Survey Round

*Notes*: This figure summarizes startups' preferences for investment attributes featured in the synthetic investor and DFI profiles, as captured by $\beta_k$ in Equation 3.1, shown separately for the two survey rounds. The figure also reports 95% confidence intervals for each attribute. Attributes are ordered from top to bottom by the absolute magnitude of their coefficients in the baseline specification pooling both survey rounds, as shown in Figure 4.

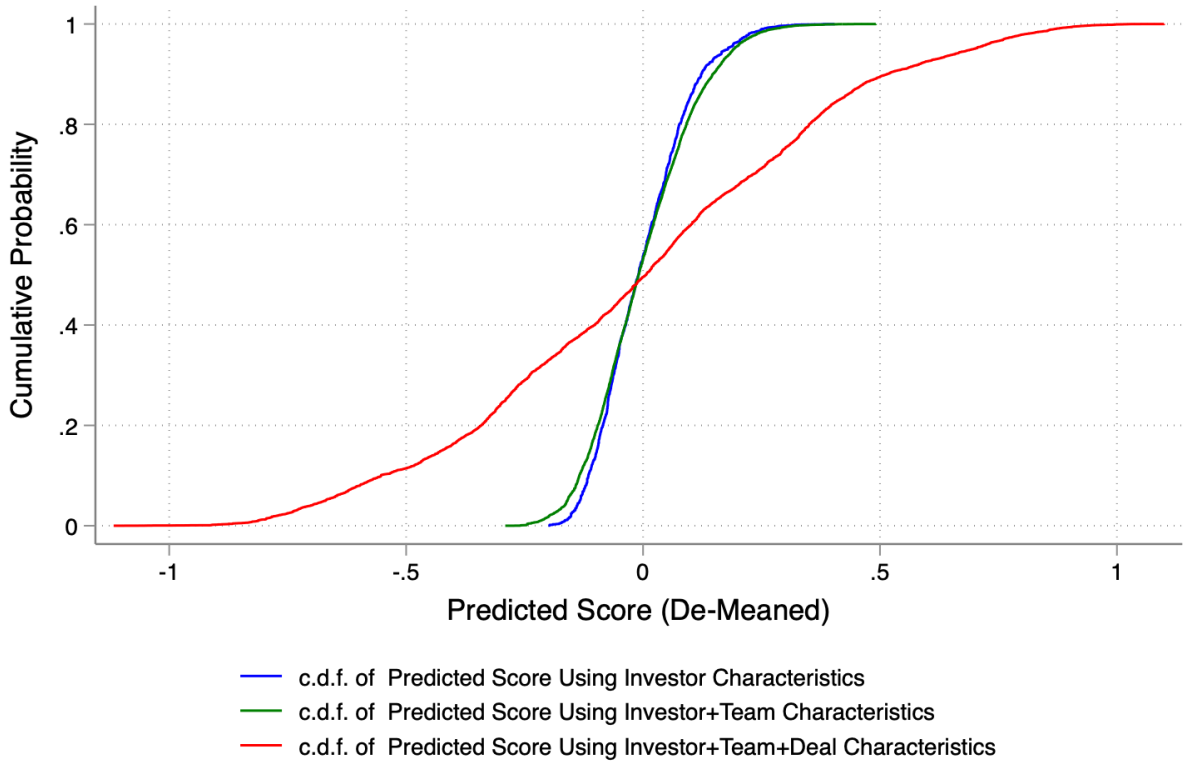



FIGURE A9. Preferences for Types of Capital and Types of Investors

*Notes*: The figure displays cumulative distribution functions (c.d.f.s) of predicted investor-interest scores based on regressions with investor fixed effects shown in Equation 3.1. We compare models that incorporate (1) *Investor Characteristics*, (2) *Investor + Team Characteristics*, and (3) *Investor + Team + Deal Characteristics*, following the variable groupings in Figure 4. Predicted scores are demeaned to make distributions comparable. The relatively flat c.d.f. (in red) reflects a broader range of predicted interest when all characteristics are included, highlighting that deal-specific factors significantly sharpen the distinction among investor preferences.

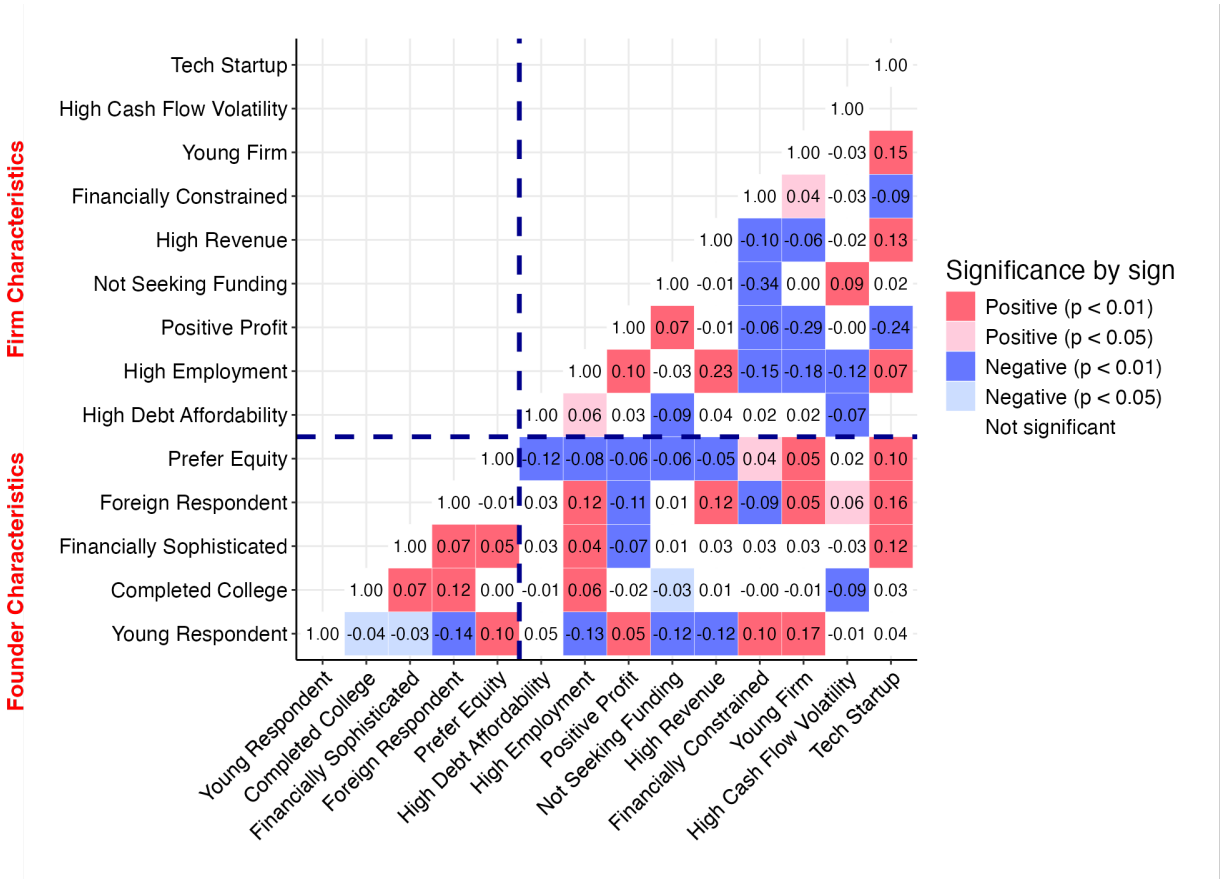
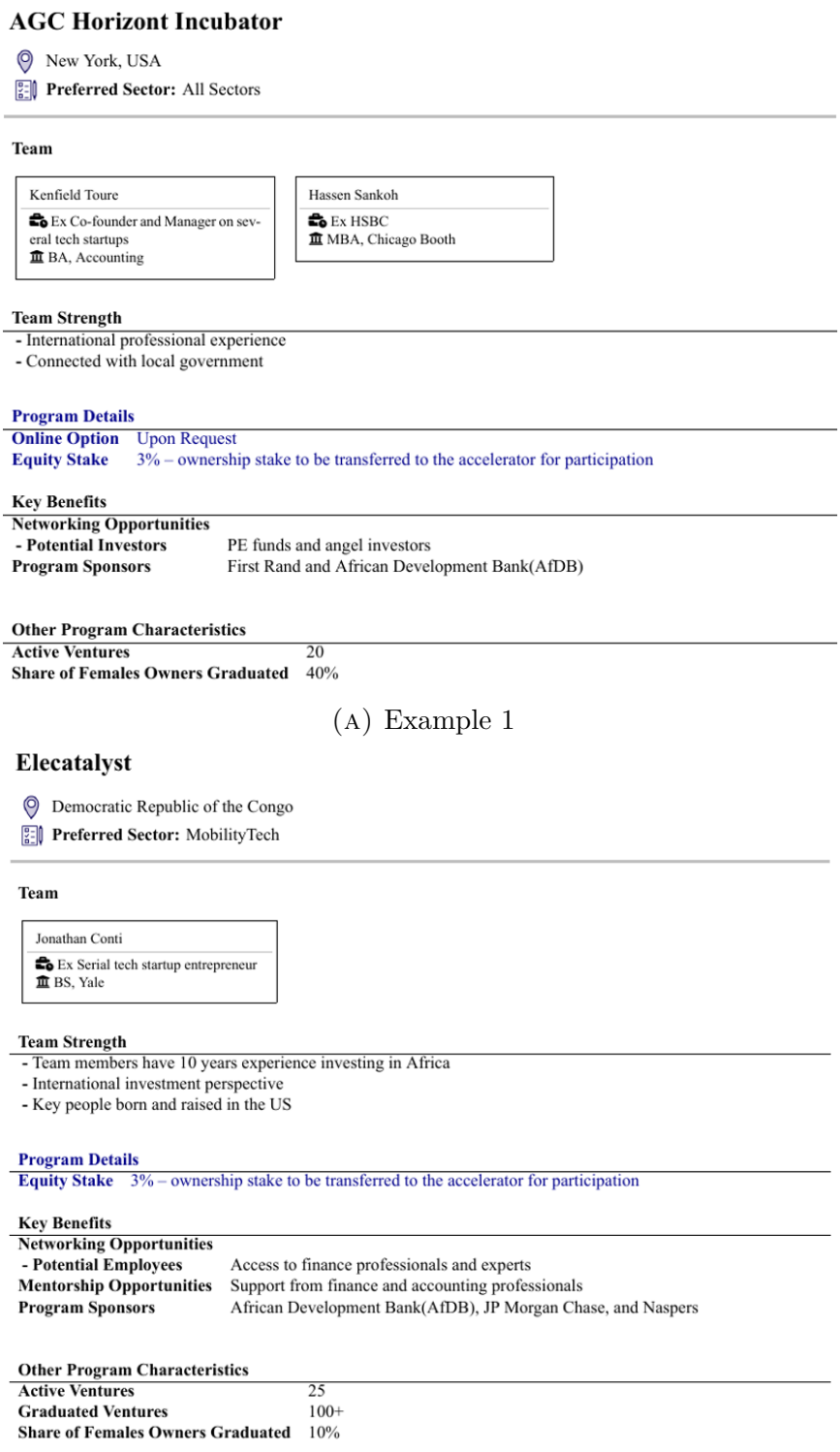



FIGURE A10. Correlation Heatmap of Different Heterogeneity Groups

*Notes*: This figure presents Pearson pairwise correlations among the heterogeneity groups in our survey, with colors indicating the sign and statistical significance of the correlations. Definitions of the heterogeneity groups are provided in Appendix Figure 5. Due to survey design, *"Tech Startup"* is constructed only for first-round respondents, while *"High Debt Affordability"* and *"Low Cashflow Volatility"* are constructed only for second-round respondents. Therefore, correlations between *"Tech Startup"* and the latter two groups are not defined and are shown as missing.




(A) Example 1




(B) Example 2

FIGURE A11. Example of Accelerator Profiles

*Notes*: This figure shows two examples of synthetic profiles of accelerators. Each component in the figure is randomly generated based on predefined (conditional) probability distributions. Different sections may also appear in varying colors randomly. For details, refer to Appendix A.2.

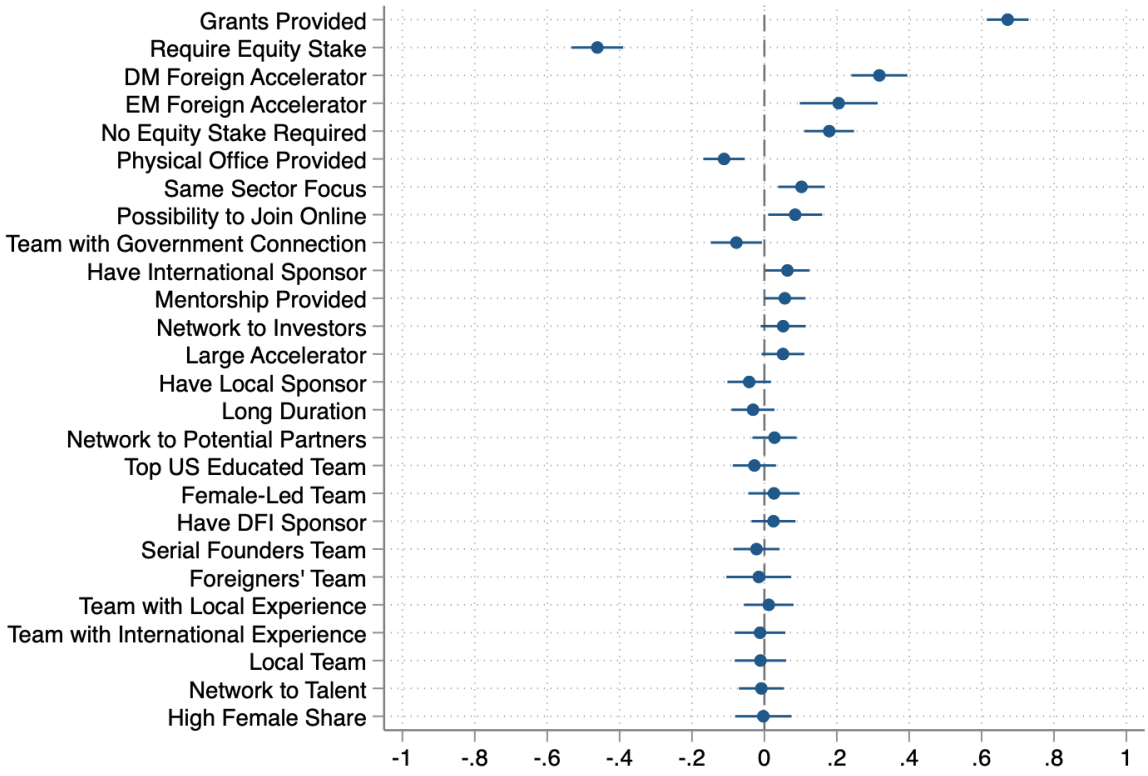
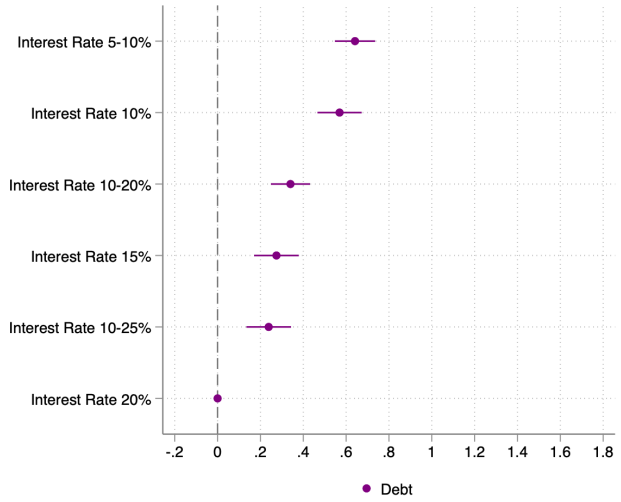
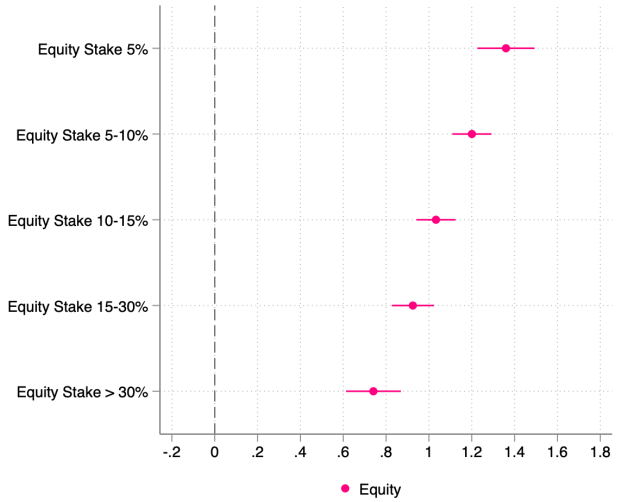



FIGURE A12. Startup Preferences for Accelerators

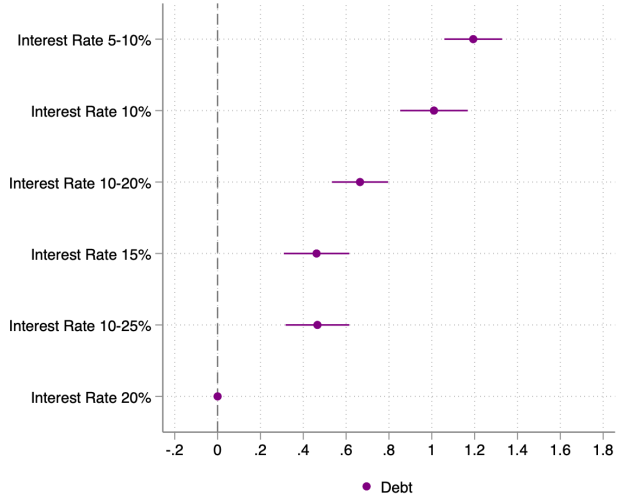
*Notes*: This figure summarizes startups' preferences for attributes shown in the synthetic accelerator profiles. The figure also displays 95% confidence intervals for each attribute. Attributes are ordered from top to bottom by the absolute magnitude of their coefficients. Detailed explanations for each accelerator attributes are shown in Appendix Table A9.



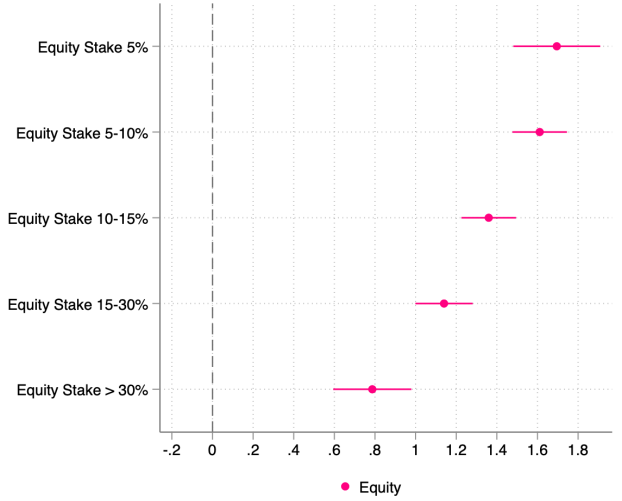

(A) Preference for Debt, First Round




(B) Preference for Equity, First Round



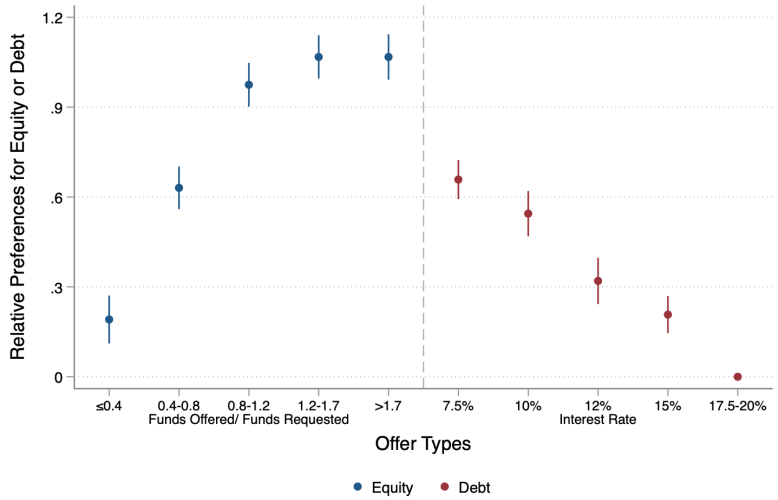

(C) Preference for Debt, Second Round



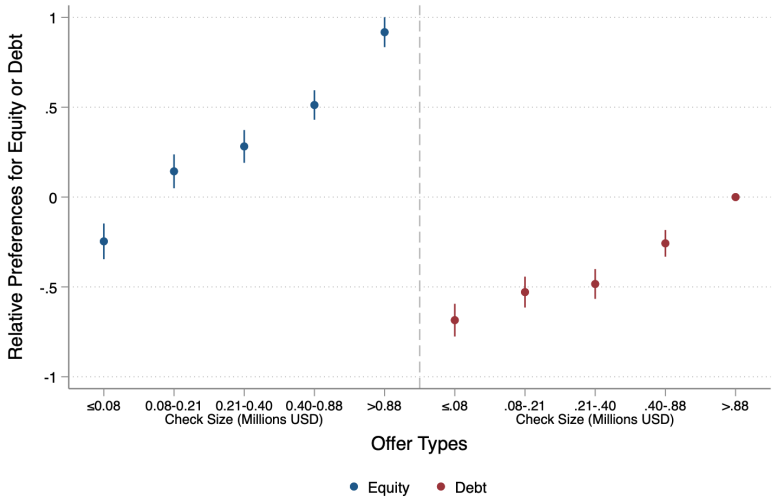

(D) Preference for Equity, Second Round

FIGURE A13. Heterogeneity Analysis: Startup Preferences for Debt vs. Equity by Survey Round

*Notes*: This figure reports the result shown in Appendix Figure 6 separately for two survey rounds. Panel A and C presents relative preferences for debt, split by different interest rates. Panel B and D presents relative preferences for equity, split by different equity stake requirement. We modified the specification of Equation 3.1 by replacing the indicator for *Equity*, *LowInterestRate* and *LowEquityStake* with six indicators for debt offers split by different *InterestRate*, and five indicators for equity offers split by different *EquityStake*. *InterestRate* denotes the annual interest rate associated with the debt offer in the synthetic profile, while *EquityStake* denotes the share of equity required in exchange for equity financing.



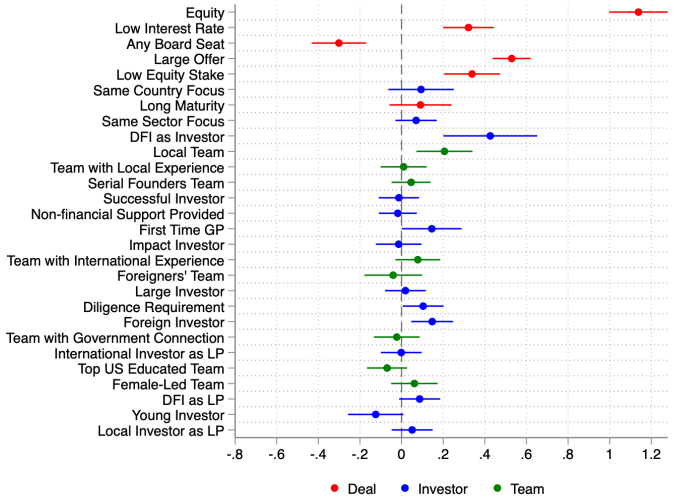

(A) Preference Across Attractiveness



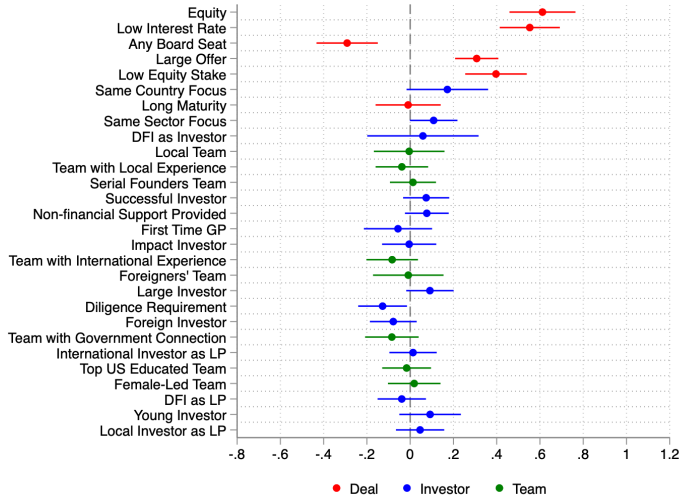

(B) Preference Across Check Sizes

FIGURE A14. Heterogeneity Analysis: Debt vs. Equity — Offer Attractiveness and Debt Affordability

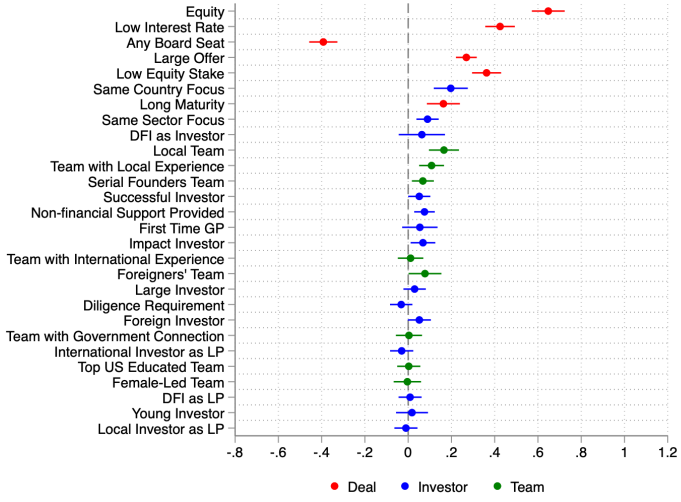
*Notes*: This figure shows the heterogeneity in preferences for debt and equity financing shown in the synthetic investor and DFI profiles. Panel A presents relative preferences for equity and debt, split by quintiles of key features associated with each financing type. Panel B presents relative preferences for debt and equity, split by quintiles of check sizes for each type of offer. Specifically, Panel A modifies the specification of Equation 3.1 by replacing the indicators for *Equity*, *Low Interest Rate* and *Large Offer* with five indicators for equity offers split by *OfferRequestRatio* quintiles, and five indicators for debt offers split by *InterestRate quintiles*. *OfferRequestRatio* is defined as the ratio of the amount of funds offered in the synthetic profiles to the median response to the "filtering" question: "How much investments are you looking for (in US dollars)?", as discussed in Appendix A.2. *InterestRate* is defined as the annual interest rate of debt offered showed in synthetic profiles. Panel B modifies the specification of Equation 3.1 by replacing the indicators for *Equity* and *Large Offer* with five indicators for equity offers split by *EquSize*, and five indicators for debt offers split by *DebtSize*. *EquSize* and *DebtSize* denote the amount of funds offered in the synthetic profiles for equity and debt offers, respectively.



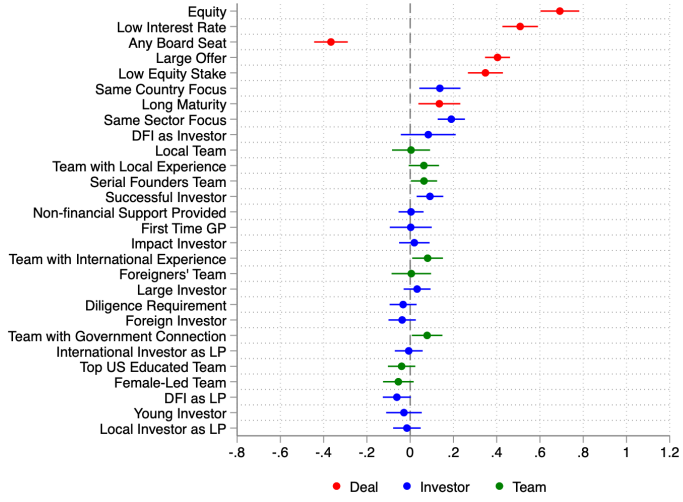

(A) Northern Africa




(B) Southern Africa



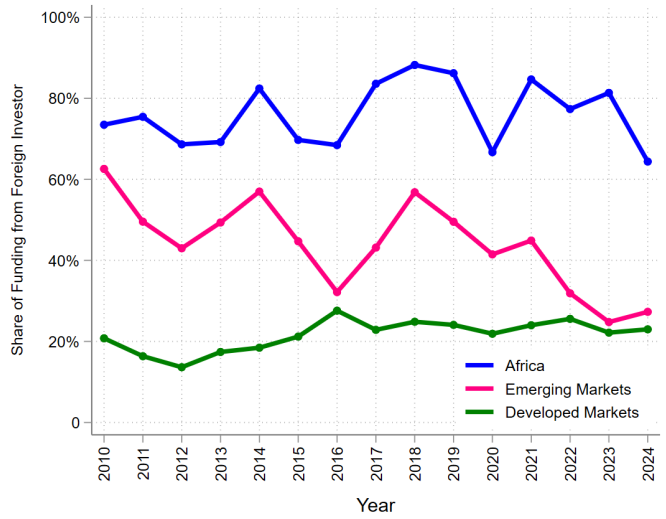

(C) Eastern & Central Africa



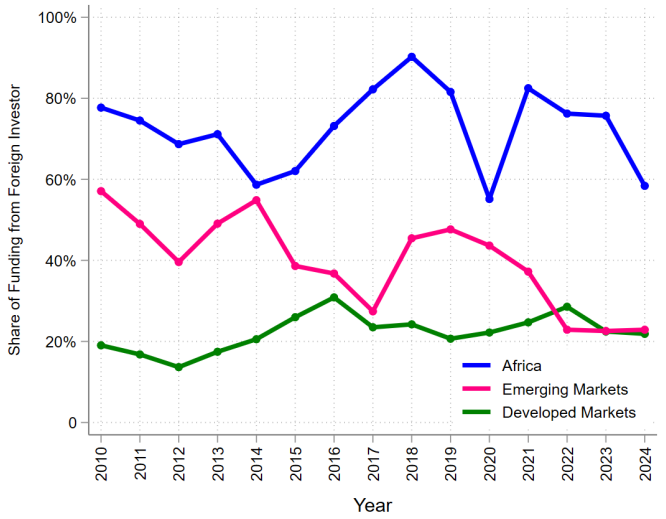

(D) Western Africa

FIGURE A15. Heterogeneity Analysis: Startup Preferences by Region

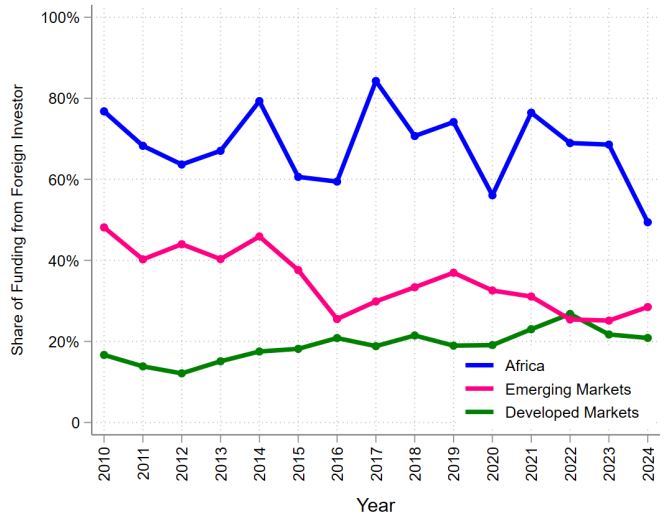
*Notes*: This figure summarizes startups' preferences for investment attributes featured in the synthetic investor and DFI profiles, as captured by the coefficients $\beta_k$ in Equation 3.1, shown separately by African subregion. Subregions are defined according to the United Nations geoscheme (see https://unstats.un.org/unsd/methodology/m49/). The figure reports point estimates and 95% confidence intervals for each attribute. Attributes are ordered from top to bottom by the absolute magnitude of their coefficients in the baseline specification pooling all respondents, as shown in Figure 4.



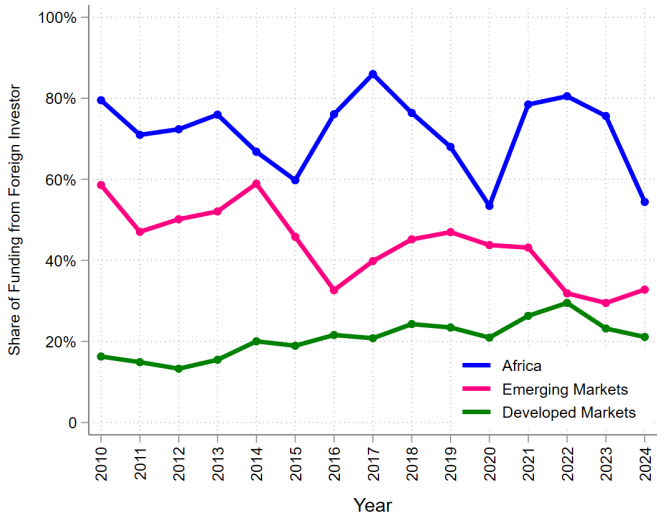

(A) Evenly Split Deal Size Across Investors




(B) Assign Foreignness By Lead Investor



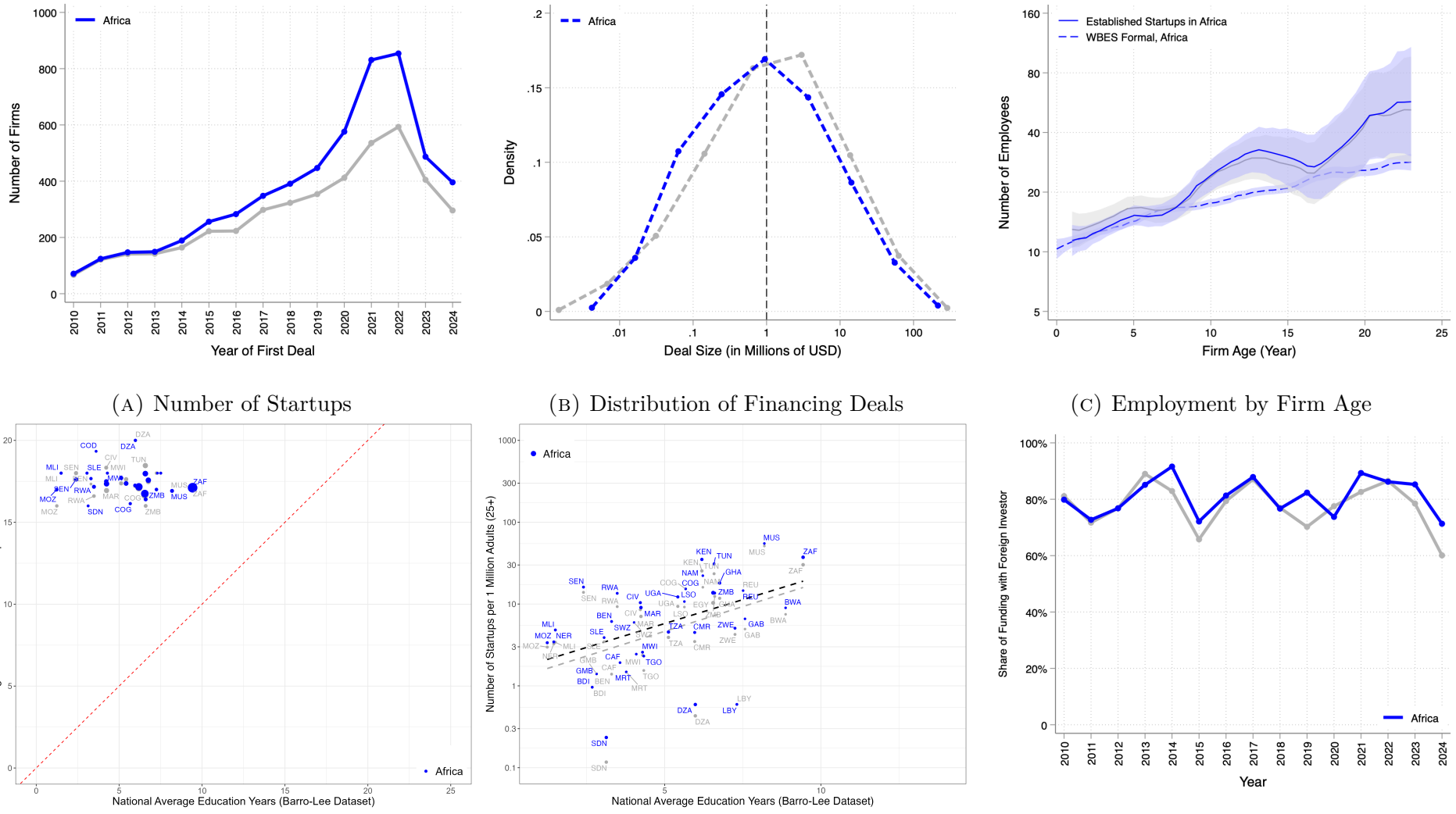

(C) Impute Missing Deal Size




(D) Weight Deal Size By Investor Size

FIGURE A16. Dominance of Foreign Capital: Robustness Checks

*Notes*: This figure presents robustness checks for the dominance of foreign capital in Africa shown in Figure 8 Panel A, by allocating deal size to participating investors using different methods. Panel A allocates each deal's size equally across all participating investors. Panel B allocates deal size only to lead investors. Panel C allocates deal size equally across all participating investors, and imputes missing deal sizes at the deal–investor level using cells defined as investor origin country × startup country × sector × deal type × deal year. Panel D allocates deal size based on investor weights, calculated by the investor's total investment amount. Market classifications follow criteria from MSCI, FTSE, and S&P. Investor "foreignness" is defined using seven regions: Africa, Northern America, Europe, Latin America, China, India, and Rest of the World (RoW).




(A) Number of Startups (B) Distribution of Financing Deals (C) Employment by Firm Age

(D) Education: Startup Founders vs. Country (E) N. of Startups and Country Education (F) Foreign participation in Startups' Funding

FIGURE A17. Descriptive Facts Comparing PitchBook and Pitchbook+

*Notes*: This figure displays descriptive statistics on Established Startups in Africa, using data derived from deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges from 2010 to 2024, covering 5,801 companies. Results derived from PitchBook data are shown in light grey color as comparison. Panel A presents the number of firms receiving their first deal each year from 2010 to 2024. Panel B shows the density of deal amounts received by established startups. Panel C presents the average number of employees by firm age, including data from established startups and the WBES dataset (sample size: 48,086 companies). Panel D compares the average years of education at the country level between startup founders and the national average, with marker size representing the total number of established startups per country. Panel E plots the number of established startups per million people against average years of education at the country level. Marker size indicates the population in each country in 2015. National average education and population measures are drawn from Barro and Lee (2013), restricting the sample to individuals aged 25–45, the relevant age group for startup founders The y-axis is log-transformed, but the labels represent the original values before log transformation to simplify interpretation. Panel F shows the share of total deal amounts with at least one investor from outside of Africa.

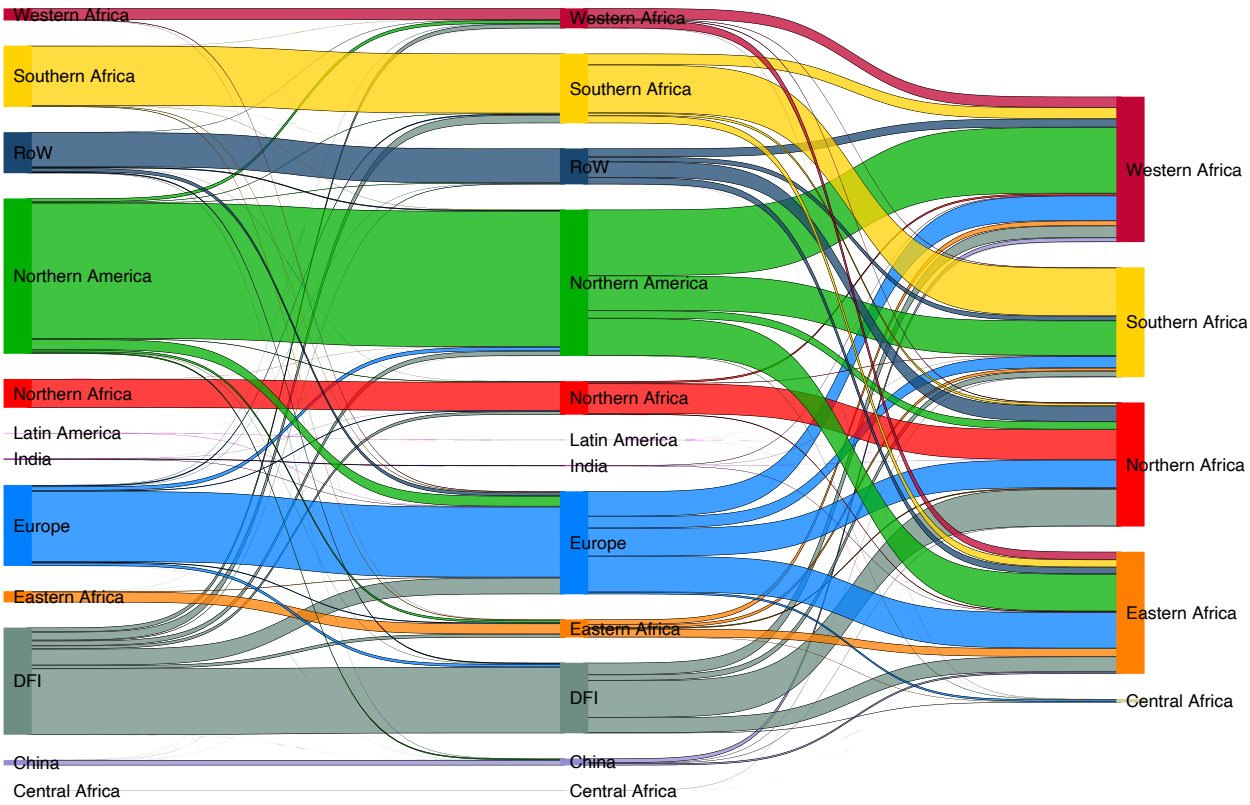
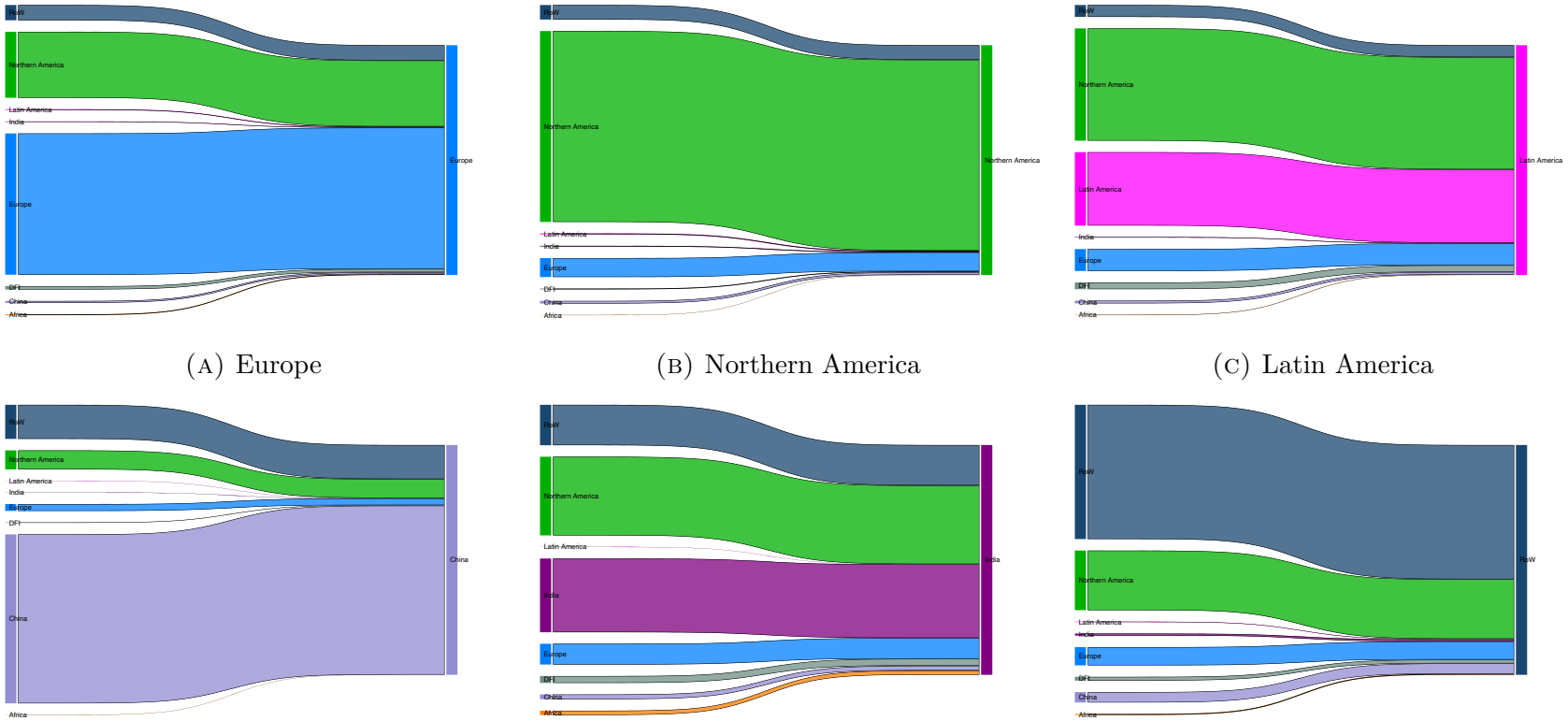



FIGURE A18. Who Finances Startups in Africa? LP to GP to Company

*Notes*: This figure shows the investment flows to Africa, showing the origins of capital from Limited Partners (LPs) as well as Development Financial Institutions (DFIs) via General Partners (GP) to African startups using PitchBook data from 2010 to 2024. The size of the flows represent the amount of funds in millions of USD. Where GP information is available but LP information is missing, we attribute LP identity based on the associated GP. We exclude LP-GP-company deal pairs when deal size, GP region, or LP region is unknown, resulting in the exclusion of 36.6% of observations.

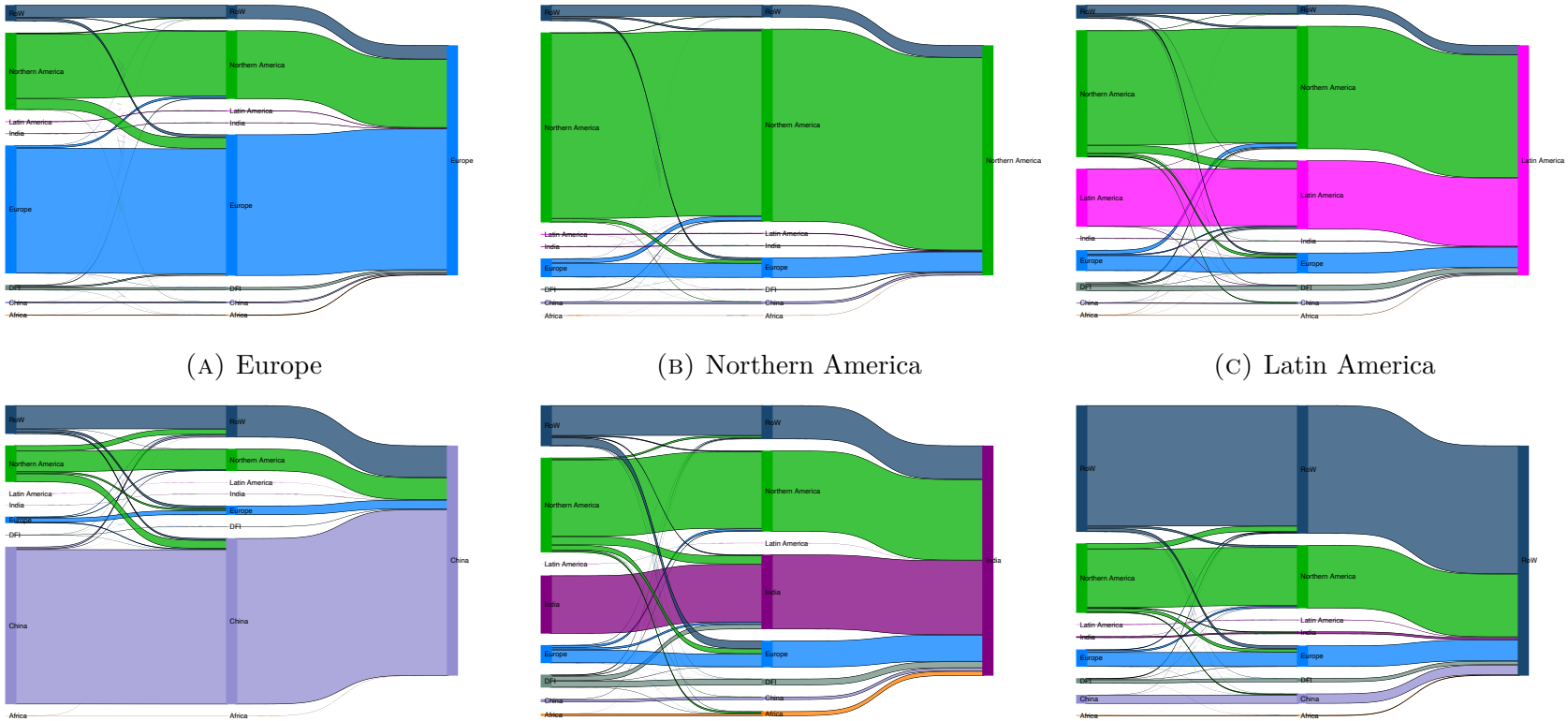



(A) Europe (B) Northern America (C) Latin America

(D) China (E) India (F) Rest of the World

FIGURE A19. Who Finances Startups in Other Regions?

*Notes*: This figure shows the investment flows from General Partners (GP) to established startups in other regions of the world (Europe, Northern America, Latin America, China, India, and the Rest of the World) using PitchBook data. The size of the flows reflects the amount of funds in million USD. We exclude GP-company deal pairs with unknown deal size or unknown GP region (excluded 30.9% for Europe, 24.5% for Northern America, 33.1% for Latin America, 52.5% for China, 25.7% for India and 32.8% for RoW, respectively).




(A) Europe (B) Northern America (C) Latin America

(D) China (E) India (F) Rest of the World

FIGURE A20. Who Finances Startups in Other Regions? LP to GP to Company

*Notes*: This figure shows the investment flows from Limited Partners (LP) via General Partners (GP) to established startups in other regions of the world (Europe, Northern America, Latin America, China, India, and the Rest of the World) using PitchBook data. The size of the flows reflects the amount of funds in million USD. Where GP information is available but LP information is missing, we attribute LP identity based on the associated GP. We exclude LP-GP-company deal pairs with unknown deal size, unknown GP region, or unknown LP region (excluded 26.0% for Europe, 18.1% for Northern America, 29.6% for Latin America, 46.8% for China, 17.5% for India and 29.0% for RoW, respectively).

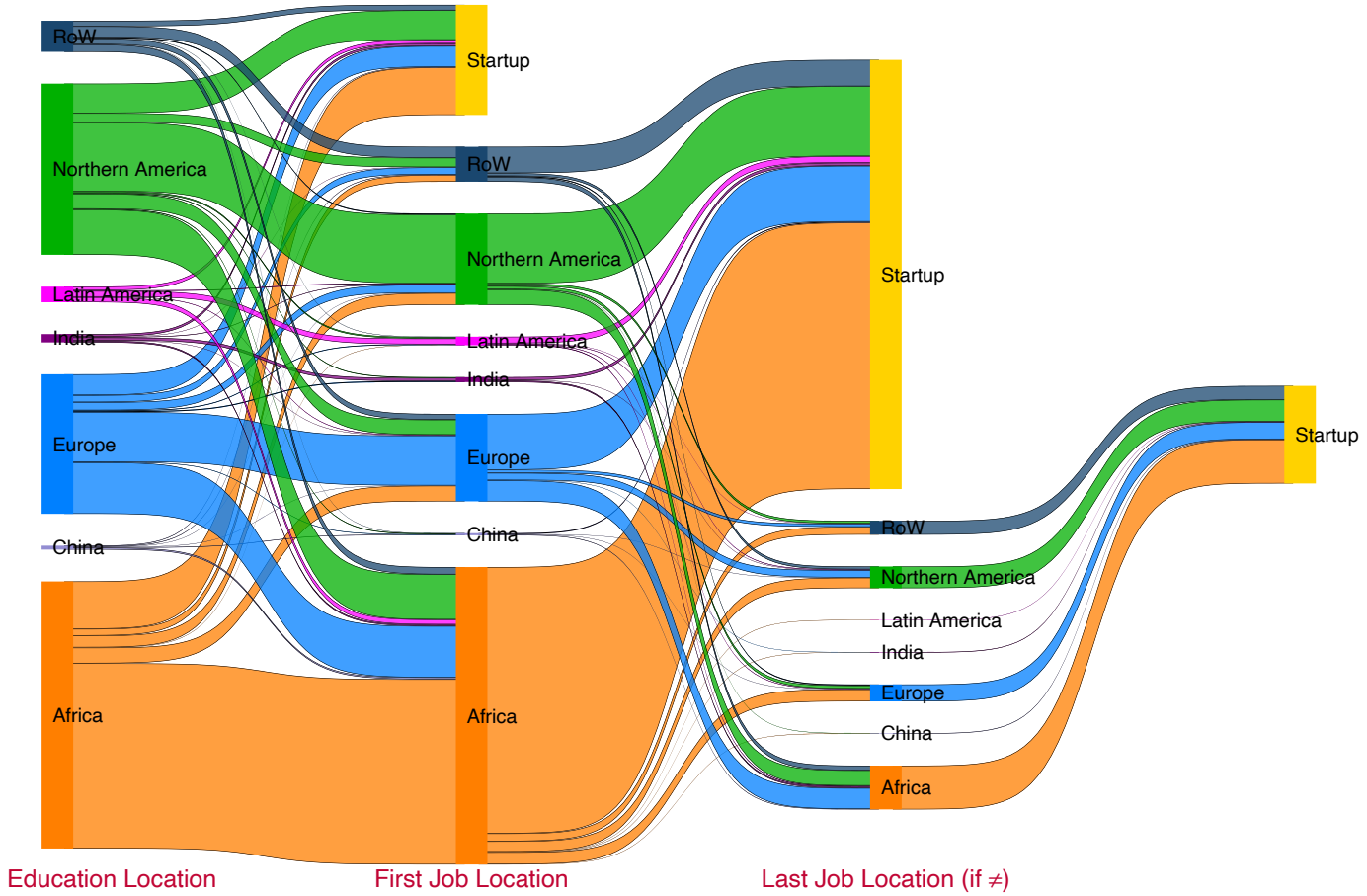
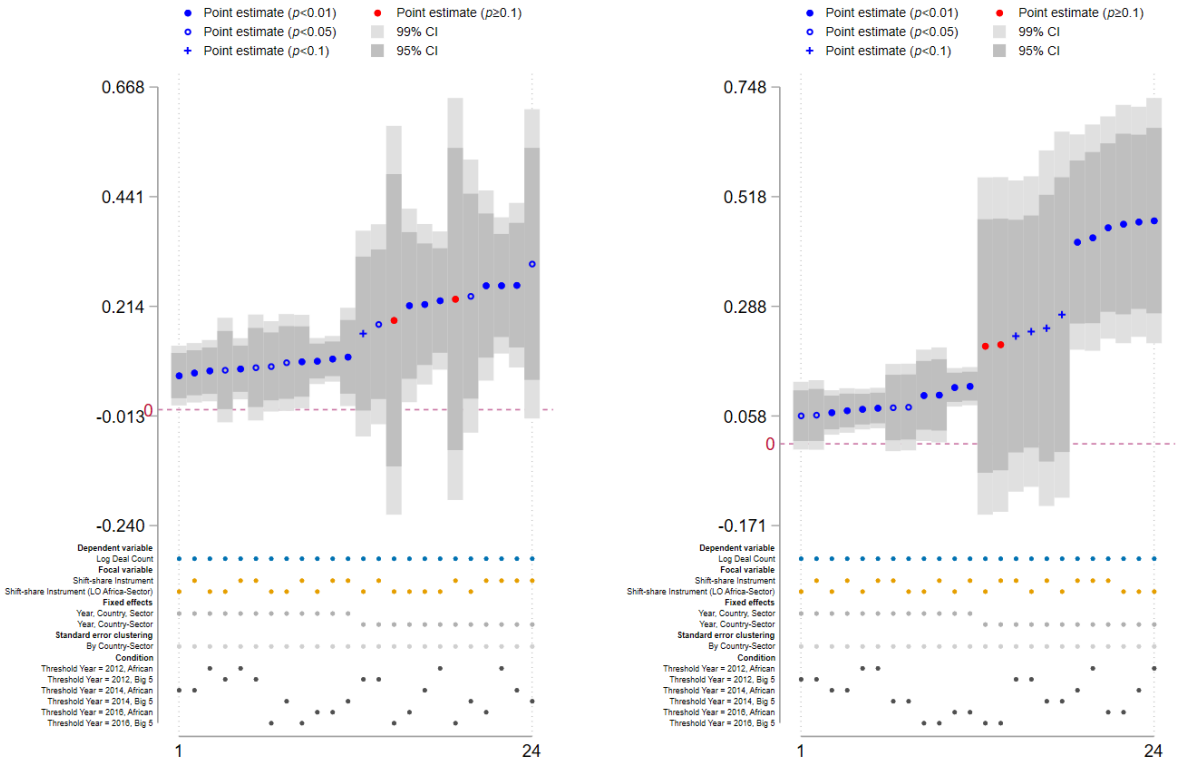



FIGURE A21. Typical Job Trajectory of African Startup Founders

*Notes*: This figure illustrates the typical education and career trajectories of African startup founders, tracing their paths from the location of their last completed education, to the location of their first job, to the location of their last job prior to founding a startup (if different from the first job). The data is sourced from all Established Startup founders using records in PitchBook, Africa: The Big Deal, and Briter Bridges, supplemented with individual-level employment and education records from Revelio Labs.




(A) Bartik Robustness: Size (B) Bartik Robustness: Count

FIGURE A22. Robustness to Different Sample, "Leave-Out Means" and Controls

*Notes*: This figure shows the estimated effects of foreign capital exposure shocks on log deal size (Figure A) and log deal count (Figure B) for African countries, using a Bartik-style shift-share instrument constructed from PitchBook data. Each panel plots results from 24 unique combinations of specifications, based on: (i) two focal variables (instruments), defined as destination-sector pair and leave-one-out destination-sector pair; (ii) two fixed effects structures (year-country-sector FE and year and country-sector FE); and (iii) six conditions combining three threshold years for pre-period shares (2012, 2014, and 2016) and two subsamples (all African countries vs. the Big 5: Kenya, Egypt, Nigeria, South Africa, and Uganda). The x-axis indicates each specific regression specification, and the y-axis shows the estimated coefficient for foreign capital exposure. Gray shaded areas represent 95% and 99% confidence intervals, and different point markers denote levels of statistical significance. See Section 4.3.3 for further details.

TABLE A1. Comparison of PitchBook and PitchBook+

| | PitchBook | Not in PitchBook | PitchBook+ |
|---|---|---|---|
| **A. Counts of Companies, Deals, and Investors** | | | |
| Companies | 4,372 | 1,429 | 5,801 |
| Deals | 6,293 | 2,771 | 9,064 |
| Investors | 5,361 | 1,577 | 6,938 |
| **B. Deal Year** | | | |
| 2010–2014 | 12.07% | 1.33% | 9.31% |
| 2015–2019 | 30.19% | 20.64% | 27.74% |
| 2020–2024 | 57.74% | 78.03% | 62.95% |
| **C. Deal Size** | | | |
| USD 0–100K | 14.30% | 10.21% | 12.90% |
| USD 100K–250K | 12.88% | 31.00% | 19.10% |
| USD 250K–1M | 18.58% | 18.05% | 18.39% |
| USD 1M–2.5M | 18.52% | 15.94% | 17.63% |
| USD 2.5M–10M | 18.85% | 14.34% | 17.29% |
| USD >10M | 16.87% | 10.47% | 14.67% |
| **Panel D. Company Sector** | | | |
| Information Technology (IT/SaaS/AI) | 27.55% | 4.75% | 22.90% |
| Manufacturing/Robotics | 12.07% | 3.71% | 10.37% |
| Finance/FinTech | 9.13% | 26.83% | 12.74% |
| Health/BioTech | 7.12% | 8.71% | 7.44% |
| Media/Art/Entertainment | 6.74% | 5.95% | 6.58% |
| Energy/CleanTech | 5.42% | 5.78% | 5.49% |
| Transportation/Logistics/MobilityTech | 5.06% | 8.11% | 5.68% |
| Retail/eCommerce | 5.00% | 8.46% | 5.70% |
| Agriculture/AgriTech | 4.97% | 7.08% | 5.40% |
| Real Estate/Construction | 3.54% | 0.43% | 2.90% |
| Education/EdTech | 3.45% | 5.87% | 3.94% |
| Hospitality/Smart Hospitality Solutions | 2.34% | 0.60% | 1.99% |
| Water/Sanitation/Waste Management | 1.24% | 2.16% | 1.43% |
| Other | 6.37% | 11.56% | 7.43% |
| **Panel E. Company Country** | | | |
| South Africa | 23.33% | 15.63% | 21.77% |
| Nigeria | 15.61% | 20.14% | 16.53% |
| Egypt | 11.63% | 14.19% | 12.15% |
| Kenya | 11.31% | 13.76% | 11.81% |
| Other Countries | 38.12% | 36.28% | 37.74% |

*Notes:* This table reports comparative summary statistics for the established-startup sample across PitchBook and PitchBook+. "PitchBook" refers to the original PitchBook dataset. "Not in PitchBook" includes observations recorded in Briter Bridges or Africa: The Big Deal (or both) but not in PitchBook. "PitchBook+" denotes the final administrative dataset obtained by augmenting PitchBook with Briter Bridges and Africa: The Big Deal. In Panel C, deal size intervals are defined as left-open and right-closed.

TABLE A2. Merging of PitchBook+ with the Revelio Labs' LinkedIn Dataset

| Company HQ | Companies | | | |
|---|---|---|---|---|
| | (1) Total | (2) % in Revelio | (3) % with employees | (4) % with founders |
| **Africa** | 5,801 | 94.3 | 84.9 | 66.4 |
| N Africa | 1,262 | 97.2 | 87.6 | 71.5 |
| E Africa | 1,470 | 94.0 | 84.2 | 63.7 |
| C Africa | 129 | 78.3 | 70.5 | 51.9 |
| W Africa | 1,615 | 92.8 | 83.4 | 64.8 |
| S Africa | 1,325 | 95.0 | 86.3 | 67.8 |
| Europe | 71,096 | 93.1 | 90.7 | 78.1 |
| Northern America | 101,575 | 92.4 | 89.5 | 81.1 |
| Latin America | 5,985 | 91.6 | 89.4 | 81.4 |
| India | 9,051 | 94.8 | 93.1 | 84.1 |
| RoW | 35,992 | 82.9 | 79.8 | 65.1 |

*Notes*: This table reports matching statistics between PitchBook+ (the aggregated dataset combining PitchBook, Africa: The Big Deal, and Briter Bridges, as discussed in Section 2.2) and LinkedIn data from Revelio Lab. Column (2) reports the share of companies in PitchBook+ that are successfully matched to the Revelio Lab dataset. Column (3) reports the share of PitchBook+ companies that are successfully matched and have at least one employee record in Revelio Lab. Column (4) reports the share of PitchBook+ companies that are successfully matched and whose founder is successfully identified in Revelio Lab. For details on the matching procedure, see Appendix A.3.3.

## Table A3. Survey Representativeness

| | Survey | Average | N. Startups | N. VCPE Deals | $ VCPE Deals | GDP | Population |
|---|---|---|---|---|---|---|---|
| Nigeria | 20.8% | 16.3% | 16.0% | 16.1% | 21.1% | 12.7% | 15.4% |
| Kenya | 17.8% | 9.7% | 14.8% | 15.0% | 11.3% | 3.8% | 3.7% |
| South Africa | 10.2% | 15.3% | 18.8% | 18.6% | 21.4% | 13.2% | 4.3% |
| Uganda | 9.7% | 2.1% | 2.5% | 2.6% | 0.3% | 1.7% | 3.3% |
| Egypt | 6.4% | 12.1% | 13.9% | 13.8% | 11.4% | 13.8% | 7.7% |
| Ghana | 4.5% | 3.2% | 3.6% | 3.5% | 3.9% | 2.8% | 2.3% |
| Democratic Republic of the Congo | 3.4% | 2.0% | 0.1% | 0.1% | 0.1% | 2.3% | 7.2% |
| Morocco | 2.9% | 4.8% | 4.7% | 4.5% | 7.0% | 5.0% | 2.5% |
| Cameroon | 2.3% | 1.7% | 2.2% | 2.1% | 0.4% | 1.7% | 1.9% |
| Tanzania | 1.9% | 2.2% | 1.8% | 1.6% | 0.2% | 2.8% | 4.5% |
| Côte d'Ivoire | 1.5% | 2.2% | 2.4% | 2.6% | 1.2% | 2.8% | 2.1% |
| Tunisia | 1.4% | 1.5% | 2.1% | 2.4% | 0.5% | 1.7% | 0.8% |
| Burundi | 1.4% | 0.3% | 0.1% | 0.1% | 0.0% | 0.1% | 0.9% |
| Rwanda | 1.3% | 1.2% | 1.7% | 2.1% | 0.7% | 0.5% | 0.9% |
| South Sudan | 1.3% | 0.3% | 0.1% | 0.1% | 0.0% | 0.3% | 0.8% |
| Niger | 1.2% | 0.5% | 0.1% | 0.1% | 0.0% | 0.6% | 1.8% |
| Senegal | 1.2% | 1.6% | 2.6% | 2.6% | 0.5% | 1.1% | 1.2% |
| Zambia | 0.8% | 0.9% | 1.0% | 1.0% | 0.3% | 1.0% | 1.4% |
| Benin | 0.8% | 0.4% | 0.1% | 0.1% | 0.0% | 0.7% | 1.0% |
| Malawi | 0.8% | 0.4% | 0.1% | 0.1% | 0.0% | 0.4% | 1.4% |
| Mozambique | 0.8% | 0.8% | 0.6% | 0.5% | 0.1% | 0.7% | 2.3% |
| Somalia | 0.8% | 0.4% | 0.1% | 0.1% | 0.0% | 0.4% | 1.2% |
| Zimbabwe | 0.7% | 0.6% | 0.3% | 0.3% | 0.1% | 1.2% | 1.1% |
| Ethiopia | 0.6% | 3.9% | 1.1% | 1.1% | 2.9% | 5.6% | 8.7% |
| Burkina Faso | 0.5% | 0.6% | 0.3% | 0.3% | 0.2% | 0.7% | 1.6% |
| Mauritius | 0.4% | 1.0% | 0.7% | 0.6% | 3.2% | 0.5% | 0.1% |
| Angola | 0.4% | 1.2% | 0.3% | 0.3% | 0.0% | 3.0% | 2.5% |
| Comoros | 0.3% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.1% |
| Mali | 0.3% | 0.5% | 0.1% | 0.1% | 0.0% | 0.9% | 1.6% |
| Mauritania | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.4% | 0.3% |
| Togo | 0.3% | 2.5% | 0.3% | 0.3% | 10.9% | 0.3% | 0.6% |
| Chad | 0.3% | 0.4% | 0.1% | 0.1% | 0.0% | 0.7% | 1.3% |
| Gabon | 0.3% | 0.2% | 0.1% | 0.1% | 0.0% | 0.7% | 0.2% |
| Madagascar | 0.3% | 0.7% | 0.3% | 0.4% | 0.0% | 0.6% | 2.1% |
| Algeria | 0.2% | 2.5% | 0.4% | 0.5% | 0.1% | 8.6% | 3.1% |
| Djibouti | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.1% |
| Guinea | 0.2% | 0.4% | 0.1% | 0.1% | 0.0% | 0.8% | 1.0% |
| Sierra Leone | 0.2% | 0.3% | 0.1% | 0.1% | 0.5% | 0.2% | 0.6% |
| Central African Republic | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.3% |
| Republic of the Congo | 0.2% | 0.5% | 0.7% | 0.8% | 0.1% | 0.5% | 0.4% |
| Botswana | 0.2% | 0.2% | 0.1% | 0.1% | 0.0% | 0.7% | 0.2% |
| Eswatini | 0.2% | 0.1% | 0.1% | 0.1% | 0.0% | 0.2% | 0.1% |
| Namibia | 0.2% | 0.4% | 0.8% | 0.8% | 0.0% | 0.4% | 0.2% |
| Libya | 0.1% | 0.5% | 0.1% | 0.1% | 0.0% | 1.6% | 0.5% |
| Sudan | 0.1% | 1.1% | 0.3% | 0.3% | 0.1% | 1.4% | 3.4% |
| Gambia | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.2% |
| Liberia | 0.1% | 0.2% | 0.3% | 0.3% | 0.0% | 0.2% | 0.4% |
| Cape Verde | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.0% |
| Guinea-Bissau | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.1% |
| Lesotho | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.2% |
| Sao Tome and Principe | 0.1% | 0.1% | 0.1% | 0.1% | 0.0% | 0.0% | 0.0% |
| Equatorial Guinea | – | 0.2% | 0.1% | 0.1% | 0.0% | 0.4% | 0.1% |
| Eritrea | – | 0.1% | 0.1% | 0.1% | 0.0% | 0.1% | 0.2% |
| Seychelles | – | 1.1% | 1.9% | 1.8% | 1.5% | 0.1% | 0.0% |
| Total | 100% | 100% | 100% | 100% | 100% | 100% | 100% |

*Notes*: This table reports the country distribution of survey respondents and compares it to several benchmark distributions. "Average" is defined as the mean share across all benchmark measures listed below. "N. Startups" denotes the number of companies that received at least one VCPE deal recorded in PitchBook+ (the aggregated dataset combining PitchBook, Africa: The Big Deal, and Briter Bridges, as discussed in Section 2.2) in 2024. "N. VCPE Deals" refers to the total number of VCPE deals recorded in PitchBook+ in 2024. "$ VCPE Deals" is the aggregate dollar value of VCPE deals recorded in PitchBook+ in 2024. "GDP" is country-level total GDP in 2024, and "Population" is total population in 2024.

# TABLE A4. Description of Investor Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Investor Name (1) | NA | **1. VC Name (0.5)**<br>XP5 Ventures; AFR54 Capital; 5G Fund; AFR Venture Fund; Emerging Growth Partners; BTA Capital; Future-A Holdings; Founders Capital; Y5 Holdings; 8G Capital; AF54 Ventures; 5FX Fund; AFI Venture Fund; 2A Capital; One Capital United; AFR Founder Fund; GIC Capital LLC; AFX Investments; EWA Capital LLC; eVentures; Forward Investments; KLJ Ventures; V Capital; ASX Investments; MHG Capital; Pangea Venture Capital Fund; UA5 Investments LLC; Walia Capital; SVH Venture Fund; AFR-VC Investments; Adwoa Capital LLC; NIA Investments; AF-VC Fund; Kofi Investments; Lion Investments; HEZA Capital Management LLC; AFR Horizont Fund; 54G Asset; Fund4A Capital; Founder Index Investments | | **2. PE Name (0.5)**<br>Luminary Equity Partners; Helix Capital Management; VantagePoint Capital; Zenith Investment Partners; Ascend Capital Group; Frontier Development Partners; Summit Capital Group; Eden Capital Partners; Frontier Catalyst Capital; Oasis Capital Partners; Terra Firma Equity Partners; Swift River Investments; Nexus Emerging Markets; Horizon Capital Advisors; Rising Tide Partners; Alpha Horizon Investments; Pantheon Equity Partners; Sankofa Equity Partners; Juniper Capital Management; Blue Nile Investment Partners; Altitude Capital Partners; Emerging Markets Bridge; Tropicana Capital Advisors; Safari Equity Partners; Emerge Capital Management; Nexus Frontier Capital; Atlas Investment Advisors; Kudzu Capital Management; Savannah River Investments; Bridge Capital Group; Oceanic Capital Advisors; Unity Equity Group; Terra Firma Capital Management; Golden Savannah Partners; Zebra Capital Advisors; Nile Capital Advisors; Lion's Den Capital; Emerald Growth Partners; Emerald Capital Management; Emerald Peak Advisors; Emerald Ventures; Emerald Ridge Capital; Emeraldstone Capital; Fuxing Capital; EVA Partners |
| Subtitle (0.5) | ***Young Investor:***<br>**1 if established after 2013 [1].**<br><br>***Impact Investor:***<br>**1 if impact investor [3].** | **1. Establishing Year, Young (0.3)**<br>Since 2013; Since 2014; Since 2015; Since 2016; Since 2017; Since 2018; Since 2015; Since 2016; Since 2017; Since 2018; Since 2019 | | **2. Establishing Year, Old (0.2)**<br>Since 2000; Since 2001; Since 2002; Since 2003; Since 2004; Since 2005; Since 2000; Since 2001; Since 2002; Since 2003; Since 2004; Since 2005; Since 2006; Since 2007; Since 2008; Since 2009; Since 2010; Since 2011; Since 2012 | |
| | | **3. Impact Investor (0.5)**<br>Bridging the gap between financial, environmental, and social returns; With a mission to bring positive financial, environmental, and social impacts; Investing for a positive social and environmental impact; Empowering communities through innovative and impactful investments; Investing in impactful solutions for a sustainable future; Combining social and environmental impact with a positive financial return | | | |
| Ticket Size (Round 1) (1) | ***Large Offer:***<br>**1 if Ticket Size ≥ group median (cutoffs are 150k, 650k, 1750k for AMO1/2/3 respectively)** | **1. AMO1**<br>10,000-25,000; 25,000-50,000; 50,000-75,000; 75,000-100,000; 100,000-125,000; 125,000-150,000; 150,000-175,000; 175,000-200,000; 200,000-225,000; 225,000-250,000; 250,000-300,000; 300,000-500,000; 10,000; 20,000; 25,000; 40,000; 50,000; 60,000; 75,000; 80,000; 100,000; 125,000; 150,000; 175,000; 200,000; 225,000; 250,000; 275,000; 300,000; 400,000; 500,000; 10,000; 25,000; 50,000; 75,000; 100,000; 150,000; 200,000; 250,000; 100,000; 150,000; 200,000; 250,000; 275,000; 300,000 | | | |
| | | **2. AMO2**<br>50,000-100,000; 100,000-150,000; 150,000-250,000; 250,000-300,000; 300,000-350,000; 350,000-400,000; 400,000-450,000; 450,000-500,000; 500,000-550,000; 550,000-600,000; 600,000-650,000; 650,000-700,000; 700,000-750,000; 750,000-800,000; 800,000-850,000; 850,000-900,000; 900,000-950,000; 950,000-1,000,000; 1,000,000-1,250,000; 1,250,000-1,500,000; 1,500,000-2,000,000; 50,000; 100,000; 150,000; 200,000; 250,000; 300,000; 350,000; 400,000; 450,000; 500,000; 550,000; 600,000; 650,000; 700,000; 750,000; 800,000; 850,000; 900,000; 950,000; 1,000,000; 1,250,000; 1,500,000; 2,000,000; 2,500,000; 150,000; 200,000; 250,000; 500,000; 750,000; 1,000,000; 250,000; 500,000; 750,000; 1,000,000; 1,250,000; 1,500,000 | | | |
| | | **3. AMO3**<br>250,000-500,000; 500,000-750,000; 750,000-1,000,000; 1,000,000-1,250,000; 1,250,000-1,500,000; 1,500,000-1,750,000; 1,750,000-2,000,000; 2,000,000-2,250,000; 2,250,000-2,500,000; 2,500,000-2,750,000; 2,750,000-3,000,000; 3,000,000-4,000,000; 4,000,000-5,000,000; 250,000; 500,000; 750,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 2,250,000; 2,500,000; 2,750,000; 3,000,000; 4,000,000; 5,000,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 500,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 3,000,000; 4,000,000; 5,000,000 | | | |
| Ticket Size (Round 2)[30] (1) | ***Large Offer:***<br>**1 if Ticket Size ≥ group median (cutoffs are 24k, 138k, 277k, 582k, 897k for AMO1/2/3/4/5 respectively)** | **1. AMO1**<br>10,000 (0.264); 10,000-25,000 (0.132); 20,000 (0.132); 25,000 (0.264); 25,000-50,000 (0.044); 40,000 (0.044); 50,000 (0.119) | | | |
| | | **2. AMO2**<br>10,000 (0.014); 10,000-25,000 (0.007); 20,000 (0.007); 25,000 (0.014); 25,000-50,000 (0.014); 40,000 (0.014); 50,000 (0.037); 60,000 (0.030); 50,000-75,000 (0.030); 75,000 (0.060); 50,000-100,000 (0.021); 80,000 (0.030); 75,000-100,000 (0.030); 100,000 (0.110); 100,000-125,000 (0.030); 125,000 (0.030); 100,000-150,000 (0.021); 125,000-150,000 (0.030); 150,000 (0.130); 150,000-175,000 (0.020); 175,000 (0.020); 175,000-200,000 (0.020); 150,000-250,000 (0.014); 200,000 (0.087); 200,000-225,000 (0.020); 225,000 (0.020); 225,000-250,000 (0.020); 250,000 (0.123) | | | |
| | | **3. AMO3**<br>25,000-50,000 (0.004); 40,000 (0.004); 50,000 (0.011); 60,000 (0.009); 50,000-75,000 (0.009); 50,000-100,000 (0.006); 75,000 (0.018); 80,000 (0.009); 75,000-100,000 (0.009); 100,000 (0.034); 100,000-125,000 (0.009); 100,000-150,000 (0.006); 125,000 (0.009); 125,000-150,000 (0.009); 150,000 (0.040); 150,000-175,000 (0.017); 175,000 (0.017); 175,000-200,000 (0.017); 200,000 (0.072); 150,000-250,000 (0.011); 200,000-225,000 (0.017); 225,000 (0.017); 225,000-250,000 (0.017); 250,000 (0.103); 250,000-300,000 (0.056); 275,000 (0.066); 300,000 (0.089); 300,000-350,000 (0.023); 350,000 (0.023); 250,000-500,000 (0.038); 350,000-400,000 (0.023); 400,000 (0.035); 300,000-500,000 (0.021); 400,000-450,000 (0.014); 450,000 (0.014); 450,000-500,000 (0.014); 500,000 (0.111) | | | |
| | | **4. AMO4**<br>60,000 (0.003); 50,000-75,000 (0.003); 50,000-100,000 (0.002); 75,000 (0.006); 80,000 (0.003); 75,000-100,000 (0.003); 100,000 (0.011); 100,000-125,000 (0.003); 125,000 (0.003); 100,000-150,000 (0.002); 125,000-150,000 (0.003); 150,000 (0.013); 150,000-175,000 (0.006); 175,000 (0.006); 175,000-200,000 (0.006); 150,000-250,000 (0.004); 200,000 (0.028); 200,000-225,000 (0.006); 225,000 (0.006); 225,000-250,000 (0.006); 250,000 (0.040); 275,000 (0.021); 250,000-300,000 (0.018); 300,000 (0.029); 300,000-350,000 (0.007); 350,000 (0.007); 350,000-400,000 (0.007); 250,000-500,000 (0.012); 400,000 (0.032); 300,000-500,000 (0.019); 400,000-450,000 (0.013); 450,000 (0.013); 450,000-500,000 (0.013); 500,000 (0.100); 500,000-550,000 (0.018); 550,000 (0.018); 550,000-600,000 (0.018); 600,000 (0.018); 600,000-650,000 (0.018); 500,000-750,000 (0.029); 650,000 (0.018); 650,000-700,000 (0.018); 700,000 (0.018); 700,000-750,000 (0.018); 750,000 (0.082); 750,000-800,000 (0.015); 800,000 (0.015); 800,000-850,000 (0.015); 850,000 (0.015); 850,000-900,000 (0.015); 750,000-1,000,000 (0.024); 900,000 (0.015); 900,000-950,000 (0.015); 950,000 (0.015); 950,000-1,000,000 (0.015); 1,000,000 (0.117) | | | |
| | | **5. AMO5**<br>150,000-175,000 (0.005); 175,000 (0.005); 175,000-200,000 (0.005); 200,000 (0.020); 150,000-250,000 (0.003); 200,000-225,000 (0.005); 225,000 (0.005); 225,000-250,000 (0.005); 250,000 (0.028); 275,000 (0.014); 250,000-300,000 (0.012); 300,000 (0.019); 300,000-350,000 (0.005); 350,000 (0.005); 250,000-500,000 (0.008); 350,000-400,000 (0.005); 300,000-500,000 (0.011); 400,000 (0.018); 400,000-450,000 (0.007); 450,000 (0.007); 450,000-500,000 (0.007); 500,000 (0.057); 500,000-550,000 (0.011); 550,000 (0.011); 550,000-600,000 (0.011); 600,000 (0.011); 500,000-750,000 (0.019); 600,000-650,000 (0.011); 650,000 (0.011); 650,000-700,000 (0.011); 700,000 (0.011); 700,000-750,000 (0.011); 750,000 (0.053); 750,000-800,000 (0.017); 800,000 (0.017); 800,000-850,000 (0.017); 850,000 (0.017); 750,000-1,000,000 (0.029); 850,000-900,000 (0.017); 900,000 (0.017); 900,000-950,000 (0.017); 950,000 (0.017); 950,000-1,000,000 (0.017); 1,000,000 (0.140); 1,000,000-1,250,000 (0.034); 1,250,000 (0.089); 1,250,000-1,500,000 (0.034); 1,500,000 (0.089) | | | |
| Share (1) [Appears only if Finance Type is Equity.] | ***Low Equity Stake:***<br>**1 if required equity rate ≤ group median (cutoffs are 10%, 20%, 35%, 50% for EQU1/2/3/4 respectively)** | **1. EQU1**<br>5; 10; 15; 5-10; 10-15; 10-20; 10; Up to 10; Up to 15; Up to 20 | **2. EQU2**<br>10; 15; 20; 25; 30; 5-10; 10-20; 20-30; Up to 30; Up to 40 | **3. EQU3**<br>10; 15; 20; 25; 30; 35; 40; 45; 49; 25-50; 50; 51 | **4. EQU4**<br>10; 15; 25; 35; 51; 50-75; More than 50 |
| Location of Headquarter (1) | ***Foreign Investor:***<br>**1 if headquarter is located in US, Europe, China, UAE or Brazil. [1-3].** | **1. USA (0.2 if "Ticket Size" is of AMO1, 0.25 otherwise.)**<br>New York, USA; San Francisco, USA; Chicago, USA; Boston, USA | | **2. Europe (0.1 if "Ticket Size" is of AMO1, 0.15 otherwise.)**<br>London, UK; Frankfurt, Germany; Berlin, Germany; Rome, Italy; Madrid, Spain | |
| | | **3. Emerging Countries (0.1)**<br>Beijing, China;Dubai, UAE;Sao Paulo, Brazil | | **4. Africa (0.2 if "Ticket Size" is of AMO1, 0.25 otherwise.)**<br>Lagos, Nigeria; Nairobi, Kenya; Johannesburg, South Africa; Cape Town, South Africa | |
| | | **5. Self (0.4 if "Ticket Size" is of AMO1, 0.25 otherwise.)**<br>Country where the respondent is located. | | | |

Table A4 (cont.): Description of Investor Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Target (1) | ***Same Country Focus:*** **1 if the investor focuses exclusively on the respondent's country [5].** | **1 Global (0.2)** Global Emerging Markets Africa | **2 Africa 1 (0.4)** Subregion of Africa where the investor is located. | **3 Africa 2 (0.2)** Subregion of Africa where the investor is located and the adjacent subregion. | **4 Country 3 (0.1)** The country where the investor is located and its two neighboring countries. |
| | | **5 Self (0.1)** Country where the respondent is located. | | | |
| Finance Type (1) | ***Equity:*** **1 if the investor finances startups with equity. [2].** | **1 Debt (0.5)** Debt | | **2 Equity (0.5)** Equity | |
| Board Seat Requirement (0.5) | ***Any Board Seat*:** **1 if the investor requires any board seat [2-3].** | **1. No Board Seat (0.15)** No seats | **2. Small Board Seat (0.45)** One; Two; 10%; 15%; 20%; 25% | **3. Large Board Seat (0.40)** 35%; 40%; 50% | |
| Interest Rate[31] (1) | ***Low Interest Rate:*** **1 if interest rate is lower than 15%.** | **1. Interest Rate (1)** 5-10; 10; 12; 15; 20; 10-25; 5-10; 10-20 | | | |
| Maturity[32] (0.5) | ***Long Maturity:*** **1 if the maturity is longer than 3 years.** | **1. Maturity (1)** 1 year; 2 years; 3 years; 4 years; Up to 5 years; Up to 7 years; Up to 10 years; 1 to 3 years; 3 to 5 years; 1 to 2 years; 5 to 10 years | | | |
| AUM, in millions USD (0.7) (Round 1) | ***Large Investor:*** **1 if AUM is larger than group median (cutoffs are 9.5m, 22.5m, 55m for AMO1/2/3 respectively)** | **1. AMO1** 1; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13; 14; 15; 16; 17 | **2. AMO2** 18; 19; 20; 21; 22; 23; 24; 25; 26; 27 | **3. AMO3** 30; 35; 40; 45; 50; 60; 70; 80; 90; 100 | |
| AUM, in millions USD (0.7) (Round 2)[33] | ***Large Investor:*** **1 if AUM is larger than group median (cutoffs are 9.8m, 11.7m, 15.3m, 22.4m, 24.8m for AMO1/2/3/4/5 respectively)** | **1. AMO1** 1 (0.061); 3 (0.061); 4 (0.061); 5 (0.061); 6 (0.061); 7 (0.061); 8 (0.061); 9 (0.061); 10 (0.061); 11 (0.061); 12 (0.061); 13 (0.061); 14 (0.061); 15 (0.061); 16 (0.061); 17 (0.061); 18 (0.003); 19 (0.003); 20 (0.003); 21 (0.003); 22 (0.003); 23 (0.003); 24 (0.003); 25 (0.003); 26 (0.003); 27 (0.003) | | | |
| | | **2. AMO2** 1 (0.049); 3 (0.049); 4 (0.049); 5 (0.049); 6 (0.049); 7 (0.049); 8 (0.049); 9 (0.049); 10 (0.049); 11 (0.049); 12 (0.049); 13 (0.049); 14 (0.049); 15 (0.049); 16 (0.049); 17 (0.049); 18 (0.019); 19 (0.019); 20 (0.019); 21 (0.019); 22 (0.019); 23 (0.019); 24 (0.019); 25 (0.019); 26 (0.019); 27 (0.019); 30 (0.002); 35 (0.002); 40 (0.002); 45 (0.002); 50 (0.002); 60 (0.002); 70 (0.002); 80 (0.002); 90 (0.002); 100 (0.002) | | | |
| | | **3. AMO3** 1 (0.036); 3 (0.036); 4 (0.036); 5 (0.036); 6 (0.036); 7 (0.036); 8 (0.036); 9 (0.036); 10 (0.036); 11 (0.036); 12 (0.036); 13 (0.036); 14 (0.036); 15 (0.036); 16 (0.036); 17 (0.036); 18 (0.032); 19 (0.032); 20 (0.032); 21 (0.032); 22 (0.032); 23 (0.032); 24 (0.032); 25 (0.032); 26 (0.032); 27 (0.032); 30 (0.010); 35 (0.010); 40 (0.010); 45 (0.010); 50 (0.010); 60 (0.010); 70 (0.010); 80 (0.010); 90 (0.010); 100 (0.010) | | | |
| | | **4. AMO4** 1 (0.014); 3 (0.014); 4 (0.014); 5 (0.014); 6 (0.014); 7 (0.014); 8 (0.014); 9 (0.014); 10 (0.014); 11 (0.014); 12 (0.014); 13 (0.014); 14 (0.014); 15 (0.014); 16 (0.014); 17 (0.014); 18 (0.055); 19 (0.055); 20 (0.055); 21 (0.055); 22 (0.055); 23 (0.055); 24 (0.055); 25 (0.055); 26 (0.055); 27 (0.055); 30 (0.022); 35 (0.022); 40 (0.022); 45 (0.022); 50 (0.022); 60 (0.022); 70 (0.022); 80 (0.022); 90 (0.022); 100 (0.022) | | | |
| | | **5. AMO5** 1 (0.008); 3 (0.008); 4 (0.008); 5 (0.008); 6 (0.008); 7 (0.008); 8 (0.008); 9 (0.008); 10 (0.008); 11 (0.008); 12 (0.008); 13 (0.008); 14 (0.008); 15 (0.008); 16 (0.008); 17 (0.008); 18 (0.052); 19 (0.052); 20 (0.052); 21 (0.052); 22 (0.052); 23 (0.052); 24 (0.052); 25 (0.052); 26 (0.052); 27 (0.052); 30 (0.036); 35 (0.036); 40 (0.036); 45 (0.036); 50 (0.036); 60 (0.036); 70 (0.036); 80 (0.036); 90 (0.036); 100 (0.036) | | | |
| LP (0.7) [Each profile can have 1 to 3 LP(s), with the same probability] | ***International Investor as LP:*** **1 if international LP, except for DFIs [2].** ***DFI as LP:*** **1 if DFI as LP [3].** ***Local Investor as LP:*** **1 if institutions in Africa as LP, except for DFIs [4].** | **1. Institutional Investor (0.1)** Asset Management Firms ; Sovereign Wealth Funds ; Mutual Funds ; Fund of Funds ; Banking Institutions ; Mutual funds ; Private Investment Funds ; Wealth Management Firms | | **2. International Investor (0.3)** Family offices from Europe ; US Corporate Pensions ; US Foundations ; European Philanthropic Institutions ; US University Endowments ; Canada Public Pension Funds ; US Family Offices ; US high net worth individuals ; High net worth individuals from Europe | |
| | | **3. DFIs (0.3)** Big Society Capital (BSC); IFC - International Finance Corporation; Belgian Investment Company for Developing Countries (BDIO); Norwegian Investment Fund for Developing Countries (Norfund); East African Development Bank; DEG - Deutsche Investitions; Tesi - Finnish Industry Investment; Swiss Investment Fund for Emerging Markets (SIFEM); Alliance for a Green Revolution in Africa; African Development Bank; Proparco - Agence Francaise de Developpement; European Bank for Reconstruction and Development; Development Bank of Southern Africa; Finnish Fund for Industrial Cooperation (FINNFUND); British International Investment (BII); Asian Development Bank (ADB); Nigerian Sovereign Investment Authority | | | |
| | | **4. Local Investor (0.3)** Local Public Pension Funds; Old Mutual Investment ; Local Mutual Funds ; Family Offices in Africa ; Nedbank ; CIH Bank ; Local Banks ; National Social Security Fund-Uganda ; High net worth individuals in Africa | | | |
| Fund Vintage (0.3) | ***First Time GP:*** **1 if New Fund [1].** | **1 New Fund (0.4)** First fund; 1st fund | | **2 Old Fund (0.6)** 2nd fund; 3rd fund; 4th fund; 5th fund | |
| Professional Team Size (0.3) | NA | **1. Small (0.33)** 7; 10; 12; 13; 15; 17; 18; 19; 10+; 15+; 10-20; 5-10; 10-15; 10+ | **2. Medium (0.33)** 20; 23; 25; 27; 30; 33; 35; 20+; 25+; 30+; 20-30 | **3. Large (0.33)** 40; 44; 45; 48; 50; 53; 55; 57; 60; 63; 66; 67; 68; 70; 50+; 50+; 50+; 50-100; 75+; 40+; 60+ | |
| Sector Focus (0.74) | ***Same Sector Focus:*** **1 if showing specific sector focus (0 if sector agnostic). The investor's sector focus will always cover the respondent's sector of operation.** | **1. AGR** Agriculture (AgriTech) | **2. EDU** Education (EdTech) | **3. ENR** Energy (CleanTech/Renewable Energy) | **4. FIN** Finance (FinTech) |
| | | **5. HLT** Health (HealthTech) | **6. HSP** Hospitality (Smart Hospitality Solutions) | **7. ICT** Information Technology (IT) (Social Media/Web2/SaaS) | **8. MFG** Manufacturing (Manufacturing/Robotics) |
| | | **9. MDA** Media/Art/Entertainment (Digital Media/Streaming Services) | **10. REC** Real Estate/Construction (Construction Tech) | **11. RTL** Retail (eCommerce) | **12. TRL** Transportation/Logistics (MobilityTech) |
| | | **13. WSN** Water/Sanitation/Waste Management | | | |

[30]This section reflects the ticket-size distribution used in survey round 2.

Table A4 (cont.): Description of Investor Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Due Diligence (0.3) | ***Diligence Requirement:*** **1 if showing due diligence requirement.** | **1. Tax (0.33)** tax compliant; registered with tax authorities; legal compliant; compliance with national regulation | **2. Transparency (0.33)** high transparency required; full transparency on ownership and financial flows; full disclosure of legal history | **3. Financial Report (0.33)** audited financial books; financial books digitized and available to be audited; monthly financial reports expected; open to be audited by external auditors | |
| Previous Investments (0.5) | NA | **1. Small (0.33)** 5; 6; 7; 8; 9; 10 | **2. Medium (0.33)** 15; 17; 20; 21; 22; 23; 24; 25 | **3. Large (0.33)** 25; 30; 35; 37; 40; 50 | |
| Fund Return (0.5) | ***Successful Investor:*** **1 if high return [1].** | **1. High (0.7)** In the top 10% of industry return; In the top 15% of industry returns; Consistently beyond the average of market returns; Robust returns beyond market norms; Generating strong returns above the average; Continuously outperforming average returns; Past returns always outpacing the average; Consistently above industry's average returns; Regularly outperforming industry's benchmarks; Consistent and strong return performance | | **2. Neutral (0.3)** Returns are consistent with industry standards; Steady returns in line with market norms; Returns equivalent to peers in the industry; History of returns are similar with industry's trend; Consistently following industry's returns; Returns are following industry norms; Consistent with industry return norms | |
| Fund Return (0.5) | ***Successful Investor:*** **1 if large exits [1-2].** | **1. Large Exits 1 (only if "Ticket Size" is AMO1 & "Fund Return" is High or not showed)** past exits include two IPOs and several strategic acquisitions; Complete 2 IPO exits and multiple solid secondary sales; Completed 2 IPO exits and several M&A exits; Completed two IPO exits and 2 M&A exits; Achieved 4 IPO successes and secondary market sales; Realized gains from multiple private resales and buybacks; 5 exits, which include IPOs, M&As, and buybacks; Past exits include two IPOs and several strategic acquisitions | | **2. Large Exits 2 (only if "Ticket Size" is AMO2/3 & "Fund Return" is High or not showed)** 7; 8; 9; 10; 11; 12; 13; 14; 15; Past exits include two IPOs and several strategic acquisitions; Completed 7 IPO exits and multiple solid secondary sales; Completed three IPO exits and several M&A exits; Completed two IPO exits and eight M&A exits; Achieved 10+ IPO successes and secondary market sales; Realized gains from multiple private resales and buybacks; 9 exits, which include IPOs, M&As, and buybacks; Past exits include two IPOs and several strategic acquisitions; Completed 7 IPO exits and multiple solid secondary sales | |
| | | **3. Small Exits 1 (only if "Ticket Size" is AMO1 & "Fund Return" is Neutral or not showed)** 1; 2 | | **4. Small Exits 2 (only if "Ticket Size" is AMO2/3 & "Fund Return" is Neutral or not showed)** 1; 2; 3; 4 | |
| Additional Non-Financial Support (0.5) | ***Non-financial Support Provided*** **1 if showing any non-financial support** | **1. Network (0.2)** Powerful global network of experts, partners, and investors; Access to an international network of experts, partners, and investors; Extensive network to experts, partners, and investors in Africa; Strong networks to local experts, partners, and investors; Access to executives with international experience; Network of executives with international experience; Access to CFOs and experienced finance professionals; Network of CFOs and finance professionals; Strong links to top talent from university; Access to top graduates from university; Access to software developers and engineers | | | |
| | | **2. Mentor (0.2)** Mentoring and coaching with experts; Mentorship program with experts; Access to professional mentors and experts | | **3. Training (0.2)** Comprehensive business training and workshop; Extensive business training program | |
| | | **4. Consulting (0.2)** Strategic guidance and expert advice; Strategic advice and expert consultation | | **5. Business Development (0.2)** Support on developing business model and process; Guidance on refining business model and process | |
| | | **6. Business Administration (0.2)** Support to comply with legal and tax regulations; Assistance to satisfy legal and tax regulations | | | |
| Management Team Size (1) | NA | **1. (0.33)** 1 | **2. (0.33)** 2 | **3. (0.33)** 3 | |
| First Name of Manager(s) (1) | ***Female-Led Team*** **1 if the first manager is female [1-2].** | **1. Female West (0.06)** Chloe; Julie; Isabel; Michelle; Claire; Elizabeth; Barbara; Sandra; Caroline; Amanda; Julia; Sophie; Anne; Alison; Olivia; Ashley; Rachel; Carolyn; Pamela; Ellen; Tessa; Roberta; Victoria; Angela; Samantha; Lisa; Louise; Marie; Nicole; Patricia; Natalie; Laura; Catherine | | **2. Female Africa (0.14)** Yvonne; Marwa; Milkah; Adetayo; Wambura; Rhobhi; Neha; Miishe; Ayanda; Jadesola; Temie; Ghichini; Alyaa; Keitumetse; Malebo; Thandeka; Babajide; Tasneem; Sonto; Khadidiatou; Noha; Nneka; Ngozi; Chilufya; Jumia; Monsunmola; Zihko; Olayinka; Damilola; Malaika; Waringa; Hawa; Omotola; Wala; Tlanane; Rhoda; Sahar; Omonuwa; Tomilola; Nivi | |
| | | **3. Male West (0.24)** Adam; Frederic; Jonathan; Mark; Michael; Lucas; Thomas; Daniel; Bruno; Paul; Anthony; John; David; Peter; James; Andrew; Jacob; Jonas; Christian; Richard; Jacques; Charles; Marc; John; Kevin; Benjamin; Victor | | **4. Male Africa (0.56)** Ahmed; Olawale; Ayodeji; Kunle; Ezana; Erharuyi; Sangu; Khalid; Mawulom; Moshe; Ayet; Kenfield; Mohamed; Adewale; Adeyinka; Arun; Prathap; Atuu; Iongwa; Washikala; Mukthar; Emeka; Ripduman; Riyaz; Ashwin; Shehab; Efosa; Emeka; Olaijide; Nyimbi; Younes; Ifeanyi; Adeolu; Kwabena; Mourad; Abdallah; Mahmoud; Siraaj; Said; Hassen | |
| Last Name of Manager(s) (1) [Last names are consistent with First Name] | ***Foreigners' Team*** **1 if indicating all key people's last name is West-sounded [1].** ***Local Team*** **1 if indicating all key people's last name is African-sounded [2].** | **1. West (0.5)** Smith; Johnson; Brown; Taylor; Thomas; Jackson; White; Harris; Turner; Campbell; Rossi; Ricci; Ferrari; Romano; Greco; Marino; Rizzo; Conti; Moretti; Esposito; Silva; Santos; Ferreira; Costa; Oliveira; Pereira; Carvalho; Rodrigues; Martins; Sousa; González; López; Pérez; Hernández; García; Martínez; Fernández; Sánchez; Ramírez; Torres; Müller; Schmidt; Fischer; Meyer; Wagner; Schulz; Becker; Hoffmann; Schafer; Koch | | **2. Africa (0.5)** Abiodun; Adeyemi; Adewale; Adebayo; Akintoye; Akinwale; Amadi; Anyanwu; Balogun; Bello; Chukwuma; Dike; Dosunmu; Ekwueme; Eze; Fagbemi; Fatoyinbo; Gbadamosi; Ibrahim; Ifeanyi; Igwe; Iheanacho; Jalloh; Kamara; Kone; Lasisi; Mohammed; Ndlovu; Njoku; Nkosi; Nnamdi; Nwachukwu; Nwosu; Obi; Odumegwu; Okonkwo; Oladele; Oladipo; Olajide; Olumide; Onuoha; Osagie; Osei; Oyedele; Sow; Sankoh; Toure; Traore; Ugochukwu; Yobo | |

[31]"Interest Rate" appears only if Finance Type is Debt.

[32]"Maturity" appears only if Finance Type is Debt.

[33]This section reflects the AUM distribution used in survey round 2.

Table A4 (cont.): Description of Investor Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Previous Sector (1) | ***Serial Founders Team*** **1 if at least one of the key team members has past successful experience as a founder[3].** | **1. Manager Tech Startup (0.13)** Tech Startup's C-Suite | **2. Manager Big Tech (0.13)** Manager at Facebook; Manager at Twitter; Manager at Apple; Manager at Amazon | **3. Former Entrepreneur (0.2)** Entrepreneur; Serial Startup Entrepreneur; Co-founder of Several Startups; Serial Tech Startup Entrepreneur; Co-founder and Manager on Several Tech Startups | **4. Banking (0.13)** Citigroup Inc; HSBC; JP Morgan Chase; Bank of America; BNP Paribas; Deutsche Bank; Santander Bank; Barclays Bank; Standard Bank Group; Rabobank; UBS Bank |
| | | **5. Consulting (0.13)** McKinsey; Accenture; Deloitte Consulting; Ernst &Young; KPMG | **6. PE Fund (0.13)** Private Equity Fund; PE Fund; Private Equity Firm; PE Firm; Leading PE Fund; Leading Private Equity Fund; Leading Private Equity Firm; Leading PE Firm | **7. VC Fund (0.13)** Venture Capital Fund; VC Fund; Venture Capital Firm; VC Firm; Leading VC Fund; Leading Venture Capital Fund; Leading Venture Capital Firm; Leading VC Firm | |
| Undergrad Institution (0.1) [will not show if the "MBA University" shows] | ***Top US Educated Team*** **1 if the majority of managers (1 out of 1, 2 out of 2, 2 out of 3, and so on) are graduates from top U.S. universities/MBA programs.** | **1. Top US University (0.1)** Caltech ; Princeton ; Yale; UChicago ; MIT ; Stanford ; Harvard ; Columbia | | | |
| Undergrad Major (0.3) | NA | **1. STEM (0.50)** Physics; Engineering ; Mathematics ; Statistics ; Computer Science | **2. Business (0.35)** Economics; Business Administration; Accounting; Management | **3. Others (0.15)** English; Marketing; Law; Political Science; Sociology; Chemistry | |
| Top US MBA Program (0.2) | ***Top US Educated Team*** **1 if the majority of managers (1 out of 1, 2 out of 2, 2 out of 3, and so on) are graduates from top US universities/MBA programs.** | **1. Top US MBA Program** Yale SOM; MIT Sloan ; Harvard Business School ; Wharton ; Kellogg SOM ; Columbia Business School ; Chicago Booth ; Stanford GSB | | | |
| Team Strength (1) [Each profile can have 1 or 2 Team Strength(s), with the same probability] | ***Team with Local Experience*** **1 if indicating rich local investing experiences [1].** ***Team with Intl. Experience*** **1 if indicating rich international experiences [2].** ***Team with Gov. Connection*** **1 if indicating connection with government [3].** ***Female-Led Team*** **1 if the first manager is female [4].** ***Local Team*** **1 if all team member are African. [5]** ***Foreigners' Team*** **1 if all team members are foreigners. [6]** | **1. Team with Local Experience (0.35)** Team members have 10 years experience investing in Africa; Team members have 12 years experience investing in Africa; Team members have 15 years experience investing in Africa; Long-standing experience in African ecosystem | **2. Team with International Experience (0.35)** International professional experience; International investment perspective | **3. Team with Government Connection (0.3)** Connected with local government; Connected with local politicians; Connected with local bureaucrats | **4. Female-Led Team (if the first manager is female)** Female-Led investment team |
| | | **5. Local Team (if names of all team members are African-sounded)** Key people born and raised in the respondent's country | **6. Foreign Team (if names of all team members are Western-sounded)** Key people born and raised in the US; Key people born and raised in Europe | | |

*Notes*: This table summarizes details used to create investor profiles. Column (1) indicates the profile components, along with their probability of appearing in an investment partner profile. Column (2) indicates specific variables that are created following the randomly drawn texts from Column (3). We also assign specific probability for each text (or a collection of texts with a similar purpose) in Column (3).

# Table A5. Description of DFI Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| DFI Name (1) | ***DFI as Investor:*** **1 if the investor is DFI** | **1. DFI Name (1)** XP5 Ventures; AFR54 Capital; 5G Fund; AFR Venture Fund; Emerging Growth Partners; BTA Capital; Future-A Holdings; Founders Capital; Y5 Holdings; 8G Capital; AF54 Ventures; 5FX Fund; AFI Venture Fund; 2A Capital; One Capital United; AFR Founder Fund; GIC Capital LLC; AFX Investments; EWA Capital LLC; eVentures; Forward Investments; KLJ Ventures; V Capital; ASX Investments; MHG Capital; Pangea Venture Capital Fund; UA5 Investments LLC; Walia Capital; SVH Venture Fund; AFR-VC Investments; Adwoa Capital LLC; NIA Investments; AF-VC Fund; Kofi Investments; Lion Investments; HEZA Capital Management LLC; AFR Horizont Fund; 54G Asset; Fund4A Capital; Founder Index Investments | | | |
| Ticket Size (1) | ***Large Investment:*** **1 if Ticket Size ≥ group median (cutoffs are 150k, 650k, 1750k for AMO1/2/3 respectively)** | **1. AMO2** 50,000-100,000; 100,000-150,000; 150,000-250,000; 250,000-300,000; 300,000-350,000; 350,000-400,000; 400,000-450,000; 450,000-500,000; 500,000-550,000; 550,000-600,000; 600,000-650,000; 650,000-700,000; 700,000-750,000; 750,000-800,000; 800,000-850,000; 850,000-900,000; 900,000-950,000; 950,000-1,000,000; 1,000,000-1,250,000; 1,250,000-1,500,000; 1,500,000-2,000,000; 50,000; 100,000; 150,000; 200,000; 250,000; 300,000; 350,000; 400,000; 450,000; 500,000; 550,000; 600,000; 650,000; 700,000; 750,000; 800,000; 850,000; 900,000; 950,000; 1,000,000; 1,250,000; 1,500,000; 2,000,000; 2,500,000; 150,000; 200,000; 250,000; 500,000; 750,000; 1,000,000; 250,000; 500,000; 750,000; 1,000,000; 1,250,000; 1,500,000 | | **2. AMO3** 250,000-500,000; 500,000-750,000; 750,000-1,000,000; 1,000,000-1,250,000; 1,250,000-1,500,000; 1,500,000-1,750,000; 1,750,000-2,000,000; 2,000,000-2,250,000; 2,250,000-2,500,000; 2,500,000-2,750,000; 2,750,000-3,000,000; 3,000,000-4,000,000; 4,000,000-5,000,000; 250,000; 500,000; 750,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 2,250,000; 2,500,000; 2,750,000; 3,000,000; 4,000,000; 5,000,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 500,000; 1,000,000; 1,250,000; 1,500,000; 1,750,000; 2,000,000; 3,000,000; 4,000,000; 5,000,000 | |
| Ticket Size (Round 2)[34] (1) | ***Large Offer:*** **1 if Ticket Size ≥ group median (cutoff is 897k for AMO5)** | **1. AMO5** 50,000; 50,000-100,000; 100,000; 100,000-150,000; 150,000; 150,000-250,000; 200,000; 250,000; 250,000-300,000; 300,000; 300,000-350,000; 350,000; 350,000-400,000; 250,000-500,000; 400,000; 400,000-450,000; 450,000; 450,000-500,000; 500,000; 500,000-550,000; 550,000; 550,000-600,000; 600,000; 600,000-650,000; 500,000-750,000; 650,000; 650,000-700,000; 700,000; 700,000-750,000; 750,000; 750,000-800,000; 800,000; 800,000-850,000; 850,000; 850,000-900,000; 750,000-1,000,000; 900,000; 900,000-950,000; 950,000; 950,000-1,000,000; 1,000,000; 1,000,000-1,250,000; 1,250,000; 1,250,000-1,500,000; 1,500,000; 1,500,000-1,750,000; 1,500,000-2,000,000; 1,750,000; 1,750,000-2,000,000; 2,000,000; 2,000,000-2,250,000; 2,250,000; 2,250,000-2,500,000; 2,500,000; 2,500,000-2,750,000; 2,750,000; 2,750,000-3,000,000; 3,000,000; 3,000,000-4,000,000; 4,000,000; 4,000,000-5,000,000; 5,000,000 | | | |
| Share (1) [Appears only if Finance Type is Equity.] | ***Low Equity Stake:*** **1 if required equity rate ≤ group median (cutoffs are 10%, 20%, 35%, 51% for EQU1/2/3/4 respectively)** | **1. EQU1** 5; 10; 15; 5-10; 10-15; 10-20; 10; Up to 10; Up to 15; Up to 20 | **2. EQU2** 10; 15; 20; 25; 30; 5-10; 10-20; 20-30; Up to 30; Up to 40 | **3. EQU3** 10; 15; 20; 25; 30; 35; 40; 45; 49; 25-50; 50; 51 | **4. EQU4** 10; 15; 25; 35; 51; 50-75; More than 50 |
| Location of Headquarter (1) | ***Foreign Investor:*** **1 if headquarter is located in US, Europe, China, UAE, or Brazil. [1-3].** | **1. USA (0.25)** New York, USA; San Francisco, USA; Chicago, USA; Boston, USA | | **2. Europe (0.15)** London, UK; Frankfurt, Germany; Berlin, Germany; Rome, Italy; Madrid, Spain | |
| | | **3. Emerging Countries (0.1)** Beijing, China;Dubai, UAE;Sao Paulo, Brazil | | **4. Africa (0.3)** Lagos, Nigeria; Nairobi, Kenya; Johannesburg, South Africa; Cape Town, South Africa | |
| | | **5. Self (0.2)** Country where the respondent is located. | | | |
| Target (1) | ***Same Country Focus:*** **1 if the investor focuses exclusively on the respondent's country [5].** | **1 Global (0.2)** Global Emerging Markets Africa | **2 Africa 1 (0.4)** Subregion of Africa where the investor is located. | **3 Africa 2 (0.2)** Subregion of Africa where the investor is located and the adjacent subregion. | **4 Country 3 (0.1)** The country where the investor is located and its two neighboring countries. |
| | | **5 Self (0.1)** Country where the respondent is located. | | | |
| Finance Type (1) | ***Equity Offer:*** **1 if the firm finances startups with equity. [2].** | **1 Debt (0.5)** Debt | | **2 Equity (0.5)** Equity | |
| Board Seat Requirement (0.5) | ***Any Board Seat:*** **1 if the investor requires any board seat [2-3].** | **1. No Board Seat (0.15)** No seats | **2. Small Board Seat (0.45)** One; Two; 10%; 15%; 20%; 25% | **3. Large Board Seat (0.40)** 35%; 40%; 50% | |
| Interest Rate (1) [Appears only if Finance Type is Debt.] | ***Low Interest Rate:*** **1 if interest rate is lower than 15%.** | **1. Interest Rate (1)** 5-10; 10; 12; 15; 20; 10-25; 5-10; 10-20 | | | |
| Maturity (0.5) [Appears only if Finance Type is Debt.] | ***Long Maturity:*** **1 if the maturity is longer than 3 years.** | **1. Maturity (1)** 1 year; 2 years; 3 years; 4 years; Up to 5 years; Up to 7 years; Up to 10 years; 1 to 3 years; 3 to 5 years; 1 to 2 years; 5 to 10 years | | | |
| AUM, in billions USD (0.7) | **Large Investor: 1 if the investor is DFI.**[35] | **1. Medium (0.5)** 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7 | | **2. Large (0.5)** 1; 2; 3; 4; 5; 6; 7; 8; 9; 10 | |
| Fund Vintage (0.3) | ***First Time GP:*** **1 if New Fund [1].** | **1. Old Fund (0.6)** 3rd fund; 4th fund; 5th fund; 6th fund; 7th fund; 8th fund; 9th fund; 10th fund | | | |

[34] This section reflects the ticket-size distribution used in survey round 2.

[35] "Large Investor" is coded as 1 for all DFI profiles, as even the smallest AUM among DFI profiles exceeds the largest AUM shown in investor profiles.

Table A5 (cont.): Description of DFI Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Professional Team Size (0.3) | NA | **1. Small (0.33)**<br>7; 10; 12; 13; 15; 17; 18; 19; 10+; 15+; 10-20; 5-10; 10-15; 10+ | **2. Medium (0.33)**<br>20; 23; 25; 27; 30; 33; 35; 20+; 25+; 30+; 20-30 | **3. Large (0.33)**<br>40; 44; 45; 48; 50; 53; 55; 57; 60; 63; 66; 67; 68; 70; 50+; 50+; 50+; 50-100; 75+; 40+; 60+ | |
| Sector Focus (0.74) | ***Same Sector Focus:***<br>**1 if showing specific sector focus (0 if sector agnostic). The investor's sector focus will always cover the respondent's sector of operation.** | **1. AGR**<br>Agriculture (AgriTech) | **2. EDU**<br>Education (EdTech) | **3. ENR**<br>Energy (CleanTech/Renewable Energy) | **4. FIN**<br>Finance (FinTech) |
| | | **5. HLT**<br>Health (HealthTech) | **6. HSP**<br>Hospitality (Smart Hospitality Solutions) | **7. ICT**<br>Information Technology (IT) (Social Media/Web2/SaaS) | **8. MFG**<br>Manufacturing (Manufacturing/Robotics) |
| | | **9. MDA**<br>Media/Art/Entertainment (Digital Media/Streaming Services) | **10. REC**<br>Real Estate/Construction (Construction Tech) | **11. RTL**<br>Retail (eCommerce) | **12. TRL**<br>Transportation/Logistics (MobilityTech) |
| | | **13. WSN**<br>Water/Sanitation/Waste Management | | | |
| Due Diligence (0.3) | ***Diligence Requirement:***<br>**1 if showing due diligence requirement.** | **1. Tax (0.33)**<br>tax compliant; registered with tax authorities; legal compliant; compliance with national regulation | **2. Transparency (0.33)**<br>high transparency required; full transparency on ownership and financial flows; full disclosure of legal history | **3. Financial Report (0.33)**<br>audited financial books; financial books digitized and available to be audited; monthly financial reports expected; open to be audited by external auditors | |
| Previous Investments (0.5) | NA | **1. Medium (0.5)**<br>15; 17; 20; 21; 22; 23; 24; 25 | | **2. Large (0.5)**<br>25; 30; 35; 37; 40; 50 | |
| Fund Return (0.5) | ***Successful Investor:***<br>**1 if high return [1].** | **1. High (0.75)**<br>In the top 10% of industry return; In the top 15% of industry returns; Consistently beyond the average of market returns; Robust returns beyond market norms; Generating strong returns above the average; Continuously outperforming average returns; Past returns always outpacing the average; Consistently above industry's average returns; Regularly outperforming industry's benchmarks; Consistent and strong return performance | | **2. Neutral (0.25)**<br>Returns are consistent with industry standards; Steady returns in line with market norms; Returns equivalent to peers in the industry; History of returns are similar with industry's trend; Consistently following industry's returns; Returns are following industry norms; Consistent with industry return norms | |
| Exits (1) | ***Successful Investor:***<br>**1 if large exits [2].** | **1. Small Exits (0.5) (only if "Fund Return" is Neutral or not showed)**<br>1;1;2;2;3;4 | | **2. Large Exits (0.5) (only if "Fund Return" is High or not showed)**<br>7;8;9;10;11;12;13;14;15;Past exits include two IPOs and several strategic acquisitions; Completed 7 IPO exits and multiple solid secondary sales; Completed three IPO exits and several M&A exits; Completed two IPO exits and eight M&A exits; Achieved 10+ IPO successes and secondary market sales; Realized gains from multiple private resales and buybacks; 9 exits, which include IPOs, M&As, and buybacks; Past exits include two IPOs and several strategic acquisitions; Completed 7 IPO exits and multiple solid secondary sales | |
| Additional Non-Financial Support (0.5) | ***Non-financial Support Provided***<br>**1 if showing any non-financial support** | **1. Network (0.2)**<br>Powerful global network of experts, partners, and investors; Access to an international network of experts, partners, and investors; Extensive network to experts, partners, and investors in Africa; Strong networks to local experts, partners, and investors; Access to executives with international experience; Network of executives with international experience; Access to CFOs and experienced finance professionals; Network of CFOs and finance professionals; Strong links to top talent from university; Access to top graduates from university; Access to software developers and engineers | | | |
| | | **2. Mentor (0.2)**<br>Mentoring and coaching with experts; Mentorship program with experts; Access to professional mentors and experts | | **3. Training (0.2)**<br>Comprehensive business training and workshop; Extensive business training program | |
| | | **4. Consulting (0.2)**<br>Strategic guidance and expert advice; Strategic advice and expert consultation | | **5. Business Development (0.2)**<br>Support on developing business model and process; Guidance on refining business model and process | |
| | | **6. Business Administration (0.2)**<br>Support to comply with legal and tax regulations; Assistance to satisfy legal and tax regulations | | | |
| Management Team Size (1) | NA | **1. (0.25)**<br>1 | **2. (0.5)**<br>2 | **3. (0.25)**<br>3 | |
| First Name of Manager(s) (1) | ***Female-Led Team***<br>**1 if the first manager is female [1-2].** | **1. Female West (0.06)**<br>Chloe; Julie; Isabel; Michelle; Claire; Elizabeth; Barbara; Sandra; Caroline; Amanda; Julia; Sophie; Anne; Alison; Olivia; Ashley; Rachel; Carolyn; Pamela; Ellen; Tessa; Roberta; Victoria; Angela; Samantha; Lisa; Louise; Marie; Nicole; Patricia; Natalie; Laura; Catherine | | **2. Female Africa (0.14)**<br>Yvonne; Marwa; Milkah; Adetayo; Wambura; Rhobhi; Neha; Miishe; Ayanda; Jadesola; Temie; Ghichini; Alyaa; Keitumetse; Malebo; Thandeka; Babajide; Tasneem; Sonto; Khadidiatou; Noha; Nneka; Ngozi; Chilufya; Jumia; Monsunmola; Zihko; Olayinka; Damilola; Malaika; Waringa; Hawa; Omotola; Wala; Tlanane; Rhoda; Sahar; Omonuwa; Tomilola; Nivi | |
| | | **3. Male West (0.24)**<br>Adam; Frederic; Jonathan; Mark; Michael; Lucas; Thomas; Daniel; Bruno; Paul; Anthony; John; David; Peter; James; Andrew; Jacob; Jonas; Christian; Richard; Jacques; Charles; Marc; John; Kevin; Benjamin; Victor | | **4. Male Africa (0.56)**<br>Ahmed; Olawale; Ayodeji; Kunle; Ezana; Erharuyi; Sangu; Khalid; Mawulom; Moshe; Ayet; Kenfield; Mohamed; Adewale; Adeyinka; Arun; Prathap; Atuu; Iongwa; Washikala; Mukthar; Emeka; Ripduman; Riyaz; Ashwin; Shehab; Efosa; Emeka; Olaijide; Nyimbi; Younes; Ifeanyi; Adeolu; Kwabena; Mourad; Abdallah; Mahmoud; Siraaj; Saïd; Hassen | |

Table A5 (cont.): Description of DFI Profiles Randomized Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Last Name of Manager(s) (1)<br>[Last names are consistent with First Name] | ***Foreigners' Team***<br>**1 if indicating all key people's last name is West-sounded [1].**<br><br>***Local Team***<br>**1 if indicating all key people's last name is African-sounded [2].** | **1. West (0.5)**<br>Smith; Johnson; Brown; Taylor; Thomas; Jackson; White; Harris; Turner; Campbell; Rossi; Ricci; Ferrari; Romano; Greco; Marino; Rizzo; Conti; Moretti; Esposito; Silva; Santos; Ferreira; Costa; Oliveira; Pereira; Carvalho; Rodrigues; Martins; Sousa; González; López; Pérez; Hernández; García; Martínez; Fernández; Sánchez; Ramírez; Torres; Müller; Schmidt; Fischer; Meyer; Wagner; Schulz; Becker; Hoffmann; Schafer; Koch | | **2. Africa (0.5)**<br>Abiodun; Adeyemi; Adewale; Adebayo; Akintoye; Akinwale; Amadi; Anyanwu; Balogun; Bello; Chukwuma; Dike; Dosunmu; Ekwueme; Eze; Fagbemi; Fatoyinbo; Gbadamosi; Ibrahim; Ifeanyi; Igwe; Iheanacho; Jalloh; Kamara; Kone; Lasisi; Mohammed; Ndlovu; Njoku; Nkosi; Nnamdi; Nwachukwu; Nwosu; Obi; Odumegwu; Okonkwo; Oladele; Oladipo; Olajide; Olumide; Onuoha; Osagie; Osei; Oyedele; Sow; Sankoh; Toure; Traore; Ugochukwu; Yobo | |
| Previous Sector (1) | ***Serial Founders Team***<br>**1 if at least one of the key team members has past successful experience as a founder[3].** | **1. Manager Tech Startup (0.13)**<br>Tech Startup's C-Suite | **2. Manager Big Tech (0.13)**<br>Manager at Facebook; Manager at Twitter; Manager at Apple; Manager at Amazon | **3. Former Entrepreneur (0.2)**<br>Entrepreneur; Serial Startup Entrepreneur; Co-founder of Several Startups; Serial Tech Startup Entrepreneur; Co-founder and Manager on Several Tech Startups | **4. Banking (0.13)**<br>Citigroup Inc; HSBC; JP Morgan Chase; Bank of America; BNP Paribas; Deutsche Bank; Santander Bank; Barclays Bank; Standard Bank Group; Rabobank; UBS Bank |
| | | **5. Consulting (0.13)**<br>McKinsey; Accenture; Deloitte Consulting; Ernst &Young; KPMG | **6. PE Fund (0.13)**<br>Private Equity Fund; PE Fund; Private Equity Firm; PE Firm; Leading PE Fund; Leading Private Equity Fund; Leading Private Equity Firm; Leading PE Firm | **7. VC Fund (0.13)**<br>Venture Capital Fund; VC Fund; Venture Capital Firm; VC Firm; Leading VC Fund; Leading Venture Capital Fund; Leading Venture Capital Firm; Leading VC Firm | |
| Undergrad Institution (0.1)<br>[will not show if the "MBA University" shows] | ***Top US Educated Team***<br>**1 if the majority of managers (1 out of 1, 2 out of 2, 2 out of 3, and so on) are graduates from top U.S. universities/MBA programs.** | **1. Top US University (0.1)**<br>Caltech ; Princeton ; Yale; UChicago ; MIT ; Stanford ; Harvard ; Columbia | | | |
| Undergrad Major (0.3) | NA | **1. STEM (0.50)**<br>Physics; Engineering ; Mathematics ; Statistics ; Computer Science | **2. Business (0.35)**<br>Economics; Business Administration; Accounting; Management | **3. Others (0.15)**<br>English; Marketing; Law; Political Science; Sociology; Chemistry | |
| Top US MBA Program (0.2) | ***Top US Educated Team***<br>**1 if the majority of managers (1 out of 1, 2 out of 2, 2 out of 3, and so on) are graduates from top US universities/MBA programs.** | **1. Top US MBA Program**<br>Yale SOM; MIT Sloan ; Harvard Business School ; Wharton ; Kellogg SOM ; Columbia Business School ; Chicago Booth ; Stanford GSB | | | |
| Team Strength (1)<br>[Each profile can have 1 or 2 Team Strength(s), with the same probability] | ***Team with Local Experience***<br>**1 if indicating rich local investing experiences [1].**<br><br>***Team with Intl. Experience***<br>**1 if indicating rich international experiences [2].**<br><br>***Team with Gov. Connection***<br>**1 if indicating connection with government [3].**<br><br>***Female-Led Team***<br>**1 if the first manager is female [4].** | **1. Team with Local Experience (0.35)**<br>Team members have 10 years experience investing in Africa; Team members have 12 years experience investing in Africa; Team members have 15 years experience investing in Africa; Long-standing experience in African ecosystem | **2. Team with International Experience (0.35)**<br>International professional experience; International investment perspective | **3. Team with Government Connection (0.3)**<br>Connected with local government; Connected with local politicians; Connected with local bureaucrats | **4. Female-Led Team (if the first manager is female)**<br>Female-Led investment team |
| | ***Local Team***<br>**1 if all team member are African. [5]**<br><br>***Foreigners' Team***<br>**1 if all team members are foreigners. [6]** | **5. Local Team (if all team members are African)**<br>Key people born and raised in the respondent's country | **6. Foreign Team (if all team team members are foreigners)**<br>Key people born and raised in the US; Key people born and raised in Europe | | |

*Notes*: This table summarizes details used to create DFI profiles. Column (1) indicates the components, along with their probability of appearing in an investment partner profile. Column (2) indicates specific variables that are created following the randomly drawn texts from Column (3). We also assign specific probability for each text (or a collection of texts with a similar purpose) in Column (3).

TABLE A6. Variables in Synthetic Investor and DFI Profiles

| **Variables** | **Description** |
|---|---|
| Equity | =1 if the financing offer is equity investments. |
| Low Interest Rate | =1 if the interest rate is less than 15%. |
| Any Board Seat | =1 if board seat is required. |
| Low Equity Stake | =1 if the requested equity share is less than or equal to the group median. |
| Large Offer | =1 if the check size is larger than or equal to the group median. |
| Same Country Focus | =1 if the investor focuses exclusively on the same country where the respondent operates. |
| Same Sector Focus | =1 if the investor has specific sector focus that covers the respondent's sector of operation. |
| Long Maturity | =1 if the maturity is longer than 3 years. |
| Local Team | =1 if investor's key members are all born and raised in respondent's country of operation. |
| Team with Local Experience | =1 if the investor shows local experiences. |
| Serial Founders Team | =1 if investor's key members have founder experience. |
| First Time GP | =1 if the investor is currently managing its first fund. |
| Foreign Investor | =1 if the investor's headquarter is located in China, UAE, Brazil, USA or Europe. |
| Team with Intl. Experience | =1 if the investor shows international experiences. |
| Non-financial Support Provided | =1 if the investor offers additional non-financial support |
| Team with Gov. Connection | =1 if the investor has a connection with government. |
| Impact Investor | =1 if the investor is an impact investor. |
| Successful Investor | =1 if the investor has high return or exits. |
| DFI as Investor | =1 if the investor is a DFI. |
| Foreigners' Team | =1 if investor's key members are all born and raised in the US or Europe. |
| Diligence Requirement | =1 if the investor profile shows due diligence requirement. |
| Female-Led Team | =1 if the company is led by female. |
| International Investor as LP | =1 if the investor's LP is from Europe, Canada, or the US (except for DFIs). |
| Large Investor | =1 if the investor's AUM is larger than the group median. |
| Top US Educated Team | =1 if the majority of the investor's key members have degrees from top US universities. |
| Young Investor | =1 if the investor is a young investor (i.e., founded after 2013). |
| DFI as LP | =1 if the investor's LP is a DFI. |
| Local Investor as LP | =1 if the investor's LP is from Africa. |

*Notes*: This table illustrates the variables generated from the components from investor and DFI profiles with their definitions. See Appendix Tables A4 and A5 for details on all profile components and text options. The following variables apply only to investor profiles and are therefore coded as 0 for DFI profiles: "Young Investor", "Impact Investor", "DFI as LP", "International Investor as LP", "Local Investor as LP", and "First Time GP". "DFI as Investor" is coded as 0 for investor profiles and 1 for DFI profiles. "Large Investor" is coded as 1 for all DFI profiles, as even the smallest AUM among DFI profiles exceeds the largest AUM shown in investor profiles.

# Table A7. Preferences of Startups for Investors

| Dependent Variable: *Interest on Investors* | (1) | (2) | (3) | (4) First 5 Profiles | (5) Last 5 Profiles | (6) Ordered Probit | (7) Ordered Logit | (8) Rank Ordered Logit | (9) Probit High vs. Low | (10) Logit High vs. Low |
|---|---|---|---|---|---|---|---|---|---|---|
| Equity | 0.718*** | 0.727*** | 0.716*** | 0.707*** | 0.673*** | 0.382*** | 0.651*** | 0.366*** | 0.407*** | 0.652*** |
| | (0.026) | (0.029) | (0.026) | (0.038) | (0.040) | (0.015) | (0.026) | (0.018) | (0.019) | (0.030) |
| Low Interest Rate | 0.443*** | 0.431*** | 0.443*** | 0.413*** | 0.441*** | 0.224*** | 0.395*** | 0.222*** | 0.247*** | 0.397*** |
| | (0.023) | (0.027) | (0.023) | (0.034) | (0.036) | (0.014) | (0.024) | (0.014) | (0.017) | (0.027) |
| Any Board Seat | -0.358*** | -0.359*** | -0.356*** | -0.308*** | -0.407*** | -0.193*** | -0.327*** | -0.187*** | -0.202*** | -0.325*** |
| | (0.023) | (0.024) | (0.023) | (0.033) | (0.035) | (0.013) | (0.022) | (0.014) | (0.016) | (0.026) |
| Large Offer | 0.352*** | 0.357*** | 0.350*** | 0.352*** | 0.370*** | 0.192*** | 0.321*** | 0.195*** | 0.194*** | 0.311*** |
| | (0.017) | (0.018) | (0.016) | (0.024) | (0.026) | (0.010) | (0.017) | (0.011) | (0.012) | (0.019) |
| Low Equity Stake | 0.350*** | 0.305*** | 0.350*** | 0.324*** | 0.384*** | 0.165*** | 0.282*** | 0.179*** | 0.168*** | 0.270*** |
| | (0.023) | (0.025) | (0.023) | (0.033) | (0.036) | (0.013) | (0.023) | (0.014) | (0.017) | (0.027) |
| Same Country Focus | 0.156*** | 0.153*** | 0.155*** | 0.147*** | 0.137*** | 0.084*** | 0.145*** | 0.096*** | 0.073*** | 0.117*** |
| | (0.027) | (0.031) | (0.027) | (0.040) | (0.043) | (0.017) | (0.028) | (0.016) | (0.020) | (0.032) |
| Long Maturity | 0.133*** | 0.107*** | 0.134*** | 0.159*** | 0.089** | 0.060*** | 0.101*** | 0.073*** | 0.063*** | 0.101*** |
| | (0.026) | (0.030) | (0.026) | (0.038) | (0.041) | (0.016) | (0.028) | (0.015) | (0.019) | (0.031) |
| Same Sector Focus | 0.123*** | 0.187*** | 0.122*** | 0.163*** | 0.084*** | 0.101*** | 0.174*** | 0.054*** | 0.113*** | 0.182*** |
| | (0.018) | (0.019) | (0.018) | (0.026) | (0.028) | (0.010) | (0.017) | (0.011) | (0.012) | (0.020) |
| DFI as Investor | 0.117*** | 0.331*** | 0.117*** | 0.044 | 0.224*** | 0.183*** | 0.308*** | 0.055** | 0.177*** | 0.287*** |
| | (0.038) | (0.041) | (0.038) | (0.054) | (0.058) | (0.022) | (0.038) | (0.022) | (0.027) | (0.044) |
| Local Team | 0.105*** | 0.107*** | 0.104*** | 0.084** | 0.089** | 0.056*** | 0.096*** | 0.046*** | 0.075*** | 0.120*** |
| | (0.024) | (0.027) | (0.024) | (0.036) | (0.038) | (0.015) | (0.025) | (0.014) | (0.018) | (0.028) |
| Team with Local Experience | 0.073*** | 0.095*** | 0.074*** | 0.049* | 0.085*** | 0.046*** | 0.083*** | 0.047*** | 0.067*** | 0.108*** |
| | (0.020) | (0.022) | (0.020) | (0.029) | (0.030) | (0.012) | (0.020) | (0.011) | (0.014) | (0.023) |
| Serial Founders Team | 0.060*** | 0.028 | 0.060*** | 0.078*** | 0.052** | 0.017* | 0.028 | 0.030*** | 0.018 | 0.029 |
| | (0.017) | (0.019) | (0.017) | (0.025) | (0.026) | (0.010) | (0.018) | (0.010) | (0.013) | (0.020) |
| Successful Investor | 0.058*** | 0.076*** | 0.058*** | 0.051** | 0.069** | 0.040*** | 0.069*** | 0.039*** | 0.044*** | 0.071*** |
| | (0.018) | (0.019) | (0.017) | (0.025) | (0.027) | (0.010) | (0.018) | (0.010) | (0.013) | (0.020) |
| Non-financial Support Provided | 0.043*** | 0.040** | 0.044*** | 0.083*** | 0.041 | 0.021** | 0.035** | 0.016* | 0.016 | 0.027 |
| | (0.016) | (0.018) | (0.016) | (0.024) | (0.025) | (0.010) | (0.017) | (0.010) | (0.012) | (0.019) |
| First Time GP | 0.043 | 0.033 | 0.043 | 0.091** | -0.006 | 0.017 | 0.035 | 0.026* | 0.032 | 0.051 |
| | (0.027) | (0.031) | (0.027) | (0.040) | (0.042) | (0.016) | (0.028) | (0.016) | (0.020) | (0.032) |
| Impact Investor | 0.042** | 0.044** | 0.043** | 0.047* | 0.036 | 0.025** | 0.042** | 0.027** | 0.022 | 0.036 |
| | (0.020) | (0.022) | (0.020) | (0.029) | (0.031) | (0.012) | (0.020) | (0.011) | (0.014) | (0.023) |
| Team with International Experience | 0.037* | 0.043* | 0.039** | 0.027 | 0.051 | 0.024** | 0.037* | 0.022* | 0.021 | 0.033 |
| | (0.020) | (0.022) | (0.020) | (0.029) | (0.031) | (0.012) | (0.020) | (0.012) | (0.015) | (0.023) |
| Foreigners' Team | 0.034 | 0.069** | 0.034 | 0.084** | -0.036 | 0.037** | 0.061** | 0.015 | 0.031 | 0.050 |
| | (0.026) | (0.029) | (0.026) | (0.038) | (0.040) | (0.015) | (0.026) | (0.015) | (0.019) | (0.031) |
| Large Investor | 0.034* | 0.021 | 0.035** | 0.033 | 0.032 | 0.011 | 0.018 | 0.025** | 0.011 | 0.019 |
| | (0.018) | (0.020) | (0.018) | (0.026) | (0.028) | (0.011) | (0.018) | (0.010) | (0.013) | (0.021) |
| Diligence Requirement | -0.025 | -0.018 | -0.026 | -0.019 | -0.028 | -0.006 | -0.014 | -0.017 | -0.010 | -0.016 |
| | (0.018) | (0.020) | (0.018) | (0.026) | (0.027) | (0.011) | (0.018) | (0.010) | (0.013) | (0.021) |
| Foreign Investor | 0.024 | 0.030 | 0.025 | 0.046* | -0.010 | 0.015 | 0.025 | 0.008 | 0.024* | 0.039* |
| | (0.018) | (0.020) | (0.018) | (0.026) | (0.028) | (0.011) | (0.018) | (0.011) | (0.013) | (0.021) |
| Team with Government Connection | 0.023 | 0.048** | 0.025 | -0.031 | 0.045 | 0.023* | 0.042** | 0.012 | 0.035** | 0.057** |
| | (0.020) | (0.023) | (0.020) | (0.029) | (0.032) | (0.012) | (0.021) | (0.012) | (0.015) | (0.024) |
| International Investor as LP | -0.016 | -0.006 | -0.016 | -0.033 | -0.024 | -0.002 | -0.007 | -0.001 | -0.023* | -0.037* |
| | (0.018) | (0.020) | (0.018) | (0.027) | (0.028) | (0.011) | (0.018) | (0.011) | (0.013) | (0.021) |
| Top US Educated Team | -0.011 | -0.015 | -0.011 | -0.018 | 0.014 | -0.007 | -0.011 | -0.010 | -0.005 | -0.008 |
| | (0.018) | (0.020) | (0.018) | (0.026) | (0.028) | (0.011) | (0.018) | (0.011) | (0.013) | (0.021) |
| Female-Led Team | -0.008 | -0.007 | -0.008 | -0.035 | 0.018 | -0.004 | -0.007 | -0.012 | 0.002 | 0.003 |
| | (0.021) | (0.023) | (0.021) | (0.030) | (0.032) | (0.012) | (0.021) | (0.012) | (0.015) | (0.024) |
| DFI as LP | -0.007 | -0.005 | -0.007 | 0.015 | -0.030 | -0.001 | -0.003 | -0.001 | -0.009 | -0.015 |
| | (0.018) | (0.020) | (0.018) | (0.027) | (0.028) | (0.011) | (0.018) | (0.011) | (0.013) | (0.021) |
| Young Investor | 0.007 | 0.021 | 0.007 | -0.014 | -0.007 | 0.013 | 0.023 | 0.011 | 0.007 | 0.012 |
| | (0.024) | (0.027) | (0.024) | (0.035) | (0.037) | (0.015) | (0.025) | (0.014) | (0.018) | (0.029) |
| Local Investor as LP | 0.003 | 0.004 | 0.002 | -0.019 | 0.052* | 0.003 | 0.005 | 0.007 | 0.002 | 0.004 |
| | (0.018) | (0.020) | (0.018) | (0.027) | (0.028) | (0.011) | (0.018) | (0.011) | (0.013) | (0.021) |
| Observations | 45475 | 45475 | 45475 | 22220 | 22220 | 45475 | 45475 | 45475 | 45475 | 45475 |
| Unique Respondents | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 |
| Indiv FEs | Yes | No | Yes | Yes | Yes | No | No | No | No | No |
| Order FEs | No | No | Yes | No | No | No | No | No | No | No |
| DV Mean | 4.279 | 4.279 | 4.279 | 4.277 | 4.282 | 4.279 | 4.279 | 6.776 | 0.515 | 0.515 |
| DV SD | 1.976 | 1.976 | 1.976 | 1.961 | 1.992 | 1.976 | 1.976 | 3.065 | 0.500 | 0.500 |

*Notes*: This table presents regression results on startups' preferences for investment attributes, based on synthetic investor and DFI profiles. Column (1) reports the benchmark specification of Equation 3.1. Column (2) removes individual fixed effects. Column (3) adds profile-order fixed effects, based on the order in which profiles are shown to respondents. Columns (4) and (5) restrict the sample to the first and last five profiles shown to each respondent, respectively. Columns (6)–(8) replace OLS with Ordered Probit, Ordered Logit, and Rank-Ordered Logit estimators, using the relative ranking of scores rated by each respondent. Columns (9) and (10) replace OLS with standard Probit and Logit models, respectively, and redefine the dependent variable as an indicator for high scores (scores $\geq 5$ on the 1–7 scale). Robust standard errors are reported in parentheses. $^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$.

TABLE A8. Preferences of Startups for Investors: Reweighting Sample

| | | Reweight by PitchBook | | | Reweight by PitchBook+ | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | Sector | Country | Country × Sector | Sector | Country | Country × Sector |
| Equity | 0.718*** | 0.826*** | 0.777*** | 0.826*** | 0.809*** | 0.784*** | 0.819*** |
| | (0.026) | (0.033) | (0.033) | (0.044) | (0.031) | (0.032) | (0.041) |
| Low Interest Rate | 0.443*** | 0.438*** | 0.461*** | 0.464*** | 0.447*** | 0.459*** | 0.461*** |
| | (0.023) | (0.030) | (0.029) | (0.041) | (0.028) | (0.028) | (0.037) |
| Any Board Seat | -0.358*** | -0.380*** | -0.343*** | -0.315*** | -0.386*** | -0.346*** | -0.335*** |
| | (0.023) | (0.029) | (0.029) | (0.039) | (0.028) | (0.028) | (0.036) |
| Large Offer | 0.352*** | 0.384*** | 0.419*** | 0.425*** | 0.390*** | 0.420*** | 0.441*** |
| | (0.017) | (0.021) | (0.021) | (0.029) | (0.020) | (0.020) | (0.026) |
| Low Equity Stake | 0.350*** | 0.381*** | 0.358*** | 0.386*** | 0.384*** | 0.356*** | 0.397*** |
| | (0.023) | (0.030) | (0.030) | (0.039) | (0.028) | (0.029) | (0.036) |
| Same Country Focus | 0.156*** | 0.149*** | 0.148*** | 0.189*** | 0.145*** | 0.142*** | 0.161*** |
| | (0.027) | (0.036) | (0.035) | (0.054) | (0.034) | (0.034) | (0.048) |
| Long Maturity | 0.133*** | 0.137*** | 0.110*** | 0.111** | 0.138*** | 0.111*** | 0.116*** |
| | (0.026) | (0.034) | (0.033) | (0.044) | (0.032) | (0.032) | (0.041) |
| Same Sector Focus | 0.123*** | 0.073*** | 0.127*** | 0.065** | 0.073*** | 0.127*** | 0.076*** |
| | (0.018) | (0.023) | (0.023) | (0.031) | (0.022) | (0.022) | (0.029) |
| DFI as Investor | 0.117*** | 0.121** | 0.168*** | 0.115* | 0.120** | 0.172*** | 0.120** |
| | (0.038) | (0.050) | (0.050) | (0.063) | (0.047) | (0.048) | (0.059) |
| Local Team | 0.105*** | 0.126*** | 0.119*** | 0.099** | 0.114*** | 0.116*** | 0.092** |
| | (0.024) | (0.032) | (0.031) | (0.042) | (0.030) | (0.030) | (0.039) |
| Team with Local Experience | 0.073*** | 0.068*** | 0.055** | 0.059* | 0.065*** | 0.055** | 0.052* |
| | (0.020) | (0.026) | (0.025) | (0.034) | (0.024) | (0.024) | (0.031) |
| Serial Founders Team | 0.060*** | 0.092*** | 0.064*** | 0.096*** | 0.079*** | 0.064*** | 0.082*** |
| | (0.017) | (0.022) | (0.022) | (0.030) | (0.021) | (0.021) | (0.027) |
| Successful Investor | 0.058*** | 0.037 | 0.059*** | 0.050 | 0.038* | 0.058*** | 0.056** |
| | (0.018) | (0.023) | (0.022) | (0.030) | (0.022) | (0.022) | (0.028) |
| Non-financial Support Provided | 0.043*** | 0.046** | 0.035* | 0.032 | 0.046** | 0.034* | 0.032 |
| | (0.016) | (0.021) | (0.021) | (0.029) | (0.020) | (0.020) | (0.026) |
| First Time GP | 0.043 | 0.034 | 0.037 | 0.051 | 0.032 | 0.041 | 0.054 |
| | (0.027) | (0.035) | (0.034) | (0.049) | (0.033) | (0.033) | (0.045) |
| Impact Investor | 0.042** | 0.032 | 0.040 | 0.020 | 0.031 | 0.045* | 0.029 |
| | (0.020) | (0.026) | (0.025) | (0.033) | (0.024) | (0.024) | (0.031) |
| Team with International Experience | 0.037* | 0.015 | 0.023 | 0.004 | 0.016 | 0.025 | 0.002 |
| | (0.020) | (0.026) | (0.025) | (0.034) | (0.025) | (0.024) | (0.032) |
| Foreigners' Team | 0.034 | 0.035 | 0.019 | 0.062 | 0.040 | 0.019 | 0.058 |
| | (0.026) | (0.033) | (0.033) | (0.046) | (0.031) | (0.032) | (0.042) |
| Large Investor | 0.034* | 0.039* | 0.053** | 0.045 | 0.044** | 0.048** | 0.045 |
| | (0.018) | (0.023) | (0.022) | (0.029) | (0.022) | (0.022) | (0.027) |
| Diligence Requirement | -0.025 | -0.005 | -0.022 | -0.036 | -0.006 | -0.020 | -0.025 |
| | (0.018) | (0.023) | (0.022) | (0.032) | (0.022) | (0.022) | (0.029) |
| Foreign Investor | 0.024 | 0.052** | 0.027 | 0.058* | 0.042* | 0.030 | 0.053* |
| | (0.018) | (0.023) | (0.023) | (0.031) | (0.022) | (0.022) | (0.029) |
| Team with Government Connection | 0.023 | 0.020 | 0.013 | 0.035 | 0.019 | 0.012 | 0.024 |
| | (0.020) | (0.026) | (0.026) | (0.036) | (0.025) | (0.025) | (0.033) |
| International Investor as LP | -0.016 | -0.019 | -0.000 | -0.023 | -0.016 | -0.000 | -0.013 |
| | (0.018) | (0.023) | (0.023) | (0.030) | (0.022) | (0.022) | (0.028) |
| Top US Educated Team | -0.011 | -0.007 | -0.017 | 0.005 | -0.006 | -0.016 | 0.002 |
| | (0.018) | (0.023) | (0.023) | (0.032) | (0.022) | (0.022) | (0.029) |
| Female-Led Team | -0.008 | 0.015 | -0.007 | -0.057 | 0.009 | -0.007 | -0.047 |
| | (0.021) | (0.027) | (0.026) | (0.036) | (0.025) | (0.025) | (0.033) |
| DFI as LP | -0.007 | -0.018 | -0.007 | -0.018 | -0.023 | -0.007 | -0.020 |
| | (0.018) | (0.024) | (0.023) | (0.031) | (0.022) | (0.023) | (0.028) |
| Young Investor | 0.007 | -0.005 | 0.013 | 0.009 | -0.007 | 0.013 | 0.000 |
| | (0.024) | (0.031) | (0.031) | (0.042) | (0.030) | (0.030) | (0.038) |
| Local Investor as LP | 0.003 | 0.009 | 0.010 | 0.018 | 0.017 | 0.012 | 0.023 |
| | (0.018) | (0.023) | (0.023) | (0.030) | (0.022) | (0.022) | (0.028) |
| Observations | 45475 | 45475 | 43350 | 40345 | 45475 | 44855 | 41550 |
| Unique Respondents | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 | 4444 |
| Indiv FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| DV Mean | 4.279 | 4.279 | 4.279 | 4.279 | 4.279 | 4.279 | 4.279 |
| DV SD | 1.976 | 1.976 | 1.976 | 1.976 | 1.976 | 1.976 | 1.976 |

*Notes*: This table reports reweighted regression results on startups' preferences for investment attributes, based on synthetic investor and DFI profiles. All columns use the specification in Equation 3.1. Column (1) reports the unweighted benchmark results. Columns (2)–(4) reweight observations using the sector, country, and country × sector distributions of African companies that received VCPE investment during 2010–2024 in PitchBook. Columns (5)–(7) apply the same reweighting schemes using the corresponding distributions constructed from PitchBook, Africa: The Big Deal, and Briter Bridges (PitchBook+). Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE A9. Variables in Synthetic Accelerator Profiles

| **Variables** | **Description** |
|---|---|
| Grants Provided | =1 if there is a possibility of winning grants from the program. |
| Require Equity Stake | =1 if equity stake is required in exchange for the participation in the program. |
| DM Foreign Accelerator | =1 if the accelerator's headquarter is located in the US or Europe. |
| EM Foreign Accelerator | =1 if the accelerator's headquarter is located in China, Dubai, or Brazil. |
| No Equity Stake Required | =1 if mentions explicitly that there is no equity stake required in exchange for the participation in the program. |
| Physical Office Provided | =1 if physical office space is provided. |
| Same Sector Focus | =1 if the accelerator has specific sector focus that covers the respondent's sector of operation. |
| Possibility to Join Online | =1 if online participation is possible. |
| Top US Educated Team | =1 if the majority of the accelerator's key members have degrees from top US universities. |
| Team with Gov. Connection | =1 if the accelerator shows connection with government. |
| Local Team | =1 if accelerator's key members are all are born and raised in respondent's country of operation. |
| Have International Sponsor | =1 if the accelerator has a sponsor that is an international company. |
| Mentorship Provided | =1 if mentorship is provided. |
| Large Accelerator | =1 if number of active ventures or ventures accelerated is larger than the median. |
| Network to Investors | =1 if networking opportunities with investors is provided. |
| Have Local Sponsor | =1 if the accelerator has a sponsor that is from Africa. |
| Female-Led Team | =1 if the accelerator is led by female. |
| Long Duration | =1 if the program is longer than or equal to six months. |
| Network to Potential Partners | =1 if networking opportunities with potential partners is provided. |
| Have DFI Sponsor | =1 if the accelerator has a sponsor that is a DFI. |
| Team with Local Experience | =1 if the accelerator shows local experiences. |
| Serial Founders Team | =1 if accelerator's key members have founder experience. |
| Team with Intl. Experience | =1 if the accelerator shows international experiences. |
| Foreigners' Team | =1 if accelerator's key members are all are born and raised in the US or Europe. |
| Network to Talent | =1 if networking opportunities with talents is provided. |
| High Female Share | =1 if share of female graduated from the accelerator is larger than or equal to 40%. |

*Notes*: This table illustrates the variables generated from the components from accelerator profiles with their definitions.

## Table A10. Preferences of Startups for Accelerators

| | (1) | (2) |
|---|---|---|
| | Interest | Interest |
| Grants Provided | 0.589*** | 0.672*** |
| | (0.031) | (0.029) |
| Require Equity Stake | -0.426*** | -0.461*** |
| | (0.039) | (0.036) |
| DM Foreign Accelerator | 0.337*** | 0.318*** |
| | (0.042) | (0.039) |
| EM Foreign Accelerator | 0.273*** | 0.205*** |
| | (0.057) | (0.055) |
| No Equity Stake Required | 0.167*** | 0.179*** |
| | (0.037) | (0.035) |
| Physical Office Provided | -0.120*** | -0.111*** |
| | (0.031) | (0.029) |
| Same Sector Focus | 0.105*** | 0.103*** |
| | (0.034) | (0.033) |
| Possibility to Join Online | 0.076* | 0.085** |
| | (0.041) | (0.038) |
| Team with Government Connection | -0.066* | -0.077** |
| | (0.038) | (0.036) |
| Have International Sponsor | 0.085*** | 0.064** |
| | (0.033) | (0.031) |
| Mentorship Provided | 0.043 | 0.057* |
| | (0.031) | (0.029) |
| Network to Investors | 0.068** | 0.052 |
| | (0.034) | (0.032) |
| Large Accelerator | 0.051 | 0.051* |
| | (0.032) | (0.030) |
| Have Local Sponsor | -0.022 | -0.042 |
| | (0.033) | (0.031) |
| Long Duration | -0.057* | -0.031 |
| | (0.032) | (0.030) |
| Network to Potential Partners | 0.022 | 0.028 |
| | (0.033) | (0.031) |
| Top US Educated Team | 0.012 | -0.028 |
| | (0.032) | (0.030) |
| Female-Led Team | 0.023 | 0.027 |
| | (0.038) | (0.036) |
| Have DFI Sponsor | 0.030 | 0.025 |
| | (0.033) | (0.031) |
| Serial Founders Team | -0.032 | -0.022 |
| | (0.034) | (0.033) |
| Foreigners' Team | -0.068 | -0.015 |
| | (0.049) | (0.046) |
| Team with Local Experience | 0.058 | 0.012 |
| | (0.038) | (0.035) |
| Team with International Experience | 0.009 | -0.012 |
| | (0.038) | (0.036) |
| Local Team | -0.049 | -0.011 |
| | (0.039) | (0.036) |
| Network to Talent | -0.010 | -0.008 |
| | (0.033) | (0.032) |
| High Female Share | -0.005 | -0.003 |
| | (0.042) | (0.040) |
| Observations | 14570 | 14570 |
| Unique Respondents | 2914 | 2914 |
| Indiv FEs | No | Yes |
| Model | OLS | OLS |
| DV Mean | 4.631 | 4.631 |
| DV SD | 1.899 | 1.899 |

*Notes*: This table presents the regression results startups' preferences for different attributes shown in the synthetic accelerator profiles, as captured by $\beta_k$ in Equation 3.1. Detailed explanations for each accelerator attributes are shown in Appendix Table A9. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE A11. Reasons Why Early-Stage Startups Prefer Debt or Equity

(A) Why Prefer Debt Investments?

| | Count | Share (%) |
|---|---|---|
| Keep ownership and operational independence | 368 | 54.8% |
| Easier to manage and obtain (more familiar) | 184 | 27.4% |
| Provide incentive to work harder (to repay) | 151 | 22.5% |
| Expect better financial conditions with debt | 143 | 21.3% |
| Not ready to enter equity markets yet | 103 | 15.3% |
| Better financially (e.g., tax deductions) | 85 | 12.6% |
| Other | 49 | 7.3% |

(B) Why Prefer Equity Investments?

| | Count | Share (%) |
|---|---|---|
| Cashflow and financial flexibility (no interests payment) | 1121 | 49.0% |
| Investors have incentives to help | 906 | 39.6% |
| Access to investors' expertise, guidance, and network | 758 | 33.1% |
| Lower financial risk | 371 | 16.2% |
| No need to provide collateral | 206 | 9.0% |
| Easier to manage and obtain (more familiar) | 177 | 7.7% |
| Other | 192 | 8.4% |

*Notes:* Panel A (Panel B) reports reasons why survey respondents prefer debt over equity (equity over debt). In the first survey round, response categories were manually constructed based on respondents' open-ended answers. In the second survey round, these categories derived from the first round were presented as options in an multi-select question.

TABLE A12. Heterogeneity Analysis: Foreign Capital Supply Shocks Affect Startup Activity by Local vs. Foreign Startups

| | Africa | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Log Deal Size | | | | Log Deal Count | | | |
| | Domestic | | Foreign | | Domestic | | Foreign | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| instrument (size) | 0.029** | 0.118*** | 0.057** | 0.250*** | | | | |
| | (0.012) | (0.041) | (0.023) | (0.061) | | | | |
| instrument (count) | | | | | 0.031*** | 0.162*** | 0.053*** | 0.422*** |
| | | | | | (0.010) | (0.061) | (0.018) | (0.081) |
| Constant | 0.367*** | 0.000 | 0.618*** | -0.182 | 0.255*** | -0.065 | 0.388*** | -0.514** |
| | (0.061) | (0.169) | (0.107) | (0.253) | (0.027) | (0.148) | (0.046) | (0.199) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Sector FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Country-Sector FE | No | Yes | No | Yes | No | Yes | No | Yes |
| N Country-Sector | 147 | 147 | 147 | 147 | 147 | 147 | 147 | 147 |
| Obs. | 1,470 | 1,470 | 1,470 | 1,470 | 1,470 | 1,470 | 1,470 | 1,470 |
| R-Squared | 0.260 | 0.393 | 0.442 | 0.607 | 0.470 | 0.594 | 0.607 | 0.746 |

*Notes*: This table reports the effects of foreign capital supply on startup activity in Africa, separately for local and foreign startups. Foreign startups are defined as those with at least one founder who obtained education or work experience outside Africa prior to receiving their first VCPE deal. Columns (1)–(2) use the number of VCPE deals as outcome measures, while Columns (3)–(4) use the total U.S. dollar value of VCPE deals. The causal effects are estimated by proxying foreign capital supply shocks with Bartik-style shift–share instruments. See Section 4.3.3 for details on the empirical specification and the construction of the shift–share instruments.

TABLE A13. Observed Capital Flow $n_{j,x}$ and Solved Capital Wedge $r_{j,x}$

(A) Observed Capital Flow $n_{j,x}$ (Row-Normalized to Sum = 1)

| | Investor Origin $x$ | | | |
|---|---|---|---|---|
| Company Region $j$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 17.0% | 39.9% | 35.4% | 7.7% |
| Western Africa | 22.2% | 44.0% | 21.8% | 11.9% |
| Northern Africa | 26.7% | 19.8% | 37.5% | 16.1% |
| Southern Africa | 41.4% | 24.0% | 19.8% | 14.9% |
| Northern America | 0.1% | 83.4% | 8.3% | 8.2% |
| Europe | 0.4% | 29.4% | 62.2% | 8.0% |
| RoW | 0.9% | 32.0% | 9.1% | 57.9% |

(B) Solved Capital Wedge $r_{j,x}$ (Row-Normalized to Local = 1)

| | Investor Origin $x$ | | | |
|---|---|---|---|---|
| Company Region $j$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 1.00 | 0.49 | 0.60 | 1.08 |
| Western Africa | 1.00 | 0.63 | 1.26 | 1.12 |
| Northern Africa | 1.00 | 0.70 | 0.57 | 0.95 |
| Southern Africa | 1.00 | 0.97 | 1.54 | 0.95 |
| Northern America | 5.32 | 1.00 | 2.46 | 2.45 |
| Europe | 3.16 | 0.92 | 1.00 | 2.00 |
| RoW | 2.26 | 0.95 | 2.11 | 1.00 |

*Notes:* This table reports the observed capital flows $n_{j,x}$ used as calibration targets and the equilibrium capital wedges $r_{j,x}$ that matches the data. In Panel A, each row is normalized to sum to 1. In Panel B, each row is normalized such that the capital wedge for local investors is set to 1 as the baseline. We construct $n_{j,x}$ from the deal-size-weighted number of financed startups in region $j$ backed by investors from origin $x$, based on deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges in 2010-2024. See Section 5.5 and Appendix A.4.2 for details on the calibration targets and estimation procedure.

TABLE A14. Observed/Latent Entrepreneurs by Connection Region

(A) Observed Financed Entrepreneurs by Connection Region $n_j^k$

| | Connection Region $k$ | | | |
|---|---|---|---|---|
| Company Region $j$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 27.5% | 27.0% | 31.7% | 13.8% |
| Western Africa | 24.3% | 29.2% | 32.5% | 14.0% |
| Northern Africa | 36.1% | 16.5% | 27.8% | 19.6% |
| Southern Africa | 40.4% | 20.6% | 28.7% | 10.3% |
| Northern America | 1.4% | 67.4% | 15.8% | 15.5% |
| Europe | 2.5% | 22.0% | 59.9% | 15.7% |
| RoW | 1.7% | 24.6% | 19.6% | 54.1% |

(B) Solved Latent Entrepreneurs by Connection Region $e_j^k$

| | Connection Region $k$ | | | |
|---|---|---|---|---|
| Company Region $j$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 38.0% | 16.7% | 24.9% | 20.4% |
| Western Africa | 24.7% | 17.0% | 42.2% | 16.2% |
| Northern Africa | 45.3% | 13.6% | 17.8% | 23.3% |
| Southern Africa | 34.3% | 16.8% | 40.7% | 8.3% |
| Northern America | 2.5% | 45.0% | 26.5% | 26.0% |
| Europe | 5.1% | 16.8% | 50.5% | 27.6% |
| RoW | 3.1% | 18.6% | 34.7% | 43.6% |

*Notes:* This table reports the observed entrepreneur distribution by connection type $n_j^k$ used as calibration targets, and the equilibrium latent entrepreneur mass $e_{j,k}$ that matches the data. Each row is normalized to sum to 1 in both panels. We construct $n_j^k$ from founders of financed startups in region $j$, based on deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges in 2010–2024, and assign their connection type $k$ based on education and work experience records prior to startup founding from Revelio Lab. See Section 5.5 and Appendix A.4.2 for details on the calibration targets and estimation procedure.

## Appendix A.2. Survey and Experiment design

The Startup Survey is our primary instrument for implementing the experiment and collecting detailed information from high-growth entrepreneurs across Africa. In this section, we describe the observable attributes used to define high-growth entrepreneurs, lay out the survey methodology and data-collection timeline, and summarize the criteria and procedures used to ensure sample quality and representativeness. We then provide key implementation details and summary statistics for the entrepreneurs who participated. We invited startups to participate in the first wave between September 2023 and January 2024. After completing a comprehensive post-field analysis, we launched a second wave between October 2025 and December 2025 to strengthen representativeness, to conduct robustness checks, and to further probe mechanisms suggested by the first-wave results. We also provide the details of the second wave below.

A.2.1. **Survey Structure.** Both survey rounds follow the same fundamental structure; the second wave incorporates refinements in content and implementation, but preserves the overall flow and core modules. The survey begins by explaining the survey's goals, the incentives offered to respondents for their participation, and includes some consent-like questions to help high-growth entrepreneurs self-select themselves to participate in this study. We then provide guidance on how to assess investment partner profiles using a 1-7 scale rating system. We also explain the attributes displayed in the investment partner profiles and provide a glossary to ensure that respondents have the necessary knowledge and understanding to complete the profile rating section. We emphasize to respondents that we take into account all profile attributes when reviewing their responses and suggesting actual investment partners that match their preferences.

Following this, we request respondents to answer several "filtering" questions. The objective of these "filtering" inquiries is to gather information regarding the amount of investment respondents are seeking, the percentage of equity they would consider losing in exchange for capital, and the primary sector and an African country in which their company operates. Importantly, the respondent-specific values collected in these filtering questions determine the distribution of profile attributes they are exposed to, and this constitutes the core source of design differences across the two survey rounds. In particular, relative to the first round, the second round displays investor profiles featuring substantially smaller investment offer sizes. We describe the motivation for, and implementation details of, this refinement below in Appendix A.2.2. We use respondents' answers to these questions to ensure that we display profiles that do elicit their preferences. In the same page where we show "filtering" questions, we also inquire whether

respondents are interested in seeing accelerator profiles in addition to the investor profiles. Subsequently, we ask respondents to rate 15 unique hypothetical investor profiles (or 10 hypothetical investor profiles and 5 hypothetical accelerator profiles if they express interest in accelerator profiles). This design describes the first survey round; in the second round, for scalability and to keep the survey length manageable (and thus support completion), we do not ask this question and instead directly ask respondents to rate 10 hypothetical investor profiles.

After the completion of the profile rating, we request respondents to answer several descriptive questions. In the first descriptive part, we ask for some information related to firm basics (i.e., email address, website, LinkedIn address, ownership, etc.). We then continue by collecting the firm's employment and financial information (i.e., revenues, profits, valuations, etc.). Next, we seek information related to the firm's access to capital (i.e., financial needs and constraints, previous funding, barriers, etc.). Lastly, we close the survey by asking the respondents some basic information about themselves (i.e., age, gender, education, financial knowledge, stated preferences on investment, etc.)

The structure described above corresponds to the first survey round. In the second round, we implemented several targeted modifications. First, we revised the elicitation and input formats for selected items to reduce the likelihood of respondent error and improve data quality. Second, we streamlined a subset of prompts and questions to keep the survey length manageable without changing the core content. Third, we expanded the final module by adding additional questions on respondents' views about market conditions and financing environments, which helps validate and interpret the mechanisms suggested by our main findings. We discuss the motivation for these changes and provide further implementation details below in Appendix A.2.2.

A.2.2. **Profiles design.** The two survey rounds share the same profile design and draw from an identical underlying pool of hypothetical profiles. Investment partner profiles that we generated include basic information such as name and location, along with their investment preferences. They also provide information about team members and their strengths, as well as details regarding the financing offer. In addition to those features, if the randomization process permits, investor profiles may also offer details about fund characteristics, fund performance, and additional non-financial support. Accelerator profiles specifically provide information about program details, the key benefits of participating in the program, and other program characteristics, depending on the outcome of the randomization process. To randomize the contents of these profiles, we assign specific inclusion probabilities to components and text options below each component based on the approximate distribution of actual investment offerings as a benchmark.

Table A6 reports variables that we create from the text of the hypothetical investor and DFI profiles, and Appendix Table A9 reports variables that we create from the text of the hypothetical accelerator profiles. We expand on the description of all profile components and options from which the analysis variables are generated in Appendix Tables A4 and A5, where we report all possible mechanisms through which a given component and option may appear in the text of the synthetic profile. Column (1) of Appendix Tables A4 and A5 also present in parenthesis the unconditional inclusion probability that a given component is randomly drawn to be included in a profile. For a given component, each piece of text also has its own inclusion probability of being drawn, conditional on the component appearing in the synthetic profile. For a given component, certain pieces of text indicate when the dummy variable in our regression takes a value 1, while the others indicate when the variable takes value 0, as reported in the second column of Appendix Tables A4 and A5 that refer to the specific numbered text boxes in the third column.

This part will clarify how to read and interpret Appendix Tables A4 and A5. To illustrate the process, take the "Finance Type" component from the first column in Appendix Table A4 as an example. Below the "Finance Type" text in the first column, value 1 indicates the probability that this variable appears in a particular investment partner profile (i.e., which means that this component always appears on every investment partner profile, unlike any other components that, for instance, have 0.5 probability or any probability below 1). To the right of "Finance Type" text in the first column, specifically in the third column, we put *all* available text options for this component. In this "Finance Type" case, there are only two options; "Debt," with a probability of 0.5, and Equity, with a probability of 0.5. Still, in the same row, the second column indicates how the selected option is stored as a variable in our dataset following the randomization. Next, we discuss the general structure of a synthetic investment partner profile.

*Basic Information and Investment Preferences.* At the top of the investment partner profiles, we include basic information related to the investment partners and their preferences. For investor profiles, components that always appear include the firm's name, the location of their headquarters, and their geographical preferences. In some investor profiles, additional information on whether an investor is a young firm, old firm, or concerned with Environmental, Social, and Governance (ESG) outcomes (i.e., impact investors) is included, if the randomization permits. For accelerator profiles, the components that are consistently included are the firm's name, their location, and their sector preferences.

*Team Members.* Below the part where we show basic information about an investment partner, we present team members of the investment partners. We randomize the number of team members shown, which can be 1, 2, or 3 for investor profiles and 1 or 2 for accelerator profiles. We consistently show prior working experience for all team members listed in the investment partner profiles. For each team member, we also randomize their first and last name across two dimensions; (i) Western/American-sounded or African-sounded and (ii) female-sounded or male-sounded. Depending on the outcome of the randomization process, we may also present the details about team members' education, indicating if they attended either (i) an elite undergraduate institution in the United States or (ii) an elite MBA program in the United States. If the randomization permits, we may also add information on the degree that the member obtained from their undergraduate education.

*Team Strength.* To highlight the strengths of a specific team within an investment partner profile, we employ randomization in presenting phrases related to (i) team's experience in Africa, (ii) their international experience, (iii) connection that they have to the government or politicians, (iv) female leadership of the investment team, (v) whether key members of their team were born and raised in the respondent's country, and (vi) whether key members of their team were born and raised in the United States or Europe.

*Details of Offer.* For each investor and DFI profile that we show to the respondents, we assign equal probabilities for both equity and debt investments to appear. The supplemental information related to the financing offer will be different across equity and debt investments. If the financing offer that appears is an equity investment, we then randomize the exact share of equity required based on the respondent's answer to the relevant "filtering" question. In some profiles, we also display the number of board seats required. If the financing offer that appears is a debt, we randomize the interest rate and, in some profiles, we also include information about the maturity of the debt investments. We also always include and randomize the ticket size based on the respondent's answer to the relevant "filtering" question. As shown in tables, we report the ticket-size distributions used in survey rounds 1 and 2 separately. For robustness-check purposes, the round-2 design uses a finer set of ticket-size bins and, overall, smaller ticket sizes, implying a leftward shift in the distribution relative to round 1.

*Fund Characteristics.* In certain investor profiles, we include key characteristics that may not directly relate to the financing offer, but giving additional background information about an investor or DFI to the respondent. These characteristics range from financial details, such as the size of assets under management (AUM), the investor's

limited partners, the number of funds, and the count of investment professionals, to non-financial information like target sectors and the required due diligence for engaging in an investment partnership.

*Fund Performance.* Investor profiles may also display an investor's past performance. The indicators used to represent the past performance of an investor or DFI are not solely limited to the quantity of investments, as indicated by the number of previous and successful investments, but also the quality of returns from their investments in the past. This quality is indicated by a text phrase summarizing their average return on previous investments.

*Additional Non-Financial Support.* Finally, at the bottom of an investor and DFI profile, we might also highlight the additional non-financial support provided by investors or DFIs. Among the most common non-financial supports offered and presented to respondents in these profiles are related to (i) networking, (ii) mentoring, (iii) training, (iv) consulting services, (v) business development, and (vi) business administration.

*Program Details.* In accelerator profiles, right below the the part where we show basic information about an accelerator, we present program details. These details cover not only the technicalities and implementation of the program, such as the availability of an online option and program's duration, but also delve into other aspects that are common to be found in an accelerator's program. Some of those other aspects include the share of equity demanded in exchange for participation in the program and the amount of grants/prizes awarded to selected participants.

*Key Benefits.* We also showcase the key benefits from participating in an accelerator's program. The potential list of key benefits presented to respondents includes (i) amenities related to office space, (ii) access to a network of potential employees, (iii) access to a network of potential business partners, (iv) access to a network of potential investors, (v) opportunities to acquire a mentor, and (vi) information about the program's sponsors.

*Other Program Characteristics.* Lastly, at the bottom of an accelerator profile, we might also present additional program characteristics associated with the accelerator's program. We independently randomize the appearance of information that typically complements the general description of acceleration programs we have observed. These may include (i) the number of active ventures, (ii) the number of graduated ventures, and (iii) the percentage of female owners who have graduated from the program.

A.2.3. **Outreach and Sample.** In the first round, we rely on key regional players in the entrepreneurial ecosystems to recruit high-growth entrepreneurs to participate in this study. When recruiting respondents, there is no compensation involved, and therefore, the sole motivation for respondents to participate is to access several incentives that were offered as part of the "Connecting Africa's Entrepreneurs" study. To ensure that survey participants are indeed high-growth entrepreneurs with a strong understanding of their ventures, we explicitly ask potential respondents in the recruitment script to complete the survey if they meet the following criteria: (i) they are the founder/manager of a company with at least 2 full-time employees that has been operating for less than 10 years and primarily focuses on Africa, (ii) they are seeking funding to grow their company, and (iii) they are interested in participating in the IFC's matchmaking opportunity. Our collaboration with the implementing partner also added an additional layer of screening, as they were tasked to target this specific group of entrepreneurs when extending the invitation.

In the second round, we use LinkedIn, PitchBook+, and additional commercial and public sources to identify startups with valid email contact information for founders or senior executives.[36] In addition to the startup eligibility criteria described above, we restrict the sample to firms with fewer than 50 employees and exclude nonprofit organizations and public-sector entities. To increase response rates, we also send reminder emails to respondents who did not respond to or complete the survey after the initial outreach, reiterating our survey incentives to encourage participation.

A.2.4. **Survey Data Treatment.** To ensure the reliability of self-reported startup information, the research team at the International Finance Corporation (IFC) conducted a detailed manual review of each respondent. This process focused on two distinct aspects: identifying and removing fake startups, and correcting implausible revenue and valuation data. In both cases, the judgment was grounded in the consistency across multiple variables, rather than rigid application of numeric thresholds.

*Identifying Likely Fake Startups.* The IFC research team assessed whether a respondent represented a genuine startup based on a *multi-dimensional evaluation* of consistency across all available information. No single piece of information—such as website validity or revenue level—was treated as more important than others. Instead, the team evaluated each observation *holistically*, considering whether its reported firm characteristics, financial data, and external signals formed a coherent and plausible profile.

[36]Additional commercial and public sources include Preqin, Refinitiv, VC4A, Crunchbase, Gali, AfriLabs, and IFC data.

Specifically, the IFC team reviewed each respondent using the following dimensions: **firm age**, **number of full-time employees**, **reported revenue**, **follow-up revenue**, **reported valuation**, **online presence** (including website and social media), **local macroeconomic context** (such as GDP per capita or institutional stability), and **industry characteristics**. These factors were never used in isolation. Rather, the team considered whether the values across these dimensions made sense *jointly*—for example, whether a high revenue figure was credible given the firm's age, size, online presence, and country context, and whether follow-up data corroborated the initial report.

Only when multiple dimensions simultaneously showed strong internal inconsistency, and the IFC research team found no counter-evidence to explain or justify the reported information, did they classify the respondent as a likely fake. For instance, if a firm had no valid digital presence, reported implausible figures for both revenue and valuation, showed no alignment between initial and follow-up responses, and was based in a country or industry where such figures are highly unlikely, the team viewed the case as non-credible. Even in such situations, the team remained cautious: the presence of a minimally functional online profile or some consistency in follow-up responses was often sufficient for the team to retain the observation, unless the broader evidence base was overwhelmingly implausible.

Ultimately, the IFC research team's classification of fake startups was not driven by fixed thresholds or rules, but by whether all available signals jointly supported or undermined the plausibility of the firm's existence. Based on this approach, the team identified 7 respondents in the sample as likely fake startups and excluded them from further analysis.

*Adjusting Implausible Revenue and Valuation.* The IFC research team assessed the plausibility of reported revenue and valuation figures through a consistent review of multiple dimensions. These included firm age, number of full-time employees, reported revenue and valuation, follow-up survey responses, online presence, sector and country context, and the implied price-to-sales ratio. No single dimension was prioritized; adjustments were made only when the overall body of information supported a clear and internally coherent interpretation.

When discrepancies emerged between initial reports and follow-up data—for example, when revenue reported in the main survey differed from the follow-up response by several orders of magnitude—the research team considered whether unit confusion had occurred. In such cases, the team applied corrective dividers such as dividing by 1,000 or 1,000,000, but only when the adjusted figure was more consistent with the firm's other

characteristics. The team also accounted for potential currency mismatches: although the survey question specified "dollars," some respondents may have reported in local currency. The team assumed that follow-up revenue values were more accurate, and in cases where the reported revenue in the main survey could be reconciled with the follow-up value by dividing by the exchange rate, the team treated this as evidence that the original response may have been recorded in local terms. Exchange rate adjustments were applied only when they improved the overall consistency of the record.

Online presence was reviewed alongside financial and structural data. The IFC team examined whether a startup had a functioning website, whether its LinkedIn page or other social media platforms (such as Facebook or Instagram) reflected a formal business identity, and whether its digital footprint aligned with the scale and professionalism implied by its self-reported data. A professional online presence reinforced the plausibility of higher valuations or revenues, while a weak or incomplete presence required stronger support from other indicators to be considered credible.

Additional consistency checks included the alignment between valuation and revenue levels, the relationship between firm scale and financial claims, and the coherence of choice-implied valuation based on equity offered and funding sought. The team also reviewed whether respondents' reported financials were reasonable given their stated sector, local economic conditions, and whether they had a plausible fundraising history.

When no correction could reconcile inconsistencies across these dimensions, or when conflicting signals remained after considering potential adjustments, the IFC research team conservatively set the revenue or valuation field to missing. All adjustments were made only when supported by clear and reinforcing evidence across the full set of available indicators.

## Appendix A.3. Data Sources and Treatment

A.3.1. **Data sources.** The following are the data sources from which we track deals and companies tied to venture investments in Africa.

- **PitchBook:** PitchBook provides extensive data on the near universe of deals and players in the VC and PE markets. Its coverage includes detailed information on deals, companies, investors, funds, LPs, service providers, and key individuals, as well as relational datasets that link these entities. Notably, while PitchBook provides comprehensive data on commitments between GPs, funds, and LPs, it does not report the full history of cash flows (i.e., capital contributions and distributions).[37]
- **Briter Bridges:** Briter Bridges provides comprehensive datasets that offer detailed insights into the distribution of capital across sectors, geographies, and stages of company development. Briter Bridges is also well-known for employing a robust methodology for data collection and validation, incorporating a mix of primary and secondary sources, including direct submissions from investors and companies, public disclosures, and proprietary research.
- **Africa: The Big Deal**: Africa: The Big Deal is renowned for its comprehensive coverage of startup financing activities in Africa, including detailed information on venture capital flows, private equity investments, and other significant business transactions. Africa: The Big Deal employs a rigorous methodology for data collection, drawing on a diverse set of sources, including investor announcements, startup disclosures, and news reports from reputable media outlets within the African entrepreneurial ecosystem.

A.3.2. **Data Matching and Consolidating.** This subsection details our methodology for matching and harmonizing data from PitchBook, Briter Bridges, and Africa: The Big Deal.

[37] As stated in Brown, Harris, Jenkinson, Kaplan, and Robinson (2015), *"To obtain fund-level data, PitchBook and Preqin gather information from public sources and make direct requests for submission. Freedom of Information Act (FOIA) requests (or their parallel outside the U.S.) requiring LPs to reveal certain information are often used, combined with requests to both LPs and GPs to voluntarily make their information public. For instance, PitchBook states that 'The methods of obtaining fund performance information rely heavily on FOIA requests to a variety of public pensions, with additional data being obtained from online sources, listed private equity sources, filings and those GPs who choose to report their performance data.'.* Furthermore, as noted in the same source, *"A downside of the public approach is that reliance on FOIA disclosures and voluntary submissions may lead to a sample that is not representative of the universe of funds. FOIA taps only certain types of investors (e.g., public pension funds); moreover, voluntary submission (especially by GPs) may introduce selection and survivorship biases. Moreover, this process may make it more difficult to check the data for accuracy or create comprehensive performance histories."*

*Data Matching.* We conduct data matching at three distinct levels: the company level, the deal level, and the investor level. At each level, we first consolidate Briter Bridges and Africa: The Big Deal into an intermediate BB–AfricaTBD dataset, and subsequently consolidate PitchBook with the already-combined BB–AfricaTBD dataset. Hence, each consolidation step involves matching and merging two datasets at a time. Below, we describe our general procedure for consolidating two datasets.

At the company level, we begin with strict matching based on company names and websites after basic text standardization (e.g., capitalization and website format normalization). This procedure inevitably leaves a nontrivial number of true matches unmatched. For all unmatched companies in each dataset, we therefore conduct extensive searches against the full counterpart dataset (not limited to unmatched observations) using all available identifiers, including company name, legal name, former name, and website, to identify omitted matches. The same procedure is applied for investor-level matching.

Conditional on company-level matches, we then perform deal-level matching within each matched company. We first apply strict matching based on deal dates. For remaining unmatched deals, we conduct extensive manual verification and assess potential matches using all available deal characteristics, including deal size, deal stage, and investor composition.

*Data Consolidating.* In constructing the final dataset, we treat PitchBook as the primary data source, Briter Bridges as a secondary source, and Africa: The Big Deal as a tertiary source. Accordingly, when overlapping or conflicting information is available across multiple datasets, we retain the version reported by the dataset with the higher priority in this hierarchy.[38]

Following this rule, we harmonize all variables across datasets. Two variables require special treatment: company industry and deal type. For company industry, we manually recategorize all reported industries into the 13 sector categories used in our IFC survey, with an additional residual "Other" category. For industry information from PitchBook, we primarily rely on the `PrimaryIndustryGroup` variable; however, for firms classified as "Commercial Products," "Commercial Services," "Other Business Products and Services," "Services," or "Services (Non-Financial)," we instead use the more granular information provided in the `PrimaryIndustryCode` variable. For deal type, we harmonize classifications from Briter Bridges and Africa: The Big Deal into

[38]This preference ranking applies only to overlapping or competing information across datasets. If a data point appears exclusively in a lower-priority dataset (e.g., Africa: The Big Deal), we retain that observation alongside unique information from other sources, as well as observations appearing in multiple datasets.

the five deal categories used by PitchBook: "Accelerator/Incubator," "Seed Round" (including both pre-seed and seed), "Early Stage VC" (Series A), "Later Stage VC" (Series B and later), and "PE Growth/Expansion."

A.3.3. **Data Treatments.** The following outlines the data treatments applied in the construction and processing of specific variables used in this paper.

- **How do we define foreignness?** We partition the world into seven regions (Africa, Northern America, Europe, Latin America, China, India, and Rest of the World). For a startup located in region $r$, we define an entity (e.g., an investor or founder) as foreign if its origin region is not $r$; otherwise it is local.
- **How do we measure founders' foreignness, education, and experience profiles?** We measure these characteristics at the time the founder's startup receives its first financing (i.e., in the year of the first deal), and classify a founder as having overseas experience based on information observed up to that point.
- **How do we treat missing values?** We do not apply any specific imputation method for missing values. If a value is missing in the raw data, the corresponding cleaned variable will also be missing. Additionally, if the raw field is present but we are unable to assign a value to it (e.g., due to ambiguity), the cleaned variable will remain missing. For instance, if a raw "location" field (pertaining to work experience, education, or company headquarters) contains a city that cannot be identified on OpenStreetMap (e.g., due to misspelling or reference to a building rather than a city), the cleaned location variable will be coded as missing. Similarly, if the raw "degree" field contains an unrecognizable string (e.g., "LIX Q4"), the cleaned degree variable will be missing.
- **How do we measure degrees obtained and years of education in Revelio Labs' LinkedIn data?** We run a program that scans degree-related information for each individual in Revelio Labs' LinkedIn data. The program searches for keywords indicating educational attainment across multiple languages, as LinkedIn profiles are filled out in the original languages of users. Based on these keywords, degree levels such as High School, Bachelor's, Master's, and PhD are imputed. For instance, if "M.Sc." appears in the string, a master's degree is assigned. An individual is considered to hold a college degree if at least one reported educational experience is at the Bachelor's degree level or higher. This logic also applies when assigning higher degrees, such as Master's or PhD.
- **How do we define the location of entities in Revelio Labs' LinkedIn data?** We obtain the specific location of an entity (e.g., company, employee) by using self-reported location fields and mapping it to OpenStreetMap to retrieve

latitude and longitude coordinates. This procedure allows us to geolocate the headquarters location of a company and the working location of an employee.

- **How do we identify employees and founders in Revelio Labs' LinkedIn data?** Similar to degree identification, we run a program on the job description variable for each individual in Revelio Labs' LinkedIn data. The program searches for keywords in different languages, as the data are in the original language used by individuals to fill out their LinkedIn profiles. From this, we are able to infer whether an individual is an employee or a founder of a particular company. In addition to the automated approach, we conduct a comprehensive manual review to further improve identification accuracy. Specifically, we inspected all African startups (i.e., those present in PitchBook, Africa: The Big Deal, and Briter Bridges datasets). For companies not matched by the automated procedure, we conduct manual searches within Revelio. When founders were not identified automatically, we conducted additional searches in both Revelio and external online sources. As a result, the matching rates between PitchBook+ and Revelio are as follows. Among African startups in PitchBook+, 94.3% are covered in Revelio, with 84.9% of these companies having identified employees and 66.4% having identified founders. In other regions, the corresponding rates are as follows: Europe—93.1% coverage, 90.7% with employees, 78.1% with founders; Northern America—92.4% coverage, 89.5% with employees, 81.1% with founders; Latin America—92.4% coverage, 89.4% with employees, 81.4% with founders; India—94.8% coverage, 93.1% with employees, 84.1% with founders; and Rest of the World (RoW)—82.9% coverage, 79.8% with employees, and 65.1% with founders.
- **How do we improve the quality of Revelio Labs' LinkedIn data?** To improve the quality of gender and race classifications in Revelio's LinkedIn dataset, we employed a manual verification and correction procedure. Specifically, we manually reviewed and corrected the gender and race classifications for all African founders, as well as for a random sample of 500 founders from each other region. According to Revelio Labs' methodology (Revelio's classification), gender is predicted based on an individual's first name by estimating the probabilities that the name is male or female using data from U.S. Social Security Administration records (e.g., if 70% of people named Lauren are female, the model outputs a 0.7 probability of being female and 0.3 for being male). Similarly, ethnicity is predicted using the individual's first name, last name, and location, with the model leveraging U.S. Census data to estimate the probability of membership

in one of the following groups: White, Black, API (Asian and Pacific Islander), Hispanic, Multiple (two or more ethnicities), and Native.

To address potential inaccuracies, we manually examined LinkedIn profile pictures of sampled founders to verify gender and ethnicity. Based on this visual verification, we reassigned gender and ethnicity labels for all founders. For gender, we maintained a binary classification. For ethnicity, we adopted two classification schemes guided by U.S. Census standards (US Census standards):

- **Primary Classification:** White, Arabic, Hispanic, API (Asian & Pacific Islander), and Black.
- **Alternative Classification:** White (including Arabic), Hispanic, API, and Black.

In these schemes, "White" corresponds to the White category in the US Census; API encompasses both the Asian and Native Hawaiian or Pacific Islander categories; Hispanic corresponds to Hispanic or Latino; Black corresponds to Black or African American; and Arabic refers to individuals of Middle Eastern or North African descent. In cases where manual inspection did not yield a definitive classification, we defaulted to the original Revelio data.

- **What procedure do we use to select a random sample from Revelio Labs' LinkedIn data?** To select a random sample of companies from Revelio Labs' LinkedIn data, we begin with the list of all unique companies on present in the dataset. We exclude companies that appear in PitchBook, Africa: The Big Deal, and Briter Bridges datasets. From the remaining companies, we randomly select 500 companies per region and then append companies from PitchBook, Africa: The Big Deal, and Briter Bridges datasets to the final sample.
- **How do we measure colonial linkages and common language?** We identified colonial linkages by referring to information summarized in list of African territories and states by date of colonization accessed on July 3, 2024. We identified languages official and spoken languages by countries by referring to information summarized in official and spoken languages of African Countries accessed on July 3, 2024.
- **How do we measure the distance between countries?** We measure distances between countries in Africa (and other countries worldwide) by using pairwise country distance measures obtained from GeoDist accessed on July 3, 2024.

## Appendix A.4. Model Solution, Calibration, and Counterfactuals

This appendix provides additional details for the model in Section 5. Since the main text already presents the environment and the key equilibrium objects, we do not repeat the setup here. Instead, we first collect the proofs of the lemmas stated in the text, then describe the calibration procedure, and finally provide details on the counterfactual exercises.

### A.4.1. **Proofs of the Lemmas.**

A.4.1.1. *Proof of Lemma 1.* Proof. We proceed in three steps.

*Step 1: Free entry and equity supply.* In market $(j, x)$, the matching function is

$$n_{j,x} = s_{j,x}^{\eta} d_{j,x}^{1-\eta}.$$

An investor supplying one unit of capital is matched with probability

$$\frac{n_{j,x}}{s_{j,x}} = \left(\frac{d_{j,x}}{s_{j,x}}\right)^{1-\eta}.$$

Conditional on a successful match, the investor receives expected payoff $\beta E[z_{j,x}]$. Hence the expected return from supplying one unit of capital is

$$\left(\frac{d_{j,x}}{s_{j,x}}\right)^{1-\eta} \beta E[z_{j,x}].$$

Free entry implies

$$\left(\frac{d_{j,x}}{s_{j,x}}\right)^{1-\eta} \beta E[z_{j,x}] = r_{j,x},$$

which rearranges to

$$\frac{s_{j,x}}{d_{j,x}} = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{1}{1-\eta}}, \qquad s_{j,x} = d_{j,x}\left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{1}{1-\eta}}.$$

*Step 2: Effective demand and expected productivity.* Entrepreneurs of type $k$ in destination $j$ have mass $e_j^k$. A fraction $\mu_{j,x}^k$ searches in market $(j, x)$, and each such entrepreneur contributes $\lambda_{j,x}^k$ units of effective demand. Aggregating across entrepreneur types gives

$$d_{j,x} = \sum_{k \in \mathbb{X}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k.$$

Expected project quality in market $(j, x)$ is therefore

$$E[z_{j,x}] = \frac{1}{d_{j,x}} \sum_{k \in \mathbb{X}} \lambda_{j,x}^k \mu_{j,x}^k e_j^k \int z \, dF_j^k(z).$$

*Step 3: Search probabilities.* A type-$k$ entrepreneur searching in equity market $(j,x)$ is financed with probability

$$\frac{n_{j,x}}{d_{j,x}} = \left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}.$$

Hence the systematic utility from choosing market $x$ is proportional to

$$\bar{\tau}_{j,x}\lambda_{j,x}^{k}\left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}.$$

The outside option is debt, with systematic utility $\bar{\tau}_{j,d}^{k}$. With i.i.d. extreme-value shocks, the standard logit formula implies

$$\mu_{j,x}^{k} = \frac{\left(\bar{\tau}_{j,x}\lambda_{j,x}^{k}\left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}\right)^{\sigma}}{\sum_{c\in\mathbb{X}}\left(\bar{\tau}_{j,c}\lambda_{j,c}^{k}\left(\frac{s_{j,c}}{d_{j,c}}\right)^{\eta}\right)^{\sigma} + \left(\bar{\tau}_{j,d}^{k}\right)^{\sigma}}.$$

This proves the result. ■

A.4.1.2. *Proof of Lemma 2.* Proof. Entrepreneurs of type $k$ in destination $j$ have mass $e_j^k$. A fraction $\mu_{j,x}^k$ searches in market $(j,x)$ and contributes $\lambda_{j,x}^k\mu_{j,x}^k e_j^k$ units of effective demand. Each such demand unit is financed with probability

$$\frac{n_{j,x}}{d_{j,x}} = \left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}.$$

Hence

$$n_{j,x}^{k} = e_j^k\mu_{j,x}^{k}\lambda_{j,x}^{k}\left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta}.$$

Using Lemma 1,

$$\left(\frac{s_{j,x}}{d_{j,x}}\right)^{\eta} = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}},$$

so

$$n_{j,x}^{k} = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}}\lambda_{j,x}^{k}\mu_{j,x}^{k}e_j^k.$$

Summing over investor origins gives

$$N_j^k = \sum_{x\in\mathbb{X}} n_{j,x}^{k}.$$

Summing over entrepreneur types gives

$$n_{j,x} = \sum_{k\in\mathbb{X}} n_{j,x}^{k}.$$

Finally,

$$N_j = \sum_{x\in\mathbb{X}}\sum_{k\in\mathbb{X}} n_{j,x}^{k} = \sum_{x\in\mathbb{X}}\left[\left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}}\sum_{k\in\mathbb{X}}\lambda_{j,x}^{k}\mu_{j,x}^{k}e_j^k\right].$$

This proves the lemma. ■

A.4.1.3. *Proof of Lemma 3.* Before proving the result, define

$$\hat{\mu}^k_{j,x} \equiv \frac{\mu^k_{j,x}}{(\bar{\tau}_{j,x})^\sigma}, \qquad \hat{e}^k_{j,x} \equiv \hat{\mu}^k_{j,x} e^k_j.$$

Proof. Start from Lemma 2. Aggregating over entrepreneur types,

$$n_{j,x} = \sum_{k\in\mathbb{X}} n^k_{j,x} = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}} \sum_{k\in\mathbb{X}} \lambda^k_{j,x}\mu^k_{j,x}e^k_j.$$

Substituting $\mu^k_{j,x} = (\bar{\tau}_{j,x})^\sigma \hat{\mu}^k_{j,x}$ gives

$$n_{j,x} = \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}} (\bar{\tau}_{j,x})^\sigma \sum_{k\in\mathbb{X}} \lambda^k_{j,x}\hat{\mu}^k_{j,x}e^k_j.$$

Hence

$$\frac{n_{j,f}}{n_{j,\ell}} = \left(\frac{r_{j,\ell}}{r_{j,f}}\right)^{\frac{\eta}{1-\eta}} \left(\frac{E[z_{j,f}]}{E[z_{j,\ell}]}\right)^{\frac{\eta}{1-\eta}} \left(\frac{\bar{\tau}_{j,f}}{\bar{\tau}_{j,\ell}}\right)^\sigma \cdot \frac{\sum_{k\in\mathbb{X}} \lambda^k_{j,f}\hat{\mu}^k_{j,f}e^k_j}{\sum_{k\in\mathbb{X}} \lambda^k_{j,\ell}\hat{\mu}^k_{j,\ell}e^k_j}.$$

Using $\hat{e}^k_{j,x} = \hat{\mu}^k_{j,x}e^k_j$, the last term becomes

$$\frac{\sum_{k\in\mathbb{X}} \lambda^k_{j,f}\hat{e}^k_{j,f}}{\sum_{k\in\mathbb{X}} \lambda^k_{j,\ell}\hat{e}^k_{j,\ell}}.$$

Now apply the identity

$$\mathbb{E}_k[ab] = \mathbb{E}_k[a]\mathbb{E}_k[b] + \mathrm{Cov}_k(a,b),$$

where $\mathbb{E}_k[\cdot]$ and $\mathrm{Cov}_k(\cdot,\cdot)$ denote the average and covariance across entrepreneur types $k \in \mathbb{X}$. This implies

$$\mathbb{E}_k[\lambda^k_{j,x}\hat{e}^k_{j,x}] = \mathbb{E}_k[\lambda^k_{j,x}]\mathbb{E}_k[\hat{e}^k_{j,x}] + \mathrm{Cov}_k(\lambda^k_{j,x}, \hat{e}^k_{j,x}).$$

Since the common proportionality factor converting averages into sums cancels in the ratio, we obtain

$$\frac{n_{j,f}}{n_{j,\ell}} = \left(\frac{r_{j,\ell}}{r_{j,f}}\right)^{\frac{\eta}{1-\eta}} \left(\frac{E[z_{j,f}]}{E[z_{j,\ell}]}\right)^{\frac{\eta}{1-\eta}} \left(\frac{\bar{\tau}_{j,f}}{\bar{\tau}_{j,\ell}}\right)^\sigma \cdot \frac{\mathbb{E}_k[\lambda^k_{j,f}]\mathbb{E}_k[\hat{e}^k_{j,f}] + \mathrm{Cov}_k(\lambda^k_{j,f}, \hat{e}^k_{j,f})}{\mathbb{E}_k[\lambda^k_{j,\ell}]\mathbb{E}_k[\hat{e}^k_{j,\ell}] + \mathrm{Cov}_k(\lambda^k_{j,\ell}, \hat{e}^k_{j,\ell})}.$$

This proves the lemma. ■

A.4.1.4. *Proof of Lemma 4.* Before proving the result, define

$$A_{j,x} \equiv \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}}, \qquad \omega^k_{j,x} \equiv (\bar{\tau}_{j,x})^\sigma \lambda^k_{j,x}\hat{\mu}^k_{j,x}.$$

Proof. Start again from Lemma 2. For entrepreneur type $k$,

$$N^k_j = \sum_{x\in\mathbb{X}} n^k_{j,x} = e^k_j \sum_{x\in\mathbb{X}} \left(\frac{\beta E[z_{j,x}]}{r_{j,x}}\right)^{\frac{\eta}{1-\eta}} \lambda^k_{j,x}\mu^k_{j,x}.$$

Using $\mu^k_{j,x} = (\bar{\tau}_{j,x})^\sigma \hat{\mu}^k_{j,x}$, this becomes

$$N^k_j = e^k_j \sum_{x \in \mathbb{X}} A_{j,x} (\bar{\tau}_{j,x})^\sigma \lambda^k_{j,x} \hat{\mu}^k_{j,x} = e^k_j \sum_{x \in \mathbb{X}} A_{j,x} \omega^k_{j,x}.$$

Hence

$$\frac{N^f_j}{N^\ell_j} = \frac{e^f_j}{e^\ell_j} \cdot \frac{\sum_{x \in \mathbb{X}} A_{j,x} \omega^f_{j,x}}{\sum_{x \in \mathbb{X}} A_{j,x} \omega^\ell_{j,x}}.$$

Now apply the same identity as above, but across investor origins $x \in \mathbb{X}$:

$$\mathbb{E}_x[A_{j,x}\omega^k_{j,x}] = \mathbb{E}_x[A_{j,x}]\,\mathbb{E}_x[\omega^k_{j,x}] + \mathrm{Cov}_x(A_{j,x}, \omega^k_{j,x}),$$

where $\mathbb{E}_x[\cdot]$ and $\mathrm{Cov}_x(\cdot,\cdot)$ denote the average and covariance across investor origins. Since common proportionality factors cancel in the ratio of sums, we obtain

$$\frac{N^f_j}{N^\ell_j} = \frac{e^f_j}{e^\ell_j} \cdot \frac{\mathbb{E}_x[A_{j,x}]\,\mathbb{E}_x[\omega^f_{j,x}] + \mathrm{Cov}_x(A_{j,x}, \omega^f_{j,x})}{\mathbb{E}_x[A_{j,x}]\,\mathbb{E}_x[\omega^\ell_{j,x}] + \mathrm{Cov}_x(A_{j,x}, \omega^\ell_{j,x})}.$$

This proves the lemma. ■

### A.4.2. **Calibration Details.**

A.4.2.1. *Externally Calibrated Parameters.* We normalize and externally calibrate the following parameters:

- $\bar{\tau}^k_{j,d} = 0$ for all $(j,k)$, so we only focus on equity financing;
- $\beta = 0.5$, so matched output is split evenly between investors and entrepreneurs;
- $\eta = 0.5$ in the matching function $n_{j,x} = s^\eta_{j,x} d^{1-\eta}_{j,x}$;
- $\bar{\tau}^k_{j,x} = 1$ for all $(j,x,k)$, so entrepreneurs have homogeneous preferences over investors from all origins;
- $E[z^k_j] = 1$ for all $(j,k)$, so there is no difference in returns between local and foreign-connected entrepreneurs;
- $\lambda^k_{j,x} = \lambda$ if $k = x$, and $\lambda^k_{j,x} = 1$ otherwise, so connection advantages are concentrated on the diagonal.

A.4.2.2. *Region Aggregation.* For the baseline calibration, we group destinations as

$$j \in \{\text{Eastern \& Central Africa, Western Africa, Southern Africa, Northern Africa,}$$
$$\text{Europe, Northern America, RoW}\},$$

and investor origins and entrepreneur exposure types as

$$x, k \in \mathbb{X} = \{\text{Africa, Europe, Northern America, RoW}\},$$

where "RoW" refers to all countries outside Africa, Europe, and Northern America.[39]

[39]We exclude China from "RoW" because LinkedIn coverage there is limited, which prevents us from reliably recovering founder information.

A.4.2.3. *Empirical Construction of Estimation Inputs.* The calibration uses two sets of observed objects: deal-size weighted number of equity-financed startups in destination $j$ by investor origin $x$, denoted $n_{j,x}$, and the number of equity-financed startups in destination $j$ by entrepreneur type $k$, denoted $n_j^k$.

To construct $n_{j,x}$, we start from VCPE deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges over 2010–2024. When a deal has multiple investors, each investor receives weight $1/N$, where $N$ is the size of the syndicate. We compute deal-size weighted $n_{j,x,t}$ for each year and then take annual averages to obtain $n_{j,x}$.

To construct $n_j^k$, we first identify the founders of funded startups in our deal sample and use Revelio Labs to recover their education and employment histories before startup founding. We assign founders with no foreign education or work experience to the local region. For founders with any foreign education or work experience, we assign them to the foreign region where they spent the greatest amount of time prior to founding the startup. Let $w_j^k$ denote the share of founders in destination $j$ who belong to type $k$, with $\sum_{k\in\mathbb{X}} w_j^k = 1$. We then define

$$n_j^k = w_j^k \cdot N_j = w_j^k \cdot \sum_{x\in\mathbb{X}} n_{j,x}.$$

This construction guarantees that $\sum_{k\in\mathbb{X}} n_j^k = \sum_{x\in\mathbb{X}} n_{j,x}$, as implied by the model.

A.4.2.4. *Calibration Procedure.* Given a candidate parameter pair $(\sigma, \lambda) \in \mathbb{R}_+^2$, we proceed in four steps.

*Step 1: Recover latent entrepreneur mass and capital wedges.* For each destination $j$, conditional on $(\sigma, \lambda)$, parameters $\{\beta, \eta, \lambda_{j,x}^k, \bar{\tau}_{j,x}^k, \bar{\tau}_{j,d}^k, E[z_j^k]\}$ are externally calibrated and the counts $\{n_j^k, n_{j,x}\}$ are observed. Then based on equations in Lemma 1 and 2, the system is square in $\{e_j^k, r_{j,x}, s_{j,x}, d_{j,x}, E[z_{j,x}], \mu_{j,x}^k\}$, which allows us to recover the latent entrepreneur masses $e_j^k$ and capital wedges $r_{j,x}$ together with the associated equilibrium parameters.

*Step 2: Simulate origin-specific capital-supply shocks.* After recovering the baseline wedge structure $\{r_{j,x}\}$, we simulate 500 periods indexed by $t$. In each period, we apply an origin-specific shock to the capital wedge:

$$r_{j,x,t} = r_{j,x}\epsilon_{x,t},$$

where $\epsilon_{x,t}$ is log-normal distributed with $E[\epsilon_{x,t}] = 1$ and $\text{var}(\log \epsilon_{x,t}) = 0.1$, so the shocks perturb relative capital supply across origins without shifting the average level of wedges. We then re-solve the model, holding all other parameters fixed, to obtain the equilibrium counts $n_{j,x,t}^k$ under the perturbed capital wedge.

*Step 3: Construct simulated startup-level data.* We then round $n^k_{j,x,t}$ down to $\lfloor n^k_{j,x,t} \rfloor$ with probability

$$p_{\text{floor}} = \lceil n^k_{j,x,t} \rceil - n^k_{j,x,t},$$

and round it up to $\lceil n^k_{j,x,t} \rceil$ with probability

$$p_{\text{ceiling}} = n^k_{j,x,t} - \lfloor n^k_{j,x,t} \rfloor.$$

This preserves expected counts while delivering an integer number of simulated startup matches in each cell. We then expand the rounded counts into a simulated startup-level dataset recording destination, entrepreneur type, investor origin, and period.

*Step 4: Match simulated and empirical moments.* Using the simulated data, we replicate the two reduced-form moments targeted in the calibration. For the Bartik regression, we use the simulated foreign capital-supply shocks and startup activity in Africa. For the dyadic regression, we restrict attention to simulated matches involving African founders and foreign potential investor origins. After estimating the dyadic regression, we compute *relative dyadic intensity*, defined as the estimated dyadic coefficient divided by the mean of the dependent variable.

For each candidate $(\sigma, \lambda)$, this procedure yields a simulated Bartik coefficient $\tilde{b}_{\text{Bartik}}(\sigma, \lambda)$ and a simulated relative dyadic intensity $\tilde{b}_{\text{dyadic}}(\sigma, \lambda)$. We choose parameters to minimize

$$f(\sigma, \lambda) = \frac{\left|\tilde{b}_{\text{Bartik}}(\sigma, \lambda) - b_{\text{Bartik}}\right|}{b_{\text{Bartik}}} + \frac{\left|\tilde{b}_{\text{dyadic}}(\sigma, \lambda) - b_{\text{dyadic}}\right|}{b_{\text{dyadic}}},$$

where $b_{\text{Bartik}}$ and $b_{\text{dyadic}}$ are the empirical counterparts reported in Table 7 and 5. The best-fitting values we obtain are $\sigma = 3.01$ and $\lambda = 2.50$.

A.4.3. **Details on the Counterfactuals.** This subsection describes the counterfactual exercises in Sections 5.4 and 5.5.

A.4.3.1. *Equalizing Capital Wedges.* Appendix Table A13 reports the capital-wedge matrix $r_{j,x}$ recovered in the calibration. In each African destination, we lower the wedge faced by local investors while holding all foreign-investor wedges fixed, so that the ratio of the local-investor wedge to the North American-investor wedge matches the corresponding ratio observed in Europe.

A.4.3.2. *Equalizing the Mass of Local Entrepreneurs.* Appendix Table A14 reports the latent entrepreneur-mass distribution $e^k_j$. In Africa, the local share of latent entrepreneurs is relatively low. In this counterfactual, we increase the mass of local entrepreneurs in Africa while holding the mass of foreign entrepreneurs fixed, so that the local entrepreneur share matches the corresponding share in Europe.

A.4.3.3. *Equalizing the Connection Structure of Local Entrepreneurs.* In this counterfactual, we relax the access disadvantage faced by local entrepreneurs in Africa by allowing them to have connection intensity $\lambda$ with investors from all origins, while leaving the connection structure of foreign-connected entrepreneurs unchanged.

A.4.3.4. *Higher Human Capital.* Figure 10 shows a strong cross-country relationship between startup density and schooling. To formalize this pattern, we collapse Africa into a single destination region and partition local entrepreneurs into four education groups:

$$\mathbb{X}_{\text{AfricaEdu}} = \{\text{Low-Edu Africa, Medium-Low-Edu Africa,}$$
$$\text{Medium-High-Edu Africa, High-Edu Africa}\}.$$

The four African education groups are defined using average years of schooling for the population aged 25–45, based on Barro and Lee (2013). We assign entrepreneur exposure as in the main calibration and further classify local founders by the schooling group of the country in which the startup is located.

We then recover the latent mass of local entrepreneurs $e_j^k$ for each $k \in \mathbb{X}_{\text{AfricaEdu}}$ using the same procedure as in Step 1 above. The recovered entrepreneur mass on a per-capita basis exhibits an approximately log-linear relationship with average years of schooling. We use this relationship to predict counterfactual entrepreneur masses after raising all African education groups to the schooling level of the high-education group, and then resolve equilibrium under those counterfactual masses.