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# STARTUPS IN AFRICA

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**ABSTRACT**

We build new data on startups in Africa to study which types of financing these firms demand, how financing is allocated in practice, and the implications for startup creation and the composition of the sector. We combine a continent-wide founder survey, an incentive-compatible experiment estimating financing preferences, and venture capital (VC) deal records matched to founders' education and work histories. We find that startups strongly prefer equity over debt, but equity is supplied mainly by foreign investors and flows disproportionately to foreign-connected founders. About 80 percent of VC deals involve a foreign investor, and more than 60 percent of funded founders have studied or worked outside Africa. A simple accounting framework shows that this foreignness reflects three main forces: scarce local equity capital, a thin pool of local entrepreneurs able to access startup finance, and frictions limiting local entrepreneurs' access to foreign investors. Together, these forces reduce startup creation and tilt the sector toward foreign investors and foreign-connected founders.

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A randomized controlled trials registry entry is available at
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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. The continent has a young population, a growing skilled workforce, and rapid adoption of digital technologies. In this environment, startups could play an important role by introducing new technologies and providing platforms and inputs that allow other firms to grow (Kortum and Lerner, 2000; Acemoglu et al., 2018; Woodruff and Mohan, 2025). As a result, high-growth entrepreneurship has moved to the center of Africa's development agenda, and a key policy debate asks how to build the startup ecosystem.[1][2]

Finance is central to this debate. Governments and development finance institutions are trying to identify which forms of capital and support can help startups scale. The standard model is venture capital (VC): typically equity-based finance that shares risk while giving investors claims on future upside and, often, governance and monitoring rights. But VC developed largely in the United States and other high-income countries, in settings with deep local capital markets, strong investor protections, and reliable contracting institutions (La Porta et al., 1997, 1998). In Africa, where local capital markets are thinner and institutions weaker, the relevant question is not simply whether VC works, but which elements of the model entrepreneurs value, who supplies them, and how the resulting allocation of capital shapes the broader startup ecosystem.

This paper builds new data on startups in Africa to make progress on these questions. Our results point to a simple tension. On the demand side, startups in Africa want equity financing: flexible capital that shares risk and often comes with investor support. In this sense, core elements of the VC model fit the needs of these firms. But the supply of this type capital is scarce locally, supplied mainly by foreign investors, and harder to reach for local entrepreneurs without foreign connections. The result is a *foreignness* of Africa's startup ecosystem that reflects frictions reducing startup creation, especially among local entrepreneurs. The policy challenge is therefore not only to attract venture capital to Africa, but to build the local supply of equity capital needed for a broader startup ecosystem that includes local entrepreneurs.

We develop the argument in three steps. *First*, to characterize the demand side, we survey startup founders and embed an incentive-compatible experiment in which they rate investment opportunities that vary both the financing contract and the investor behind it. The results show that core elements of the VC model fit what Africa's startups want. *Second*, to measure who supplies this type of capital and who receives it, we combine venture

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

[2] The rapid rise and recent slowdown of startup activity in Africa make this question especially salient. See Appendix Figure A1.

capital deal data with founders' education and work histories. We show that venture capital comes overwhelmingly from abroad and often goes to entrepreneurs who are either foreign or have foreign education or work experience, establishing the *foreignness* of Africa's startup ecosystem. *Third*, to measure the drivers of this foreignness and quantify their implications, we develop a simple accounting model. The model shows that foreignness reflects scarce local equity capital, a thin pool of local entrepreneurs at the financing margin, and frictions that limit local entrepreneurs' access to foreign capital. These frictions reduce startup creation and tilt the sector away from local investors and local founders.

To implement this analysis, we build two complementary datasets. The first is a new continent-wide survey of startup founders through the International Finance Corporation (IFC), the private sector arm of the World Bank Group.[3] The survey reached 10,285 target firms and yielded 4,444 respondents across 51 African countries. It combines detailed information on founders, firms, growth, and constraints with the experiment described below, which elicits preferences over financing contracts and investor characteristics. The second is a dataset on firms that received VC financing between 2010 and 2024. We construct it by combining the standard PitchBook data with new Africa-specific data sources and linking these records to founders' education and work histories from LinkedIn. Together, the survey and deal-level data allow us to study both the demand for startup finance and the realized allocation of capital across investors and founders.

We first use the survey to study the demand for external finance. We find substantial unmet financing needs: the typical respondent seeks roughly $500,000 in external capital but secures only a minority of that amount, and cites access to finance as the main obstacle to growth. These patterns suggest that firms are financially constrained. They do not reveal, however, what form of finance is best suited for these firms, or how entrepreneurs trade off repayment obligations, dilution, control rights, investor expertise, and other contract and investor attributes. Estimating these preferences is difficult because startups typically evaluate bundles of investor–investment pairs, whose attributes are jointly determined and highly correlated.

The experiment addresses this limitation. We designed and implemented the "Connecting Africa's Entrepreneurs" study through the IFC, using a non-deceptive experimental design in the spirit of Kessler et al. (2019) and adapted to firm–investor matching as in Colonnelli et al. (2024). Startups rate profiles of potential investment opportunities that vary systematically along randomized dimensions, including deal terms, investor characteristics, and team composition. This allows us to recover preferences over key attributes in a

[3]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 entrepreneurial networks across the continent. We aim to cover young (age <10) firms with at least 2 full-time employees that are actively looking to grow.

controlled environment. The experiment is incentive-compatible: respondents are told that their answers will be used to facilitate connection with real investment partners aligned with their stated preferences.

The results point to a clear finding: entrepreneurs have a strong and pervasive preference for equity financing over debt. This does not mean that founders treat equity as free cash. They are responsive to the costs of equity: they prefer lower dilution and dislike board-seat requirements. Yet they continue to value equity even when it is bundled with monitoring and control provisions. The equity premium is even larger among respondents running more successful and established firms, and remains strong in countries with better institutions. The evidence instead points to demand for flexible capital that relaxes repayment constraints while giving investors incentives to support the firm. Consistent with the role of investor support, founders also value investors with deep local knowledge, especially those with local teams, local experience, and country or sector focus. By contrast, they do not place additional value on foreign investors once contract terms and other investor attributes are held fixed. Taken together, the experiment identifies the financing relationship entrepreneurs value in this setting: flexible equity-like capital, paired with investor capabilities and local information, rather than foreign capital per se.

We next turn from demand to supply and study who provides venture capital to Africa and which entrepreneurs receive it. We document that the investors in this market are overwhelmingly foreign. About 80% of VC deals in Africa involve at least one foreign investor, a much higher share than in other emerging or developed markets. Most of this capital comes from Northern America and Europe, with only a limited role for China and a secondary role for DFIs. Local capital markets are thin, and intra-African flows remain limited. The type of capital startups demand is therefore present in Africa, but it is supplied mainly from abroad.

Foreignness also appears on the founder side. The entrepreneurs who receive VC in Africa are almost all college educated, and about two thirds have studied or worked outside Africa or are themselves foreign. The allocation of startup finance in Africa is therefore foreign on both sides of the market: capital comes mostly from foreign investors, and funded entrepreneurs are often foreign-connected. These results raise a question: why does foreign capital flow to startups in Africa despite weaker institutions and weaker investor protections? We show that part of the answer is that VC can rely on legal and financial arrangements outside the local economy.

Finally, we develop a simple accounting model to measure why the equity capital startups demand is supplied mainly by foreign investors, why it reaches foreign-connected founders, and what this implies for startup creation. The model separates four forces that could rationalize these patterns: capital wedges across investor origins, differences in expected returns, preferences over investor origins, and the composition and access of entrepreneurs seeking finance. The last force is governed by entry wedges, which capture both the local supply of potential founders and the barriers that determine whether they reach the financing margin, and by connection frictions, which capture the ability of each founder type to access different investors. The goal is to measure which forces explain the foreignness of capital and founders, and what these same forces imply for aggregate startup activity.

We discipline the model with three additional pieces of evidence. Dyadic regressions of investor–startup matches show that founders are much more likely to raise capital from investor countries to which they are connected through education or work experience, implying that connections matter. Regressions of post-funding performance show little evidence that foreign or foreign-connected startups systematically outperform once funded, suggesting that expected-return differences are not the main driver. A shift-share design based on foreign capital supply shocks shows that startup activity responds to changes in foreign funding conditions, especially for foreign-connected founders. This moment disciplines the substitutability of capital across investor origins. It also supports the model's mechanism: foreign capital supply affects both who receives funding and the scale of startup activity in Africa.

We then invert the model to recover *capital* and *entry wedges* that match the observed allocation of equity finance across investor origins and founder types. The estimates imply that Africa stands out on two dimensions: local equity is unusually scarce relative to foreign equity, and the mass of local entrepreneurs reaching the financing margin is relatively low. Counterfactuals quantify the role of these wedges and of connection frictions. When we set Africa's local-capital wedge to a European benchmark, the local investor share rises from 26.1% to 41.7%, and the local entrepreneur share rises from 32.0% to 40.5%. Importantly, the same frictions that generate foreignness also affect scale: lowering local capital wedges raises startup activity by 13.0%, while increasing the mass of local entrepreneurs raises it by 29.0%. Connection frictions matter as well: equalizing local entrepreneurs' access to foreign investors raises startup activity by 10.9%, but shifts financing toward foreign rather than local capital. Overall, we learn that the foreignness of Africa's startup ecosystem reflects frictions that shape both who receives funding and how many startups are created.

Finally, we use qualitative responses from our startup survey as an external consistency check on these mechanisms. When asked directly why startup ecosystems in Africa are so foreign, respondents emphasize the limited availability of local capital and the importance of networks and access, consistent with the forces highlighted by our empirical and quantitative analysis.

Summing up, this paper's message is simple. A central element of the venture capital model—flexible equity-like capital—is demanded by African startups. But in Africa, this capital is supplied largely by foreign investors and flows disproportionately to foreign-connected founders. This reliance is not innocuous: it reflects frictions in local capital supply and in the composition and access of entrepreneurs. These frictions have large effects on the scale and structure of startup activity across the continent.

Our paper primarily contributes to the literature on finance and entrepreneurship in developing countries. This literature has predominantly focused on microentrepreneurs, who are motivated by subsistence and are unlikely to grow fast and scale (De Mel et al., 2010; Schoar, 2010; Breza et al., 2021; Bassi et al., 2023). Recent influential work has led to a significant body of evidence on what works (or not) to spur the growth of these microenterprises (see Woodruff 2018; Quinn and Woodruff 2019; Jayachandran 2021; McKenzie et al. 2021 for comprehensive reviews of this large and growing body of work). Most of this work has primarily focused on randomized controlled trials (RCTs) testing the effects of various specific interventions, and results have been mixed.[4] Conducting RCTs on larger and high-growth firms is challenging. As a result, the evidence on these firms remains limited (Banerjee and Duflo, 2014; McKenzie, 2017).

Because of the focus on microenterprises in traditional sectors, most work on the effects of access to finance for entrepreneurial growth has focused on debt, ubiquitous in microfinance and characterized by small loans with inflexible terms. Several recent studies show the promise of going beyond simple debt instruments and toward more flexible financial products as a way to jump-start firm growth (Field et al., 2013; Bryan et al., 2021; Battaglia et al., 2023; Bari et al., 2024; Meki, 2024).

Our paper directly contributes to this body of work by shifting the focus to a new and understudied set of entrepreneurs—tech, high-growth, and looking for large amounts of financing—in the poorest continent of the world, and by studying which financing contracts and investor attributes these firms demand. 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 startups.

Our paper also connects to the literatures on law and finance and on finance and development. The law-and-finance literature emphasizes that investor protection, legal enforcement, and contracting institutions shape the supply of external finance and the development of capital markets (La Porta et al., 1997, 1998; Djankov et al., 2003), while the finance-and-development literature shows that financial development affects capital allocation, firm entry

[4]While microfinance and business training have shown limited impacts on the growth of the average firm (De Mel et al., 2008, 2012; Banerjee et al., 2015a,b), recent evidence shows promising results for specific sets of entrepreneurs (Anderson et al., 2018; Meager, 2019; Hussam et al., 2022) and for more intensive and individualized programs (Cai and Szeidl, 2018; Iacovone et al., 2022; Anderson and McKenzie, 2022).

and growth, and aggregate productivity (King and Levine, 1993; Rajan and Zingales, 1998; Levine, 1999; Wurgler, 2000; Levine, 2002; Buera et al., 2011). These forces are especially relevant for venture capital, where investors provide funding through contracts that combine residual claims, control rights, monitoring, and staged financing, and where contracts adjust to differences in legal enforcement across countries (Shleifer and Vishny, 1997; Lerner and Schoar, 2005; Kaplan et al., 2007).[5] We contribute by studying these issues from both sides of the market: experimentally estimating what financing contracts and investor attributes high-growth firms demand, and documenting how capital is supplied and allocated in a low-income region with thin local capital markets.

Our paper also relates to the macro-development literature on financial frictions and development. A central insight of this literature is that limited access to finance can distort entry, firm growth, and aggregate productivity (Buera et al., 2011, 2015, 2021). But much of this work treats financial constraints as a single reduced-form friction, without asking what kind of financing relationship firms need or how access to different investors is allocated. Recent papers have started to unpack this distinction by focusing on heterogeneous interest rates and risk (Cavalcanti et al., 2023; Buera et al., 2024). We contribute by studying equity-like capital and investor attributes, and by showing that for high-growth firms in Africa this distinction is central: entrepreneurs strongly prefer flexible equity financing over debt, and the limited supply of such capital affects both startup creation and the allocation of entrepreneurship.

Finally, we contribute to the literature on human capital and development. While it is well established that human capital matters for growth (Nelson and Phelps, 1966; Mankiw et al., 1992; Glaeser et al., 2004; Valencia Caicedo, 2019), less is known about which parts of the distribution matter most and through which channels. Recent work emphasizes the role of high-end human capital in firm creation, managerial inputs, and R&D (Gennaioli et al., 2013; Queiró, 2022; Akcigit et al., 2025; Engbom et al., 2025). We provide more evidence for this channel, but also add a new angle: human capital affects not only firm quality, but also access to capital. In particular, foreign education and work experience help entrepreneurs connect to foreign investors, suggesting that part of the return to human capital operates through improved access to finance.

The rest of the paper proceeds as follows. Section 2 illustrates the data and the descriptive facts. Section 3 studies the demand for startup financing contracts using the survey experiment. Section 4 describes the supply and allocation of startup financing in Africa. Section 5 introduces and estimates the model and uses it for counterfactual analyses. Section 6 concludes.

[5] A growing literature on venture capital and economic development remains small, in part due to data limitations (Colonnelli et al., 2024; Lerner et al., 2024; Colonnelli et al., 2025).

## 2. Data

Data on firms with growth potential in Africa are scarce. Firm-level surveys are common, but few large-scale efforts have focused on high-growth entrepreneurship and young tech startups. To address this gap, we build two novel and complementary datasets. First, we conduct a large-scale survey of *early-stage startups* through the IFC, which allows us to measure founders' constraints and their demand for different financing contracts and investor attributes. Second, we assemble a dataset on *established startups* using venture capital (VC) deal-level records from both global and local commercial sources, supplemented with detailed founder background information on education and work experience. These data allow us to study the realized supply and allocation of startup financing across investors and founders.

Section 2.1 describes the survey implementation, structure, and outreach strategy. Section 2.2 describes how we assemble the deal- and founder-level data. Section 2.3 presents a descriptive analysis of the data.

2.1. **Survey of Africa's Startups.** We designed and conducted a survey to collect comprehensive information on Africa's startups. Our goal was to obtain a broad continent-wide sample of firms close to the external-finance margin, in order to understand their characteristics, their key challenges in financing and firm growth, and their demand for different financing contracts and investment partners. We target high-potential startups that have been in operation for less than ten years, operate primarily in Africa, employ at least two full-time workers, and are actively looking to grow.

There is no formal census of "startups" in Africa. As a result, it is not possible to construct a complete sampling frame and a clean benchmark for representativeness. We instead define startups as young firms designed to grow fast, and use a dissemination strategy aimed at obtaining a large sample of respondents broadly matching these criteria.[6] Eligibility did not depend on prior fundraising history or on whether firms were seeking debt, equity, or any other specific form of capital.

First, we identified and contacted more than 30 regional partners active in Africa's high-growth entrepreneurship ecosystem. These partners include standard business associations, accelerators, incubators, venture capital associations and advisory firms, and entrepreneurship and university networks with connections to local startup communities across all African regions. To reduce the possibility that partner-based dissemination would select firms already oriented toward equity financing, we asked partners to circulate the survey broadly among eligible startups and emphasized that they should not screen firms by prior fundraising history or preferred form of capital. Second, we conducted targeted outreach to startups

[6] Our definition of *startup* is common in entrepreneurship. For example, Y Combinator—the leading startup accelerator in the world—states: "The term "startup" typically refers to a small, early stage company designed to grow fast." See What is a startup?.

identified from the LinkedIn data discussed in Section 2.2.3. Specifically, we restrict the sample to tech-enabled companies matching our eligibility criteria, and we then sent direct emails to a random subset of these firms. We required responses to come from startup founders and manually verified that this was the case.[7] As a check on the resulting sample composition, Section 2.3 below shows that respondents report a broad mix of funding sources, with VCs accounting for only a small share of main funding sources.

We conducted two large-scale survey rounds: the first in Q4 of 2023 and the second in Q4 of 2025. Across the two rounds, we contacted 10,285 target startups in 51 of Africa's 54 countries. We obtained 3,121 responses in the first round and 1,323 in the second, for a final sample of 4,444 respondents and an overall response rate of about 40%, broadly similar across rounds.[8] Throughout the paper, we refer to this combined sample as "early-stage startups" and use the pooled sample for our main analysis.[9]

The survey has two main sections. 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 elicits startups' preferences over financing contracts and investor attributes, as described in detail in Section 3.2.

Respondents had the option to do the survey in English, French, Portuguese, and Arabic. The survey also included a glossary and clickable explanations to clarify the design and terminology.

2.2. **Venture Capital Data on Africa and Global Startups.** Our survey sample captures early-stage startups: young firms looking to grow. We also construct a dataset on more "established startups," defined as firms that have raised venture capital. We focus on the period 2010–2024.

We build 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 combines PitchBook's broad global coverage with the greater depth of local sources in Africa. We then link these 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.

[7]Using detailed founder and firm information, including company websites, we verified that all startups in the sample were operational and active.

[8]This response rate compares favorably to other large-scale surveys in similar settings (e.g., Da Rin and Phalippou, 2017; Bernstein et al., 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 et al., 2016; Gompers et al., 2020; Colonnelli et al., 2024).

[9]The two rounds differed slightly in wording and outreach. For example, in the first round, the first page of the survey solicited responses from firms looking for funding to grow; in the second round, we removed this criterion. In the Appendix, we show that our results are strongly consistent across survey rounds.

2.2.1. *PitchBook.* PitchBook is a leading venture capital (VC) database designed to provide comprehensive coverage of startup financing deals around the world (Lerner et al., 2024; Colonnelli et al., 2025). The database includes deal-, company-, fund-, and investor-level data. Investor and fund data cover both general partners (GPs), the fund managers that invest directly in startups, and limited partners (LPs), the original sources of capital. PitchBook collects information from a range of sources, including direct contacts with investment funds and portfolio companies, news articles, regulatory filings, and press releases.

We keep a broad set of venture financing events: accelerator and incubator deals, seed rounds, early-stage VC, late-stage VC, and growth or expansion rounds.

After these restrictions, we are left with 6,293 deals between 2010 and 2024, involving 4,372 unique companies. We also apply the same restrictions to non-Africa deals in PitchBook, which we keep to construct a global dataset of VC activity.

2.2.2. *Briter Bridges and Africa: The Big Deal.* Due to the confidential nature of these transactions, there is no perfect dataset able to measure every single VC deal in the world (Kaplan and Lerner, 2017). For example, because of the nature of its data collection process, 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.

We address this potential issue by augmenting PitchBook with information from two specialized Africa-focused sources: Briter Bridges and Africa: The Big Deal. These sources are the leading providers of VC data in Africa and leverage extensive on-the-ground networks to achieve near-universal coverage of local deals.

We match and disambiguate these data with PitchBook. After this process, our data on Africa VC includes a total of 8,751 deals involving 5,470 unique companies. The additional local data leads to an increase of 39% (25%) in the number of deals (companies), highlighting the importance of this data construction step to provide a comprehensive analysis of Africa's startup ecosystem.[10]

Throughout this paper, we refer to startups in our combined dataset as "established startups," and to the dataset itself as PitchBook+. This includes both the augmented Africa data and the global, standard PitchBook data.

2.2.3. *LinkedIn Data from Revelio Labs.* We further enrich our PitchBook+ data with data on founders and employees from LinkedIn profiles, which are obtained from workforce intelligence data provider Revelio Labs. LinkedIn profiles generally document users' work experience, education, and skills. For every job listed, they provide the employment dates,

[10]Appendix Table A1 shows that the additional deals recovered from the local sources tend to be more recent, smaller, and less concentrated in South Africa. Additional details on the matching process across datasets is provided in Appendix Section A.2.1.

employer name, job title, and location. Revelio Labs standardizes these data using advanced natural language processing techniques to create a structured dataset where they also impute information on gender, race, and salary, among others. We use data updated as of early 2025.

There are certain standard potential concerns about representativeness when using LinkedIn data, such as varying coverage across sectors and regions, and the higher representation of college-educated and white-collar professionals. As Amanzadeh et al. (2024) discuss, these concerns are likely less relevant for research on startups, as startup founders and employees are predominantly young, educated individuals with a strong digital presence. Indeed, we are able to match 94.3% of firms in our PitchBook+ data to Revelio Labs. We also conduct a number of validation checks, which we discuss together with our data cleaning steps in Appendix Section A.2.2.

2.3. **Descriptive Analysis.** We now present descriptive evidence on startups in Africa, with some benchmarks to both emerging and developed markets.

Figure 1 documents the geographic distribution of startups in both our survey sample and the PitchBook+ sample. Startup activity is highly concentrated in a small number of hubs. The main country hubs are Nigeria, Kenya, South Africa, and Egypt. We see a strong clustering in specific urban hubs, with the cities of Lagos, Nairobi, Cape Town, and Cairo capturing a large share of VC activity. To illustrate the extent of this concentration, in 2024 the "Big 4" countries accounted for 72.2% of Africa's VC deal value while representing only 41.6% of the continent's GDP; similarly, the Top-4 cities accounted for 46.3% of VC deal value while representing only around 10% of GDP.

Our survey sample broadly mirrors the PitchBook+ sample in terms of geographic concentration. Relative to PitchBook+, we are slightly overrepresented (underrepresented) in East Africa (North Africa). We further assess representativeness in Appendix Table A2, which compares our geographic distribution with several benchmarks (as of 2024), namely the PitchBook+ sample, VC deals in both count and value, GDP, and population. The distribution of our survey sample is broadly consistent with most of these benchmarks.

Our PitchBook+ data cover Africa as well as other countries around the world. Appendix Figure A2 illustrates the global distribution of startup activity, with different colors denoting Africa, Emerging Markets, and Developed Markets, a split we will use often throughout this paper.[11] Startup "hubs" appear on a global scale as well, with massive activity concentrated in the Bay Area, the U.S. East Coast, London, as well as a few specific emerging markets hubs in China, Singapore, and, to a lesser extent, Brazil and India. The figure also clearly highlights that Africa remains a tiny part of the global startup market.

[11]We classify a country as a Developed Market if it is designated as such by at least one of MSCI, FTSE, or S&P. All non-African countries that do not meet this criterion are classified as Emerging Markets.

Using information from deals with disclosed investment amounts, in 2022—the peak year of VC activity in Africa—the continent accounted for only 0.96% of global VC deal value, despite representing 2.97% of world GDP.

We next turn to the characteristics of firms and deals in our data. Tables 1 and 2 report summary statistics for our survey sample and the sample of established startups, respectively. Panel A of Table 1 focuses on the startup founders responding to our survey. Founders are on average 37.8 years old, younger than the U.S. startup founders in Azoulay et al. (2020). They are highly educated: 95.5% report at least some college education, and 34.2% hold a graduate degree. Foreign exposure is also common: 42.6% of founders report foreign education or work experience, and 20.9% of executives, on average, are born outside Africa. Founders are predominantly male, and a substantial share report prior entrepreneurial experience.

Consistent with our targets, Table 1, Panel B shows that firms in our survey sample are young, with an average age of four years. They are relatively small, with a median of six employees. Established startups, unsurprisingly, are older and larger. As shown in Panel C of Table 2, they are typically four to seven years old at the time of their first recorded deal and employ, on average, roughly 25 to 40 workers at that point, with consistent patterns across Africa, Emerging Markets, and Developed Markets.

Both samples span a broad range of industries. Panel C of Table 1 reports the sectoral composition of early-stage startups in our survey, while Panel A of Table 2 reports the corresponding distribution for established startups. Information Technology and Finance/FinTech are the two most prominent sectors in both samples. One notable difference is Agriculture/AgriTech, which accounts for a substantially larger share of early-stage startups in our survey than among established startups. Aside from this difference, the sectoral composition of the two samples is broadly similar.

Panels B and C of Table 2 show the composition and size of VC deals. Panel B shows that later-stage VC deals account for only 17.1% of deals in Africa, versus more than 27% in both Emerging and Developed Markets. Panel C shows that the median deal size in Africa is $0.9 million, less than half of that in other Emerging and Developed Markets. In short, startups in Africa raise lower amounts of capital and are less likely to continue raising capital to grow.

## 3. Estimating Startup Preferences

We begin by estimating startups' demand for external finance. We first use the survey to document self-reported financing constraints among early-stage startups. We then use the experiment to estimate which contract terms and investor attributes entrepreneurs value.

### 3.1. **Descriptive Evidence on Financing Constraints.** 

Figure 2 summarizes the amount of external capital that early-stage startups sought over the previous three years and the share of that amount that they were able to secure, plotted by startup size as measured by the number of full-time employees. Panel A shows that larger startups report larger financing needs, as expected, but also that even relatively small firms seek substantial amounts of outside capital. Overall, the typical respondent reports seeking roughly \$500,000 in external finance. Yet these funding needs do not translate into realized financing. Panel B shows the share of desired capital that firms were able to raise, again by startup size. The distribution is heavily concentrated at low success rates, and the mean firm secures only about 25% of the capital it seeks.

Table 3 provides further evidence on funding sources and perceived obstacles to growth. Panel A shows that most firms, especially smaller ones, rely primarily on internal funds, including founders' own resources and family and friends. External finance becomes more important only among larger startups: for firms with 21 or more employees, the main source of funding shifts toward angel investors, venture capital, and bank loans. Panel B shows that access to finance is by far the most frequently cited constraint, selected by 78.2% of respondents overall and by 71.2% of firms with 21 or more employees.

These descriptive results show that finance is a central constraint, but not which form of finance is best suited to these firms. We therefore turn to the experimental module, which estimates how entrepreneurs value different contract terms and investor attributes.

3.2. **Experimental Design.** Early-stage investors differ in the contracts and support they offer. They can provide debt or equity, require different degrees of dilution, control, and due diligence, and vary in local presence, sector knowledge, and non-financial support. The experiment measures how entrepreneurs trade off these features, rather than assuming ex ante that the standard U.S.-style VC model is the appropriate one in this setting.

Estimating these preferences from observational data or stated preferences is difficult. First, contract terms and investor attributes are bundled together and correlated. Foreign investors, for example, may be larger, more likely to provide equity, and more likely to offer mentorship or other non-financial support. Local investors may be more likely to provide debt, require different forms of monitoring, or have stronger local and government connections. Second, the matching of entrepreneurs to investment opportunities is endogenous: specific investors may approach specific firms, and only successful matches are observed. Third, direct stated-preference questions may confound the financing entrepreneurs want with the financing they think they can obtain.

Our experimental survey is designed to address these challenges. We aim to estimate startup preferences for each specific characteristic of a broad range of investment opportunities while holding other characteristics fixed—thus overcoming the first and second issues outlined above—and to isolate these preferences from the perceived likelihood of success in obtaining the investment—overcoming the third issue above. Our design is inspired by the non-deceptive incentivized resume rating design by Kessler et al. (2019) used in labor economics.[12]

We invite entrepreneurs from early-stage startups in Africa to rate a set of 10–15 synthetic profiles of investment opportunities.[13] Each profile combines an investor with a financing contract. Contracts can be debt or equity, and investor profiles vary along dimensions common in early-stage startup finance. The profiles are designed to appear realistic, but respondents are told that the opportunities are hypothetical, so the design involves no deception. The experiment takes place after the qualitative component of the survey.

3.2.1. *Matching Incentives.* A key feature of the experiment is that it provides incentives for truthful and accurate responses. Respondents are told that their rating of *hypothetical* investment opportunities will help us identify *real* investment opportunities aligned with their preferences. In practice, the specific support ranged from soft versions such as a personalized list of investment partners aligned with their preferences, to stronger ones such as training sessions and direct engagements with IFC associates. We refer to Appendix Figure A3 for the specific language used in the communication with startups, both in the IFC website and on the actual survey. The incentives delivered by the IFC—which took place a few months after each survey round—were developed using a broad global dataset on investors and deals from commercial sources, as well as our own data collection, allowing for a correspondence between startup preferences and investors with specific characteristics and types of financial and non-financial support.[14] In essence, our experimental incentive structure is analogous to the matching of employers to UPenn's students looking for jobs based on incentivized resume ratings (IRR) as in the original design by Kessler et al. (2019), and comparable to similar designs in different contexts, as reviewed by Macchi (2025).

3.2.2. *Creating Investment Partner Profiles.* Respondents are shown profiles of investment opportunities that contain concise textual and structured descriptions highlighting the key characteristics of the investor and the financing deal. To construct these profiles, we first conducted a structured manual review of over 5,000 real profiles from a number of sources such as PitchBook and local counterparts. Our analysis involved evaluating the structure

[12]More broadly, these designs are recent adaptations of the classic correspondence audit studies used to estimate preferences for specific characteristics, largely used to measure discrimination (Bertrand and Mullainathan, 2004; Bertrand and Duflo, 2017).

[13]In the first survey round, each respondent is shown at least 10 synthetic profiles of investment opportunities, followed by 5 additional synthetic profiles of either investment opportunities or accelerators/incubators, depending on the respondent's stated interest. In the second round, we present only 10 profiles of investment opportunities and do not include accelerator or incubator options.

[14]In the second round, due to time and resource constraints, 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 associates—for a random sample of the respondents grouped by preferences—to discuss best approaches to target specific types of investment opportunities.

and content of the profiles, identifying common elements, or "components," such as investor region and sector focus, typical investment amounts, preference for debt vs. equity deals, team background, among several others, as well as identifying the language commonly used to describe these attributes.

We build the final pool of thousands of potential investment opportunity profiles by randomizing components based on pre-specified inclusion probabilities. The probabilities are informed by the distribution observed in the actual profiles on the platforms we analyzed. We further refined our profiles and validated their realism and clarity through dozens of pilot discussions with investors and startups. Appendix A.3.1 together with Appendix Tables A3 and A4 show in greater detail how the profiles are generated. In particular, they list the overall profile structure, profile components, the probabilities with which each component and textual option appears, and how the randomly drawn text determines the variables used in the analysis. In Appendix Figure A4, we provide two examples of synthetic profiles.

3.2.3. *Filtering Out Unreasonable Profiles.* Before showing profiles, we ask four filtering questions to ensure that the opportunities are broadly relevant to each startup. We ask about the investment range they are seeking, the ownership stake percentage range they may be willing to give up in exchange for funding (including 0%), and the country and sector in which the company primarily operates.[15] Our survey then dynamically selects a set of profiles that are aligned with these basic preferences. This filtering step addresses a common challenge with IRR-style designs where evaluation items may not be relevant at all due to clear mismatch, and preference estimation becomes noisy because respondents disregard most or all of the information they are shown (Colonnelli et al., 2023). This would be the case, for example, if a startup operating in South Africa and looking for $50,000 is shown a potential investment of $2,000,000 from an investor focused exclusively on North Africa. Our design avoids such cases, while maintaining randomization of attributes conditional on the basic filters.

3.2.4. *Rating Investment Opportunities.* To assess startup preferences for specific characteristics of investment deals and partners, we ask them to rate a randomly selected set of 10 or 15 synthetic profiles of investment opportunities.

Our main dependent variable is captured by the following question:

(1) *"How <u>interested</u> would you be in this investment opportunity?"*

[15]The investment ranges are "Less than 250k" (45.12% of respondents), "250k-1M" (39.22%), and "More than 1M" (15.66%). Equity ranges are "0-15%" (62.85% of respondents), "16-30%" (26.80%), "31-50%" (8.73%) and "More than 51%" (1.62%).

In the instructions, we explicitly ask respondents to take into account both the investor and the proposed deal terms. We employ a 7-point Likert scale to assess ratings, where 1 corresponds to "Somewhat interested" and 7 represents "Extremely interested."[16]

A key advantage of the experimental design is that it separates the attractiveness of an investment opportunity from the perceived likelihood of receiving it. We first instruct respondents: "Please assume the investment partner is already interested in investing in your organization. Focus only on the attractiveness of the investor and proposed terms." We then ask a separate question about how likely the investor is to provide capital.[17] This second question reinforces the distinction between the attractiveness of an opportunity and the perceived probability of receiving it. We also use the perceived-likelihood rating as a robustness control in the regressions.

3.3. **Startup Preferences.** We use the experimental survey data to estimate preferences over investment opportunities by estimating regressions of the form

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

where $i$ indexes the early-stage startup responding to the survey and $j$ indexes the investment profile evaluated by startup $i$. The dependent variable $y_{ij}$ is startup $i$'s 1–7 rating of profile $j$. The coefficients of interest are the $\beta_k$'s, which capture startups' preferences over the $N$ attributes of the investment opportunity. $Characteristics_{jk}$ is a vector of binary indicators for whether a given attribute appears in profile $j$. Appendix Table A5 summarizes the main indicators included in the analysis. Our baseline specification includes startup fixed effects, $\alpha_i$, which absorb differences in average rating levels across startups. We report heteroskedasticity-robust standard errors, following Abadie et al. (2023).

Figure 3 reports the main results. The figure groups profile attributes into three categories. Panel A focuses on *deal* attributes, including whether the contract is debt or equity and the associated contract terms, such as interest rates, maturity, equity stakes, and board-seat requirements. Panel B focuses on *investor* attributes, that is characteristics of the fund or organization making the investment, such as whether the investor is foreign and whether it specializes in particular sectors or geographies. Panel C focuses on *team* attributes, namely

[16]We set the lowest rating to "Somewhat interested" because our filtering questions are designed to ensure that respondents have at least some interest in all profiles shown to them. See Appendix Figure A5 for details about the profile rating instructions.

[17]Specifically, we ask:

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

Responses are measured on a scale from 1 to 7, where 1 denotes "Unlikely" and 7 denotes "Likely." The question is incentivized with the following language: "*As an additional incentive to this goal, we also analyze the data on investors' reciprocal interest towards organizations like yours. If you are able to predict potential investors' interest accurately [...], you will receive additional support from the IFC research team to match you with the right partners.*"

characteristics of the individuals in the investment team, such as prior experience or whether team members are foreign.

3.3.1. *Demand for Equity Capital.* The largest estimate in Panel A of Figure 3 is the preference for *equity* financing over debt. By construction, this comparison *holds fixed* all other investment attributes, including the source of capital and the amount invested.

The magnitude is economically large. The estimated coefficient is 0.718 on the 1–7 rating scale, equal to 16.5% of the average rating.[18] The survey design also allows us to benchmark this effect against other deal attributes. Respondents value switching from a debt contract to an equity contract as much as moving from an investment that covers less than 25% of the amount sought to one that covers the full amount.[19] Equivalently, the debt-to-equity switch is valued as much as an 11 percentage point reduction in the interest rate on a debt contract.

Figure 4 provides an additional benchmark. We group interest rates and equity stakes into ranges, use the highest debt interest rate in the experiment (20%) as the omitted category, and estimate relative preferences for alternative debt and equity contracts, again holding all other attributes—including investment size—fixed. The most attractive debt contracts in our experiment, with interest rates of 5–10% (well below typical rates in the region), are valued about as highly as the least attractive equity contracts, which require the startup to give up at least 30% of the firm. All other equity contracts are preferred to debt contracts. This result implies that, over any plausible range of contract terms, equity contracts are preferred to debt contracts.

3.3.2. *Is the Equity Premium Driven by a Preference for Non-Repayable Cash?* Given entrepreneurs' strong preference for equity, a natural concern is that respondents may value equity primarily because they perceive it as non-repayable capital. We address this interpretation using several pieces of evidence and show that it provides, at best, an incomplete account of the observed equity premium.

First, the equity profiles are not presented as costless "grants." Respondents face dilution and board seats as explicit contractual costs of equity, and their choices indicate that they internalize these costs. Panel A of Figure 3 shows that, holding all other equity-contract characteristics fixed, respondents penalize board-seat requirements and prefer contracts requiring smaller equity stakes. Figure 4 reinforces this interpretation: respondents exhibit monotonic preferences for both lower interest rates and lower equity stakes, which supports the validity of the elicited preferences. These patterns are difficult to reconcile with a pure

[18]Appendix Figure A6 reports the distribution of ratings.

[19]To derive this result, we replace the "Large Investment" indicator with 10 bins defined by the "Fund Offered/Fund Requested" ratio. See Appendix Figure A7 for details.

"free money" interpretation. If respondents valued equity simply because it provides non-repayable cash, their valuations should be relatively insensitive to contractual terms such as dilution and board control, which affect ownership and governance rather than the immediate cash value of the offer.

Second, we examine how the relative preference for equity varies when equity is bundled with other investor characteristics, especially those related to investor control or monitoring. To do so, we estimate Equation 3.1 within subsamples of profiles that include specific monitoring-related attributes, such as an explicit due-diligence requirement. The top part of Figure 5 Panel A shows that, although respondents penalize board-seat requirements and higher equity stakes, the preference for equity remains positive even when equity is bundled with these stringent forms of investor control. We also find no attenuation of the equity premium when equity is paired with other attributes that may facilitate closer monitoring, including due diligence, local investors, local teams, same sector focus or same country focus.

Third, we examine heterogeneity by respondent and firm characteristics, using both self-reported answers in the survey and externally validated measures constructed by matching respondents to commercial data sources, including PitchBook+ and Revelio Labs. These data allow us to proxy for respondent quality along several dimensions: founders' education and work experience, firm employment records, actual financing outcomes, and self-reported characteristics such as founder financial sophistication, firm revenue, and high-tech startups. The middle and bottom parts of Figure 5 Panel A show that the preference for equity is robust across these splits. Importantly, the equity premium is consistently and significantly larger among respondents classified as higher quality according to externally validated measures. For example, we find that the preference for equity is stronger for firms that end up surviving longer and growing more after the survey took place, and for firms that actually obtain external financing.[20]

We then turn to country-level heterogeneity. A "free money" interpretation would likely predict a stronger preference for equity in countries with weaker institutions, weaker rule of law and, most of all, poorer protection of investor rights. The data appear inconsistent with this. Panel B of Figure 5 reports heterogeneity across several standard measures of investor protection, governance, and quality of doing business, drawing on the IMF Financial Development Index, World Bank Worldwide Governance Indicators, as well as the World Bank Ease of Doing Business ranking (Djankov et al., 2002). Across these measures, the preference for equity remains large throughout and, if anything, stronger in countries with higher financial development. Repeating the exercise by subregion and other basic country characteristics, we find that the preference for equity is positive in every subregion, though it

[20]The externally validated measures were collected as of April 2026, thus capturing information current 2.5 years (6 months) after our first (second) survey. We provide detailed definitions of all the constructed heterogeneity groups in Appendix A.3.2.

is strongest in North Africa. The preference is also somewhat larger in countries with higher GDP per capita and human capital, but with a thin venture capital market (measured as total VC investment in 2024 relative to GDP). The latter are likely countries where demand for equity financing is strong also because of the limited local supply.

Lastly, we turn to respondents' self-reported reasons for preferring equity as qualitative evidence.[21] Appendix Table A6 shows that, among respondents who prefer equity, 48.4% cite cash-flow and financial flexibility, 39.6% cite investors' incentives to help, and 33.1% cite access to investors' expertise, guidance, and networks. These responses further indicate that the respondents' preference for equity goes well beyond a simple desire to avoid repayment obligations.

3.3.3. *Investor Attributes: Local Information, Expertise, and Support.* Figure 3 reports several additional preference estimates. Panel A focuses on other "deal" characteristics, largely as a sanity check: all else equal, startups prefer larger investment amounts; among debt offers, they prefer lower interest rates and longer maturities.

Panels B and C turn to "investor" and "team" characteristics. Startups prefer investors with an explicit focus on their sector and country, and they assign a premium to DFIs. They also value signals of investor quality and support, including prior success and non-financial services such as mentorship. These estimates indicate that startups weigh positively the value investors can add beyond capital.

On the other hand, startups do not place additional value on foreign investors once other attributes are held fixed. This goes somewhat against anecdotal evidence, according to which foreign investors may be considered more attractive because of the visibility or additional reputation they may bring (Bernstein et al., 2022). Our results suggest that such advantages operate through observable investor attributes—such as contract type, investment size, track record, or non-financial support—rather than through foreignness itself.[22]

We find, instead, a preference for investors with *local* teams (Panel C). Profiles receive higher ratings when the investment team is local—that is, when key team members are described as having been born and raised in the startup's country of operation—or when the team has several years of experience in Africa. Respondents also value teams that include former successful entrepreneurs. By contrast, we do not find a preference for teams with international experience, foreign teams whose key members were born and raised in the U.S. or Europe, or teams whose members attended a top U.S. university. Together, these

[21]After the experiment takes place, in the qualitative component of our survey we ask directly: "Do you prefer debt or equity investments?" We then follow up and ask "Could you explain in more detail why you prefer equity over debt?" if they stated they preferred equity, and vice versa in case they said debt.

[22]We replicate the heterogeneity analysis in Figure 5 for the coefficient on "Foreign Investor." The results, reported in Appendix Figure A8, show little heterogeneity in preferences for foreign investors across the different groups.

patterns suggest that startups value investor expertise, support, and local information when evaluating potential investment opportunities.

3.3.4. *Heterogeneity and Robustness.* We conduct several checks on the preference estimates reported in Figure 3. The results are stable across alternative specifications (Appendix Table A7), across reweighting schemes based on different representativeness benchmarks (Appendix Table A8), and across African subregions (Appendix Figure A9). They are also robust to controlling for respondents' perceived likelihood of receiving the investment (Appendix Figure A10).

We also test whether differential salience of profile components affects the estimates. To do so, we randomized whether parts of each profile appeared in blue and bold font. Appendix Figure A11 shows that preferences are stable across profile subsets defined by the highlighted section.

Finally, we replicate both our main results and the detailed analysis of equity vs debt separately by survey wave in Appendix Figures A12 and A13, respectively. Results are consistent across the two survey rounds. This comparison is useful for assessing sample selection concerns because the second round replaced the IFC dissemination strategy with direct outreach from the broad LinkedIn-based company list described in Section 2.1. The stability of the estimates suggests that the equity result is not simply an artifact of surveying firms that one may worry are more embedded in the VC ecosystem.

## 4. The Supply and Allocation of Venture Capital in Africa

The previous section showed that startups in Africa value flexible equity-like capital, especially when paired with investor capabilities and local information. We now ask who supplies equity capital and which entrepreneurs receive it. To do so, we combine VC deal records with founders' education and work histories from LinkedIn. This allows us to characterize the realized allocation of startup equity in Africa and compare it to other startup ecosystems around the world.

We start by placing Africa in a global context. Figure 6 plots several measures of VC activity against GDP per capita across countries. Panel A shows the number of financed startups per capita, Panel B shows VC investment received by startups, and Panel C shows VC investment originated by domestic investors. The relationship with income becomes stronger as we move from startup activity to capital received and then to domestic capital supplied. African countries lie near the bottom of these distributions, with the largest gaps appearing on the domestic-investor margin. Local VC markets are therefore thin even relative to the level of startup activity observed on the continent.

This pattern suggests that the supply-side constraint is not simply that Africa has few startups, but that local investors originate little of the equity capital that startups demand.

The rest of this section quantifies the resulting reliance on foreign capital and shows that foreignness appears not only on the investor side, but also on the side of the entrepreneurs accessing capital.

4.1. **Where Does Capital Come From?** We begin by documenting a defining feature of Africa's startup equity market: its pronounced reliance on foreign capital. We define foreign capital as funding provided by investors whose headquarters are located outside the African continent.[23]

Panel A of Figure 7 plots the share of startup funding involving at least one foreign investor for Africa, Emerging Markets, and Developed Markets over 2010–2024.[24] The differences across regions are stark. In Africa, the foreign-investor share typically ranges 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.[25]

Panel B of Figure 7 shows the same pattern at the country level by plotting the share of startup funding involving at least one foreign investor against GDP per capita. The figure reveals a clear negative relationship between income and reliance on foreign capital: poorer countries depend more heavily on foreign investors for startup financing. African countries are concentrated in the upper-left region of the figure, combining low income levels with foreign-investor shares often above 80%.

Panel A of Figure 8 examines where this foreign capital comes from and how it is allocated within the continent. Inflows are overwhelmingly sourced from Northern America and Europe. Capital from China, India, and Latin America remains limited. DFIs and Rest of the World investors also contribute, but Africa-based investors account for a secondary

[23]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. Unless specified otherwise, by investor we mean the GP, namely the fund manager investing directly into the startups.

[24]For each country, we define the share of startup funding involving at least one foreign investor (the "foreign funding share") as the proportion of total deal value coming from deals that involve at least one investor headquartered outside the region in which the country is located. We classify regions as Africa, Europe, Northern America, Latin America, China, India, and the Rest of the World (RoW), following the UN geoscheme. Investors with unknown headquarters regions are not classified as foreign. For example, a deal in Africa involving two African investors and one European investor is classified as foreign, whereas a deal in Africa involving two African investors and one additional investor with unknown headquarters information is not. For each year, we calculate the overall foreign funding share for Africa, EM, or DM as the weighted average of country-level foreign funding shares, where each country is weighted by its total deal value in that year.

[25]Appendix Figure A14 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 A15 compares the result using PitchBook+ and PitchBook-only data in Panel B, along with comparisons of additional descriptive facts.

share. Financing of African startups is therefore largely intermediated through foreign investors based in developed markets.

Panel B of Figure 8 decomposes these flows by destination subregion within Africa and highlights limited intra-African financial integration. Across every African region, the dominant inflows continue to come from Northern America and Europe, while cross-subregion flows from African investors are thin. Local capital appears segmented and concentrated within subregions rather than broadly allocated across the continent.

We then move one step upstream and ask not only where the fund managers investing in Africa's entrepreneurs are based, but also where their capital providers are located. Appendix Figure A16 traces flows from LPs to GPs and ultimately to Africa's startups, separately by destination subregion. The upstream pool of capital remains concentrated in a small set of extra-continental investor bases, most prominently Northern America and Europe, while local and locally intermediated capital remain limited. DFIs also emerge as an important upstream source of funds, consistent with their mandate.[26]

Taken together, these facts show that the market for startup equity in Africa is heavily dependent on foreign sources of capital.

4.2. **Who Does Capital Flow To?** We next turn from the investor side to the founder side and ask who receives this capital. To do so, we combine deal-level financing data with LinkedIn-based founder histories, which allow us to characterize founders' educational and professional trajectories. Two patterns stand out: founders who receive VC financing in Africa have high levels of education, and they often have foreign education or foreign work experience.

4.2.1. *College-Educated Founders.* We begin with education. Panel A of Figure 9 plots, at the country level, founders' average years of schooling against the national average from Barro and Lee (2013). First, across all regions, founder education levels lie far above national averages. Second, this selection is particularly stark in Africa: national average schooling is relatively low, but for founders who received VC, education levels are comparable to those in other Emerging and Developed Markets. The entrepreneurs who access the VC market in Africa are therefore drawn from a thin, skilled tail of the distribution.

Panel B shows that education is also closely related to the *scale* of the startup ecosystem. Countries with higher average schooling have substantially more established startups per capita, with this relationship holding across Africa, Emerging Markets, and Developed Markets.

[26]As comparison, Appendix Figures A17 and A18 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 "local."

Startup founders in Africa are therefore not less educated than founders elsewhere. The difference is that the pool of highly educated potential founders is smaller relative to the population.

4.2.2. *Dominance of Foreign Human Capital.* Panel A of Table 4 summarizes the human-capital composition of founders in VC-backed startups by the firm's headquarters region. Column (3) again shows that entrepreneurs in Africa have high levels of education, with a college attainment rate of 73.5%, comparable to that in other regions. The new results are in Columns (4) and (5): founders in Africa are much more likely to have *foreign human capital*. A total of 46.8% have foreign educational experience and 58.4% have foreign professional experience, substantially higher shares than in Europe and Northern America. When combined, Column (6) shows that 67.7% of founders in Africa have either foreign education or foreign work experience.

These patterns suggest that the founders who receive startup capital in Africa are disproportionately connected to foreign countries through schooling and work experience.[27] Appendix Figure A19 makes these links more concrete by tracing founders' cross-region trajectories, from the location of their last completed education to their first job and then to their last job before founding a startup. A common pattern is that many founders in Africa acquire education and early-career experience in Northern America or Europe before founding their companies.

Foreign human capital is also prevalent among startup employees, though less so than among founders. Panel B of Table 4 shows that 53.2% of employees are college educated, a higher share than in Europe and Latin America. It also shows that 24.5% are foreign educated and 26.2% have foreign work experience, both elevated relative to Latin America and India and comparable to Europe and Northern America on some margins. Foreign human capital is therefore present throughout startups in Africa, but is especially concentrated among founders.

4.3. **Foreign Venture Capital and Weak Local Institutions.** The dominance of foreign capital raises a question: why do weak institutions and limited investor protections, often used to explain why capital does not flow to poor countries, not hinder venture capital flows to African startups? (Lucas, 1990; La Porta et al., 1998; Djankov et al., 2003)

Part of the answer is that startups financed by global venture capital do not rely only on local institutions. Many startups are built around intangible assets, software, data, and human capital, which are harder to seize than physical capital. Venture capitalists also invest

[27] LinkedIn does not report founders' place of birth, so we cannot directly distinguish foreign-born founders from African-born returnees. As a proxy, we use Revelio Labs' imputed *race* variable, which we manually verify conservatively for Africa. Roughly half of founders in Africa's VC-backed startups are classified as white.

primarily for upside gains. Their returns depend on whether successful firms can scale, raise follow-on capital, and eventually exit. When that upside materializes, firms can partly move the relevant contracting environment outside the country in which they initially operate. They can incorporate, raise capital, list, or relocate their legal headquarters in jurisdictions with stronger investor protections.[28]

The data are consistent with this interpretation. Appendix Table A9 shows that most African startups remain headquartered in Africa. But the picture changes when firms are weighted by their overall employment: only slightly more than half of employment is in startups headquartered in Africa, while more than 30 percent is in firms headquartered in Northern America. Appendix Table A10 shows a related pattern in contracting currency. More than half of VC deals in Africa are denominated in foreign currency, mostly U.S. dollars, and this share rises to about two thirds among deals involving foreign investors.

These patterns do not imply that local institutions are irrelevant. Rather, they suggest that foreign VC can partly rely on legal and financial arrangements outside the local economy. But this route may not be available to all firms or investors. Foreign investors and foreign-connected founders may be better placed to use foreign legal and currency structures, for example. The same arrangements that make foreign VC feasible in Africa may therefore also help explain why the ecosystem remains foreign. We formalize this logic in the model below.

## 5. Foreignness in Africa: Drivers and Implications

The evidence so far points to two facts. Startups in Africa value flexible equity capital, and this capital is supplied mainly by foreign investors, often to foreign or foreign-connected founders. We now use a simple model to organize these facts and measure the forces behind them. The goal is to recover the potential frictions (or wedges) that can rationalize the foreignness of both capital and entrepreneurs, and to quantify their implications for the size and composition of the startup sector.

5.1. **A Simple Model of Startups in Africa.** The model is intentionally parsimonious. It should be read as an accounting framework that maps the empirical patterns into economically interpretable objects.

5.1.1. *Environment.* There is a set of destination countries $c$, investor origins $x \in \mathbb{X}$, and entrepreneur types $k \in \mathbb{X}$. Investors are based in origin $x$ and supply capital to startups in destination $c$. Entrepreneurs are located in destination $c$. Their type $k$ summarizes exposure to a region through prior education, work experience, or networks.[29]

[28] Reichardt and Reis (2026) document a similar pattern for Europe: firms that receive financing from U.S. investors are more likely to relocate their headquarters to the United States.

[29] Using the same partition for investor origins and founder types allows us to map founder exposure directly into investor access.

*Investors.* Each origin $x$ has a large mass of atomistic investors. When investors from $x$ finance startups in destination $c$, they face a capital wedge $r_{c,x}$. This wedge captures both the opportunity cost of capital and any barriers to deploying funds in market $(c,x)$. Investors freely enter each market until expected returns equal this wedge.

*Entrepreneurs.* In each destination $c$, there is a mass $e_c^k$ of potential entrepreneurs of type $k$. We refer to this object as an entry wedge. It captures both the latent mass of entrepreneurs of each type and the barriers they face in reaching the equity-financing margin.

Each entrepreneur draws project productivity $z_c^k \sim F_c^k(\cdot)$ and chooses whether to seek equity financing from investors in any origin $x$, or to rely on a domestic outside option, which we interpret as debt. If financed through debt, a type-$k$ entrepreneur with productivity $z$ obtains

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

If the entrepreneur searches for equity financing from origin $x$, she obtains financing with an equilibrium probability that depends on market tightness in $(c,x)$ and on her connection to that origin. If matched, output is $z$. The investor receives share $\beta$, and the entrepreneur receives share $1-\beta$.

Entrepreneurs also have preferences over financing options. The deterministic component is denoted by $\bar{\tau}_{c,m}$, for $m \in \{d\} \cup \mathbb{X}$. In addition, each entrepreneur draws idiosyncratic preference shocks across financing options. These shocks generate smooth search choices across debt and equity markets. Finally, entrepreneurs differ in their ability to reach investors from different origins, summarized by a connection term $\lambda_{c,x}^k$.[30]

*Equity markets.* For each destination–origin pair $(c,x)$, there is a separate equity market. Let $s_{c,x}$ denote capital supply and $d_{c,x}$ denote effective demand. The number of successful matches is

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

Random matching implies that an entrepreneur searching in market $(c,x)$ is financed with probability proportional to $(s_{c,x}/d_{c,x})^{\eta}$, while an investor supplying capital to that market is matched with probability $(d_{c,x}/s_{c,x})^{1-\eta}$.

Let $\mu_{c,x}^k$ denote the share of type-$k$ entrepreneurs in destination $c$ who search in equity market $(c,x)$. Given the preference shocks, this share is

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

The parameter $\sigma$ governs how strongly entrepreneurs reallocate search across financing options when relative payoffs change.

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

5.1.2. *Equilibrium and Startup Formation.* We now characterize the equilibrium allocation of startups. Let

$$E[z_{c,x}] \equiv \frac{\sum_{k\in\mathbb{X}} \lambda^k_{c,x}\mu^k_{c,x}e^k_c \int z\, dF^k_c(z)}{\sum_{k\in\mathbb{X}} \lambda^k_{c,x}\mu^k_{c,x}e^k_c}$$

denote the expected productivity of entrepreneurs searching for financing from investors of origin $x$ in destination $c$.[31]

Lemma **1.** *The number of equity-financed startups in destination $c$ is $N_c = \sum_{x\in\mathbb{X}}\sum_{k\in\mathbb{X}} n^k_{c,x}$, where $n^k_{c,x}$ are startups founded by type-$k$ entrepreneurs and financed by investors from origin $x$, and are given by*

$$n^k_{c,x} = \underbrace{\left(\frac{\beta E[z_{c,x}]}{r_{c,x}}\right)^{\frac{\eta}{1-\eta}}}_{\text{supply}} \underbrace{\lambda^k_{c,x}\mu^k_{c,x}e^k_c}_{\text{demand}}.$$

The first term captures the supply of capital from investors in country $x$. It is increasing in expected returns and decreasing in the capital wedge faced by those investors. The second term captures demand for this type of capital from entrepreneurs of type $k$. It depends on the mass of potential entrepreneurs, their search toward investors from origin $x$, and their ability to reach those investors.

*Foreignness.* We now characterize foreignness. Let $n_{c,x} \equiv \sum_k n^k_{c,x}$ denote all startups in destination $c$ financed by investors from origin $x$, and let $n^k_c \equiv \sum_x n^k_{c,x}$ denote those founded by entrepreneurs of type $k$. For expositional purposes, consider two investor origins and two founder types: foreign $f$ and local $\ell$.

Define $\hat{\mu}^k_{c,x} \equiv \mu^k_{c,x}/(\bar{\tau}_{c,x})^\sigma$, which removes the component of search intensity due to the deterministic preference shifter for investor origin $x$, and let $\hat{e}^k_{c,x} \equiv \hat{\mu}^k_{c,x}e^k_c$.

Lemma **2.** *The ratio of foreign- to locally financed startups is*

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

This decomposition shows that foreign investor dominance can arise for four reasons: foreign capital may face lower wedges, foreign investors may expect higher returns, entrepreneurs may prefer foreign investors, or the entrepreneurs who reach the financing margin may be better connected to foreign investors. The last term combines entry and connections. Foreign finance is more prevalent when the relevant entrepreneur mass is tilted toward types with stronger access to foreign capital.

Next, let $A_{c,x} \equiv (\beta E[z_{c,x}]/r_{c,x})^{\frac{\eta}{1-\eta}}$ denote the supply term from investor origin $x$, and let $\omega^k_{c,x} \equiv (\bar{\tau}_{c,x})^\sigma \lambda^k_{c,x}\hat{\mu}^k_{c,x}$ denote type-$k$'s effective access to investors from origin $x$.

[31] The proofs of the following lemmas are provided in Appendix A.4.1.

Lemma **3.** *The ratio of startups founded by foreign-type relative to local-type entrepreneurs is*

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

The founder side depends on two objects: the relative mass of foreign and local entrepreneurs who reach the financing margin, and their relative access to capital. Foreign founders create more startups when they are more numerous at the financing margin, or when they are better connected to the investor origins where capital is most available.

5.2. **Bringing the Model to the Data.** We now use the model as a measurement framework to study what drives foreignness on both the investor and founder sides. The evidence from Sections 3 and 4 already rules out some explanations and points to others. Preferences for foreign investors do not appear to be first order. Capital wedges and entry wedges remain plausible, but cannot be read directly from the raw patterns. Foreign investor dominance could reflect higher expected returns rather than cheaper foreign capital. Founder foreignness could also arise without an entry wedge if foreign founders are better connected to the investor origins where capital is cheaper.

Therefore, to unpack the drivers of foreignness, we need to introduce three additional pieces of empirical evidence. These discipline the remaining model parameters: the strength of founder–investor connections, $\lambda$; expected returns, $E[z]$; and the substitutability of capital across investor origins, $\sigma$. With these in hand, we recover capital and entry wedges as residuals that allow the model to match the observed allocation of VC capital to startups.

5.2.1. *Connections to Foreign Investors.* We measure connections ($\lambda_{c,x}^k$) using a dyadic design that links each founder in Africa to potential investor countries. The question is whether founders are more likely to raise capital from countries to which they are connected through prior education or work experience, conditional on founder background, founder location, investor-country characteristics, and time.

For example, among startup founders in Kenya, we ask whether founders who studied in the United States are more likely to receive financing from U.S. investors, while those who studied in France are more likely to receive financing from French investors.

For each founder $i$ and investor country $x$, we estimate variants of

$$\begin{aligned} y_{ix} = {}&\lambda_1 \mathbf{1}_{x=\text{EduCountry}(i)} + \lambda_2 \mathbf{1}_{x=\text{ExpCountry}(i)} + \phi \log(\text{Distance}_{c(i),x}) \\ &+ \alpha_{c(i)} + \gamma_x + \xi_{\text{EduCountry}(i)} + \kappa_{\text{ExpCountry}(i)} + \delta_{\text{DealYear}(i)} + \varepsilon_{ix}, \end{aligned} \tag{5.1}$$

where $y_{ix}$ is either an indicator for whether founder $i$ raises any VC funding from investor country $x$, or the total amount raised from that country. The two key regressors indicate whether the investor country coincides with the country of the founder's education or work experience.[32] The specification controls for geographic distance, startup-country fixed effects, investor-country fixed effects, founder education- and experience-country fixed effects, and deal-year fixed effects. These controls absorb the location of the startup, investor-country attractiveness, common time shocks, and the average propensity of founders with a given education or work background to raise capital. The coefficients $\lambda_1$ and $\lambda_2$ therefore isolate bilateral founder–investor connections. The sample includes all possible matches between founders in Africa and non-African investor countries.[33]

Table 5 shows that these connections strongly predict cross-border capital flows. A match between the investor country and the founder's education country raises the probability of receiving funding from that country by 7.7 percentage points, relative to a mean of 2.2 percent, and is associated with an additional \$1.16 million in annual funding. Work-experience ties have similar effects: they raise the probability of funding by 7.9 percentage points and are associated with \$1.11 million more in funding. When both measures are included jointly, both remain large and statistically significant on the extensive and intensive margins.

5.2.2. *Post-Funding Performance of Foreign and Foreign-Connected Startups.* Relative expected returns are another possible explanation for foreignness. The previous section shows that foreign and foreign-connected startups are more likely to match with foreign investors. If these startups systematically perform better after receiving funding, foreign investor dominance could partly reflect higher expected returns rather than lower capital wedges. While we do not observe expected returns directly, we can examine the closest observable proxy in our data: ex post performance among funded startups in Africa. Specifically, we estimate

$$y_i = \beta_1 \, \mathit{ForeignConnected}_i + \beta_2 \, \mathit{Foreign}_i + \Gamma' \mathbf{X}_i + \phi_{c(i)\times s(i)} + \eta_{\text{cohort}(i)} + \varepsilon_i, \tag{5.2}$$

where $y_i$ is measured after the first recorded deal. Outcomes include successful exits, IPOs, M&A, bankruptcy, and post-funding employment growth.[34] $\mathit{Foreign}_i$ is an indicator for whether startup $i$ has at least one founder with foreign education or work experience.

[32]Using LinkedIn profile data, we measure founders' education and work experience as of the year of the investment, excluding education or work experience acquired afterward.

[33]The set of non-African investor countries includes all countries outside Africa that have at least 5 VC deal–investor pair records in African VC deals during 2010–2024, as recorded in PitchBook+. Table 5 implements equation (5.1) 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.

[34]All exit outcomes, including bankruptcy, are measured using PitchBook+ records. Employment growth is constructed using annual employee counts from LinkedIn. For each startup, we estimate a regression of employment on year and use the implied slope as the startup's average post-funding employment growth rate.

$\mathit{ForeignConnected}_i$ indicates whether at least one founder's foreign education or work experience occurred in the same foreign country as a future foreign investor. The controls $\mathbf{X}_i$ include deal and firm characteristics, and the fixed effects absorb country–sector and first-deal cohort differences.

Table 6 provides little evidence that foreign or foreign-connected startups systematically outperform once funded. Foreign-connected startups appear to do better unconditionally along some margins, including successful exits, M&A, bankruptcy, and employment growth. But these differences largely disappear, or turn negative, once we control for characteristics at the first VC deal. The same is true for startups with foreign founders: unconditional differences are modest and mostly vanish with controls, aside from a smaller bankruptcy gap. While our exercise cannot rule out selection into funding, we interpret this evidence as suggesting that expected returns are unlikely, on their own, to be a first-order driver of foreignness.

5.2.3. *Aggregate Effects of Foreign Capital Supply Shocks.* We next use foreign capital supply shocks to discipline $\sigma$, the elasticity governing substitution across capital from different investor origins. The same exercise also validates a key mechanism of the model. If capital from different origins is imperfectly substitutable, changes in foreign capital availability should affect both total startup activity and the composition of funded founders. In the data, they do.

We use a shift–share design based on sector-specific capital supply shocks from investor countries. The design isolates variation in foreign funding availability driven by investor countries' sectoral capital cycles, rather than by contemporaneous demand conditions in Africa. We implement it at the sector–destination country–year level. Let $Y_{s,c,t}$ denote startup activity in sector $s$, destination $c$, and year $t$, measured either by total VC deal value or deal count. We instrument foreign capital inflows with

$$Z_{s,c,t} \;=\; \sum_x share_{s,c,x,t_0} \times \log\Big(shift_{s,-c,x,t}\Big), \tag{5.3}$$

where $share_{s,c,x,t_0}$ is the pre-period exposure of destination-sector cell $(s, c)$ to investor origin $x$, and $shift_{s,-c,x,t}$ is a leave-one-out measure of capital deployed by investors from origin $x$ in sector $s$ at time $t$, across destinations other than $c$. We estimate

$$\log(Y_{s,c,t}) \;=\; \beta\, Z_{s,c,t} \;+\; \eta_{s,t} \;+\; \phi_{s,c} \;+\; \varepsilon_{s,c,t}, \tag{5.4}$$

with sector–year and sector–destination fixed effects. In the baseline specification, exposure shares are constructed using PitchBook+ data from 2000–2014, and outcomes are measured over 2015–2024.[35]

[35] In constructing both the shifters and the pre-period exposure shares, we use deal flows from all investor origins to all destination countries in the world, as recorded in PitchBook+.

The identifying variation can be illustrated with Nigerian fintech. If Nigeria's fintech sector was historically more exposed to U.S. investors than fintech sectors in other countries, then a U.S. fintech funding boom outside Nigeria raises predicted foreign capital availability for Nigerian fintech more strongly. We then ask whether Nigerian fintech grows more in that year than less U.S.-exposed fintech sectors elsewhere.[36]

Table 7 shows that foreign capital supply shocks increase startup activity in Africa. The coefficients are positive and statistically significant for both deal value and deal count. The estimate of 0.154 in Column (2) implies that a 10 percent increase in foreign capital availability predicts a 1.54 percent increase in African deal value. Appendix Figure A20 shows that the results are robust to alternative leave-out definitions, fixed-effect structures, base years, and sample restrictions. Appendix Table A11 further shows that the effects are stronger for startups founded by individuals with foreign education or work experience. Foreign capital shocks therefore affect both the amount of startup activity and which founders turn those shocks into realized funding.

5.2.4. *Recovering Wedges.* We can now combine the different pieces of empirical evidence to recover the capital and entry wedges, which will allow to answer the question of what drives foreignness. We set $\beta = 0.5$ and $\eta = 0.5$, and impose three restrictions motivated by the evidence. First, entrepreneurs do not have differential tastes across equity origins, so $\bar{\tau}_{c,x} = \bar{\tau}_c$ for all investor origins $x$. Second, conditional on receiving financing, expected returns do not vary systematically across investor origins within destination $c$. Third, entrepreneurs receive a connection premium $\lambda$ when their exposure type matches investor origin.

The remaining objects are $\sigma$, $\lambda$, the capital wedges $\{r_{c,x}\}$, and the entry wedges $\{e_c^k\}$. We choose $(\sigma, \lambda)$ to match the two reduced-form moments above: the response of startup activity to foreign capital supply shocks, and the tendency of founders to raise capital from investor origins to which they are connected. Conditional on $(\sigma, \lambda)$, we recover $\{r_{c,x}\}$ and $\{e_c^k\}$ to match observed startup counts by investor origin, $n_{c,x}$, and founder type, $n_c^k$.[37] We find $\sigma = 3.904$ and $\lambda = 2.235$, implying that entrepreneurs are 2.235 times more likely to match with an investor from a country to which they have been exposed.[38]

Tables A12 and A13 report the recovered wedges. The *capital wedges* show that, outside Africa, local investors tend to have a clear home-market advantage: local capital faces lower

[36]The identifying assumption is that, conditional on sector–year and sector–destination fixed effects, the shift-share instrument is uncorrelated with unobserved destination-sector-year demand shocks in Africa. Sector–year fixed effects absorb shocks common to all countries in a sector and year, while sector–destination fixed effects absorb time-invariant differences across destination-sector cells. The remaining variation comes from differential pre-period exposure to investor-origin shocks. We interpret increases in financing by investors from origin $x$ to sector $s$ outside destination $c$ as shifts in capital supply. The main threat is that these shifters instead reflect demand shocks correlated with African cells' exposure to the same investor origins.

[37]Founder type, as in the previous section, is assigned from education and work histories prior to startup founding.

[38]Appendix A.4.2 provides additional details on the model estimation and calibration.

wedges than foreign capital. Africa looks different. In several African regions, Northern American and European investors face wedges comparable to, or even lower than, those faced by local investors. The *entry wedges* show a parallel pattern on the founder side. Relative to Europe and Northern America, African startup ecosystems feature a smaller mass of local entrepreneurs reaching the financing margin and a larger presence of entrepreneurs with foreign exposure. Taken together, the model points to two distortions in Africa's startup ecosystem: local equity is relatively scarce, and the effective pool of local entrepreneurs seeking startup finance is relatively thin.[39]

5.3. **Decompositions and Counterfactuals.** We now use the calibrated model to study how the estimated wedges affect the size and composition of startups in Africa.

5.3.1. *Unpacking Foreignness into Its Drivers.* We begin with the composition of Africa's startup ecosystem. Figure 10 reports how the shares of local investors and local entrepreneurs change under counterfactual changes in capital and entry wedges.

The first exercise lowers local capital wedges in Africa so that the ratio of the local wedge to the Northern American wedge matches the corresponding ratio in Europe. This raises the local investor share from 26.1% to 41.7%. It also raises the local entrepreneur share from 32.0% to 40.5%. The second effect operates through the access-to-capital term in Lemma 3. Because local entrepreneurs are better connected to local investors, a reduction in the cost of local capital disproportionately increases local startup formation.

The second exercise increases the latent mass of local entrepreneurs so that the local entrepreneur share matches that in Europe. This raises the local entrepreneur share among funded startups from 32.0% to 47.3%. It also raises the local investor share from 26.1% to 38.3%. This effect operates through the last term in Lemma 2: a thicker pool of local entrepreneurs increases demand for the investors to which they are more connected.

The third exercise implements both changes simultaneously. The local investor share rises to 56.0%, and the local entrepreneur share rises to 56.4%, indicating complementarity between capital and entry wedges. Overall, both wedges contribute to foreignness. Capital wedges matter more for the dominance of foreign investors, while entry wedges matter more for the low share of local entrepreneurs.

5.3.2. *Counterfactuals for Startup Activity.* We next ask how the estimated wedges affect the number of startups created. Figure 11 reports the results.

[39] This conclusion is not mechanically implied by the empirical moments. In principle, the model could have rationalized the observed patterns mainly through capital wedges, if connection-driven differences in access were strong enough. The fact that it instead recovers a comparatively low mass of local entrepreneurs reflects the balance of forces required to jointly match the foreignness of capital and the composition of funded founders.

Lowering local capital wedges raises total startup activity by 13.0%. The increase comes from locally financed startups, which rise by 21.0%, while foreign-financed startups fall by 8.0% as demand shifts toward local capital.[40] The increase is concentrated among startups founded by local entrepreneurs.

Increasing the mass of local entrepreneurs has an even larger effect, raising total startup activity by 29.0%. The increase operates almost entirely through locally founded startups. Most of these startups are financed by local investors, but some also receive foreign capital: locally financed startups rise by 23.2%, while foreign-financed startups rise by 5.8%.

We also consider two additional counterfactuals. First, we strengthen local entrepreneurs' access to foreign investors by giving them the same connection intensity as foreign-connected entrepreneurs. This raises total startup activity by 16.9%, again through an increase in startups founded by local entrepreneurs.[41] It also reallocates financing toward foreign investors: foreign-financed startups rise by 37.2%, while locally financed startups fall by 20.3%. Since foreign investors face lower capital wedges in the estimated model, better access to them partly competes away local finance.

Second, we consider a human-capital counterfactual. We increase the mass of local entrepreneurs as if all African regions had the same level of human capital as the African region with the highest human capital.[42] This raises total startup activity by 26.0%. Startup creation increases for both sources of finance: locally financed startups rise by 10.7%, and foreign-financed startups rise by 15.3%. As in the other exercises, the gains by founder type are concentrated among locally founded startups.

These results show that the same frictions underlying the foreignness of Africa's startup ecosystem also reduce the number of startups created. Scarce local equity, a thin pool of local entrepreneurs at the financing margin, and unequal access to investor markets shape both the scale and the composition of startup activity.

5.4. **Survey Evidence on Mechanisms.** In the second round of our survey, we asked respondents why Africa's startup ecosystem has such a high share of foreign investors and foreign or foreign-connected founders. The goal was to compare entrepreneurs' perceptions with the mechanisms emphasized by the empirical and quantitative analysis.[43]

[40] We express all changes as shares of the baseline number of startups. The changes by investor origin therefore sum to the aggregate effect: $21.0 - 8.0 = 13.0$.

[41] 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.

[42] Specifically, we use the relationship between local founders' educational attainment and the recovered local entry wedge across African regions to predict how the local entry wedge would change if all regions had the human-capital level of the highest-human-capital region. Appendix A.4.3 provides the details.

[43] At the end of the second-round survey, we presented respondents with two stylized facts: roughly 80% of VC investment in Africa comes from foreign investors, and about half of funded startups have foreign or foreign-connected founders. For each fact, respondents were asked to choose the single most important

Figure 12 shows that respondents' answers line up closely with the model. On the investor side, roughly half cite the limited availability of local capital, and another quarter cite the small number of local investors. Fewer than 10 percent point to stronger founder demand for foreign capital, consistent with the survey evidence that preference-based explanations are not first order.

On the founder side, respondents point mainly to easier access to capital through networks and connections, and to investor bias. These explanations map naturally into the connection parameter $\lambda$ and into entry wedges that limit the mass of local entrepreneurs reaching the financing margin. Explanations based on performance differences or easier screening receive much less support.

Overall, these responses provide an independent check that the model captures mechanisms that market participants themselves see as important.

## 6. Conclusion

High-growth entrepreneurship has become a central focus of development policy, but the policy debate has moved ahead of the evidence. Most research on firms in poor countries studies microenterprises and small and medium enterprises. Much less is known about startups: firms that seek to scale quickly, often rely on external finance, and may matter disproportionately for innovation, technology adoption, and growth. This paper studies these firms in Africa, where governments and development finance institutions are actively trying to build startup ecosystems.

We combine a continent-wide survey of startup founders, an incentive-compatible experiment, and new data on venture capital deals, founders, and investors. The first result is that financing constraints are severe, but not all types of capital are the same. Entrepreneurs prefer equity over debt, and the evidence suggests that this preference reflects demand for flexibility and investor support, rather than simply a desire for non-repayable cash. Founders also value investor attributes that are useful in environments with information and monitoring frictions, especially local presence, local experience, and sector or country knowledge.

The second result is the *foreignness* of Africa's startup ecosystem. Startup finance comes overwhelmingly from foreign investors, especially from Northern America and Europe, and flows disproportionately to foreign and foreign-connected founders.

Interpreting these patterns through a simple accounting framework yields the third result: this foreignness reflects scarce local equity capital, a thin pool of local entrepreneurs at the financing margin, and frictions limiting local entrepreneurs' access to foreign capital. These forces shape not only which investors and founders appear in the data, but also how many startups are created.

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explanation from four randomized options and to briefly explain their reasoning. All questions in this part were optional.

The broader lesson is that, for high-growth firms, financial frictions are not only about how much capital is available. The form of finance, the identity of investors, and the networks through which capital is allocated shape entry, funding, and possibly growth. In Africa, core elements of the venture capital model appear well suited to what startups demand. But the local supply of this capital is limited, and access to foreign capital is uneven. Building a broader startup ecosystem therefore may require more than attracting foreign venture capital. It also involves expanding local equity capital and improving the ability of local entrepreneurs to access external finance.

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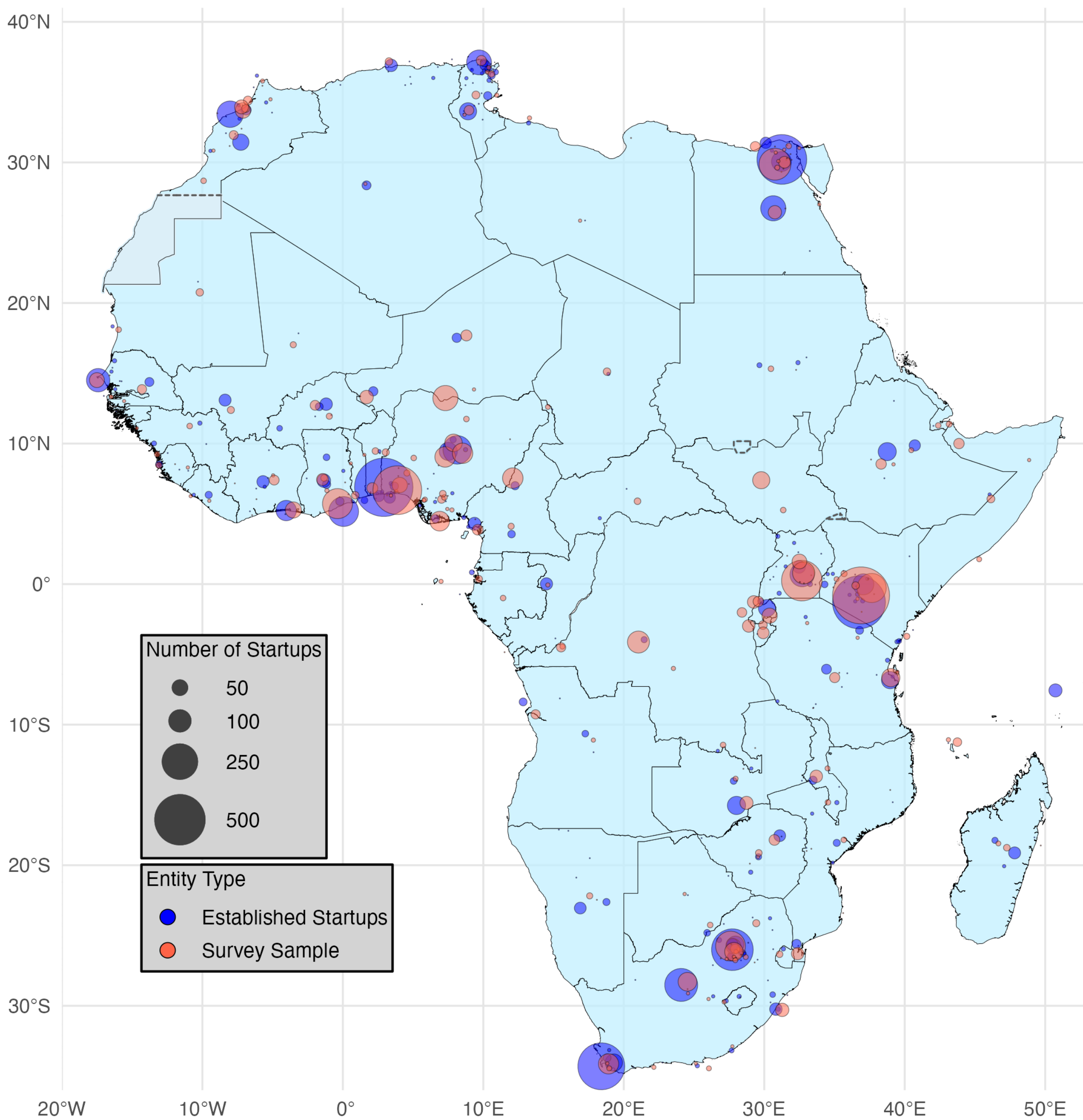
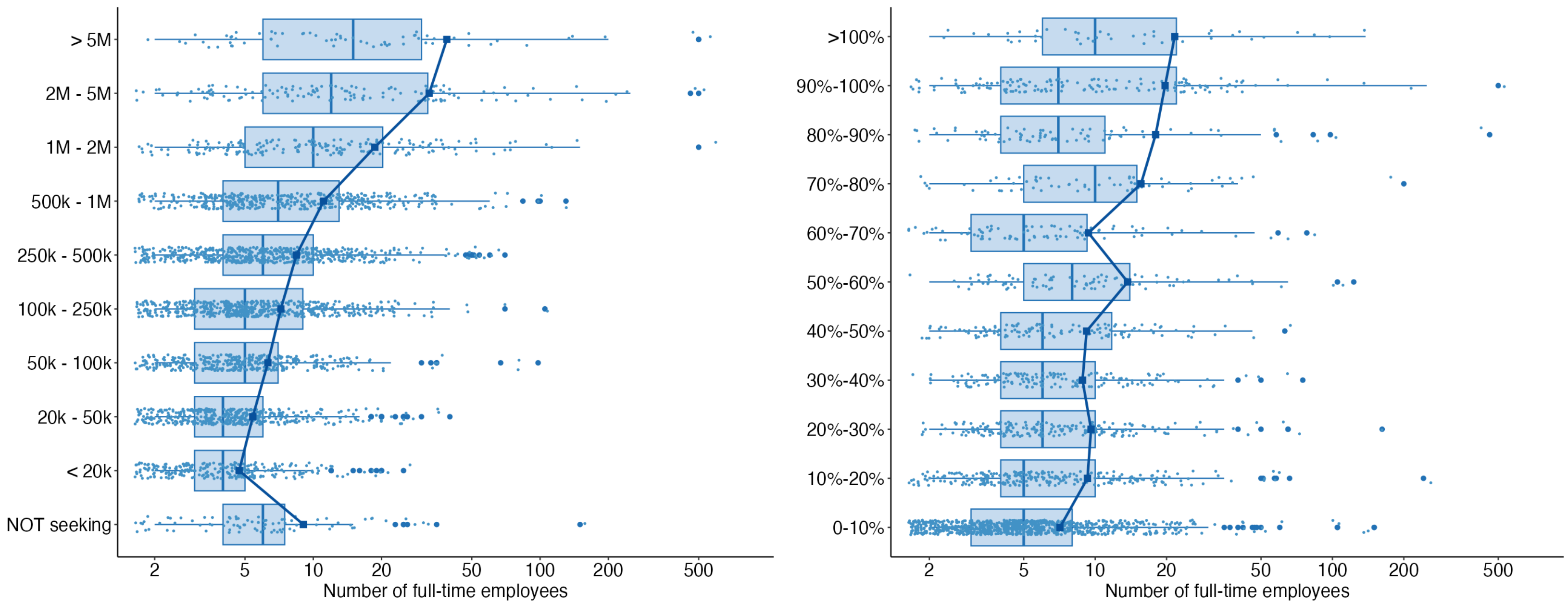



Figure 1. Geographical Distribution of Startups in Africa

*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 VC deal records in PitchBook, Africa: The Big Deal and Briter Bridges in 2010-2024. A detailed comparison of the survey sample's country distribution with the representativeness benchmark is provided in Appendix Table A2.

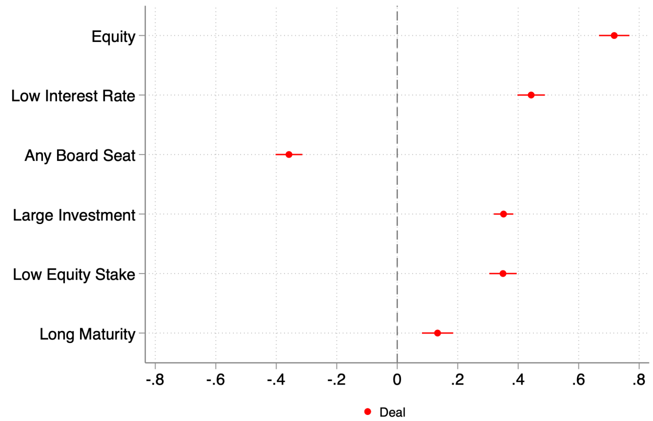



(A) Capital Sought by Startup Size

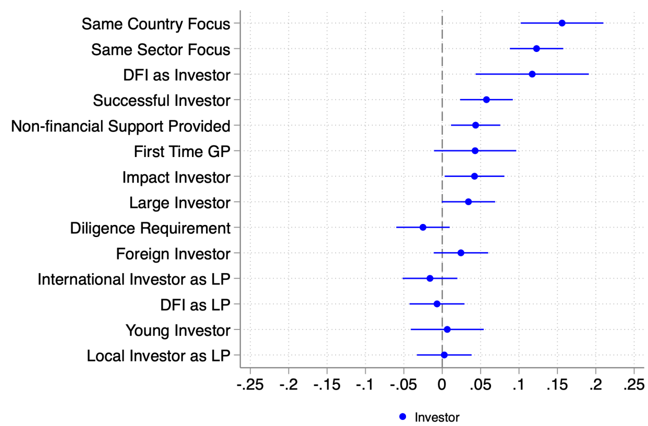
(B) Percentage of Capital Secured by Startup Size

Figure 2. Startups in Africa are Financially Constrained

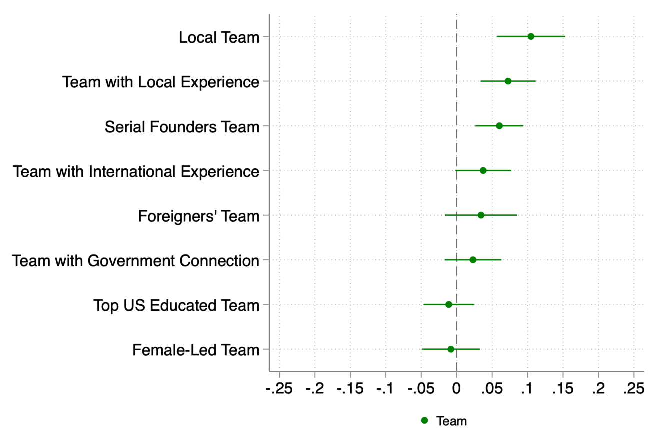
*Notes*: This figure plots survey respondents' capital needs and financing outcomes against firm size, measured by the number of full-time employees. Panel A presents the distribution of capital sought by startups, with the y-axis representing capital ranges and the x-axis representing the number of full-time employees. Panel B presents the percentage of capital needs successfully financed in the past 3 years, 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 light blue dots indicating individual observations and a dark blue line marking the mean.




(A) "Deal" Characteristics



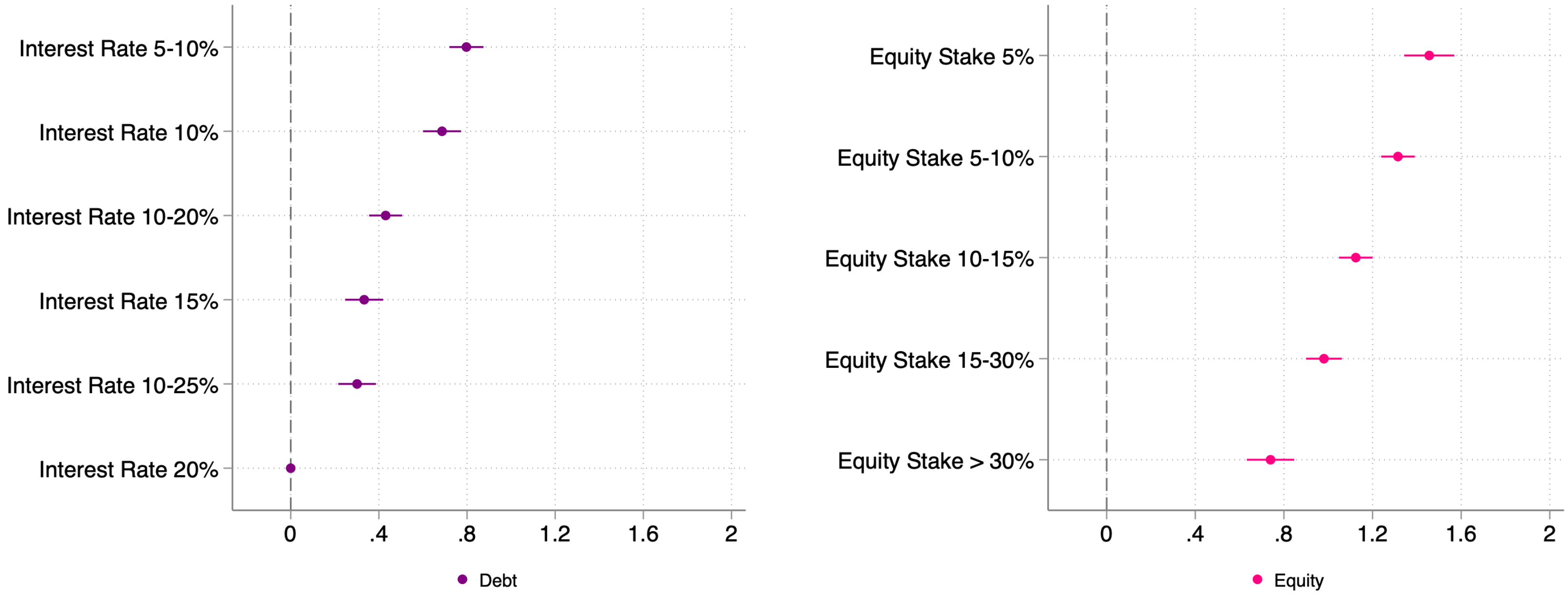

(B) "Investor" Characteristics




(C) "Team" Characteristics

Figure 3. Preferences for Investor and Financing Characteristics

*Notes*: This figure summarizes startups' preferences for different types of investment attributes featured in the synthetic profiles of investment opportunities, as captured by $\beta_k$ in Equation 3.1. Panels A, B and C show 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 A3 and A4 summarize the components and their inclusion probabilities used to generate the set of investment attributes in Table A5.

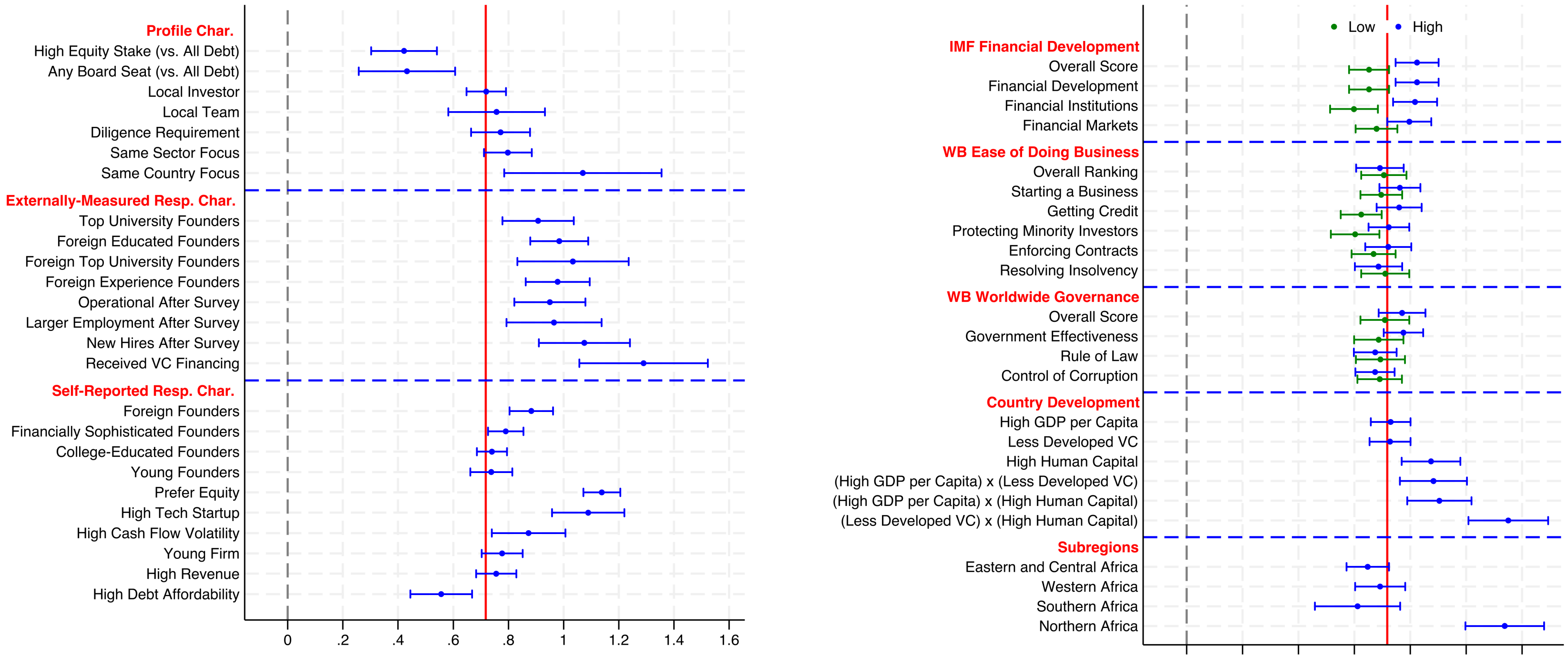



(A) Preference For Debt

(B) Preference For Equity

FIGURE 4. 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 profiles of investment opportunities. Panel A presents relative preferences for debt, split by different interest rates. Panel B presents relative preferences for equity, split by different equity stake requirements. We modified the specification of Equation 3.1 by replacing the indicator for *Equity*, *LowInterestRate*, and *LowEquityStake* with six indicators for debt financing split by different *InterestRate*, and five indicators for equity financing split by different *EquityStake*. *InterestRate* denotes the annual interest rate associated with the debt financing in the synthetic profile, while *EquityStake* denotes the share of equity required in exchange for equity financing.




(A) Profile & Respondent Characteristics

(B) Country Characteristics

FIGURE 5. Startup Preferences for Equity: Heterogeneity

*Notes*: This figure reports startups' preferences for *Equity* across heterogeneity groups. Panel A reports heterogeneity by profile characteristics and respondent characteristics, while Panel B reports country-level heterogeneity. Red vertical lines indicate the baseline coefficient estimated in the full sample. "The Profile Char." reports estimates from subsamples of profiles in which a given indicator equals one, for both equity and debt contracts. For *High Equity Stake* and *Any Board Seat*, we restrict the equity profiles to those with the relevant characteristic and compare them to all debt profiles. "Externally Measured Resp. Char." are constructed by matching respondents to external commercial datasets, including PitchBook+ and Revelio Labs. "Self-Reported Resp. Char." are constructed from respondents' survey answers. Country characteristics include subregions (defined according to the UN geoscheme), country development measures, and external indices, including the IMF Financial Development Index, the World Bank Ease of Doing Business Rankings, and the World Bank Worldwide Governance Indicators. The "High" and "Low" groups denote respondents located in countries above the top tercile and below the bottom tercile of the sample distribution, respectively. Detailed definitions of all heterogeneity groups are provided in Appendix A.3.2.

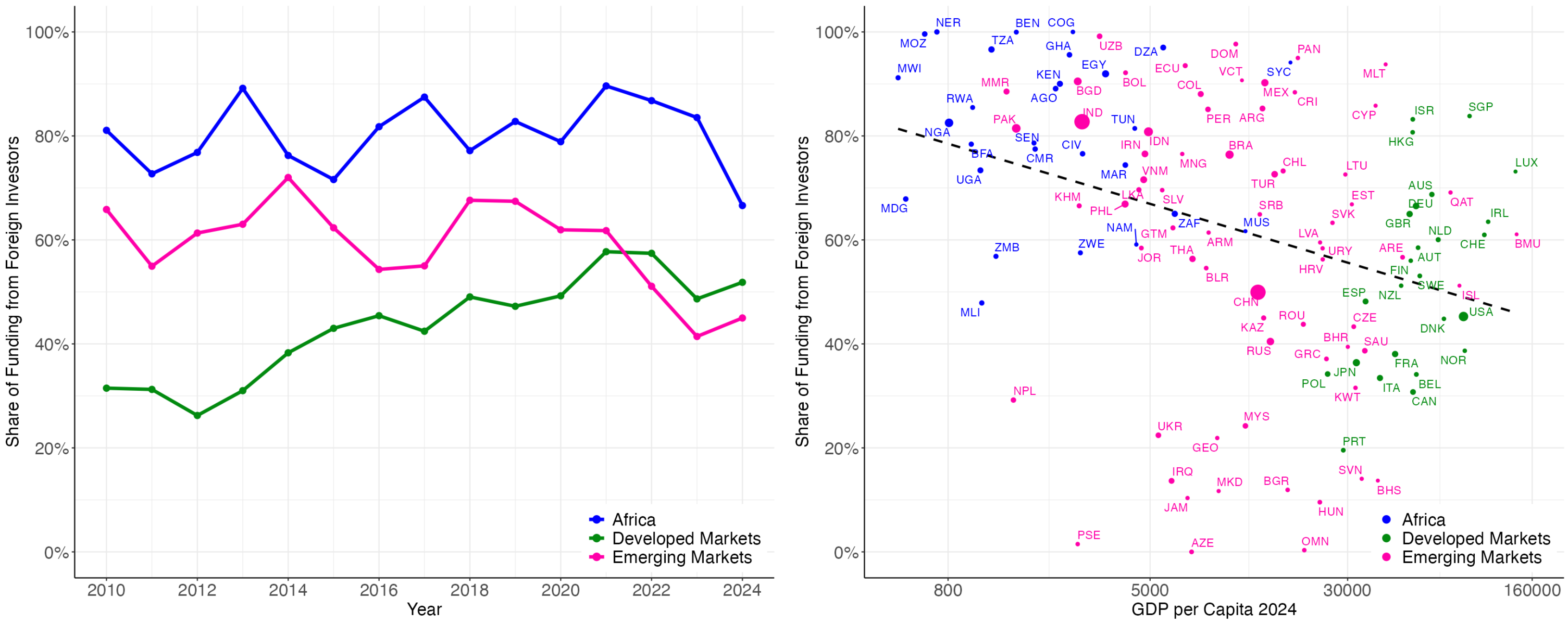

(A) Number of Financed Startups vs. GDP

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

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

Figure 6. Startup Creation and Venture Capital Across Countries

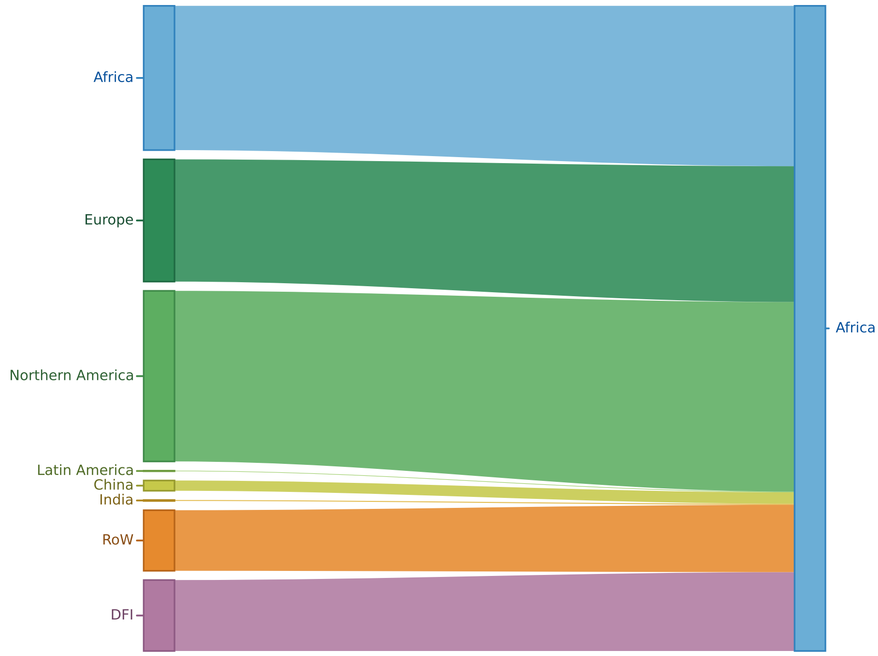
*Notes*: This figure plots several measures of venture capital (VC) activity against GDP per capita across countries in 2024, distinguishing among Africa, Emerging Markets, and Developed Markets. Panel A shows the number of financed startups per million people in each country over 2020–2024. Panel B shows the per capita USD value of VC deals received by startups in each country over 2020–2024. Panel C shows the per capita USD value of VC 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 Market and Emerging Market classifications follow the definitions in Section 2.3. The data for VC deals are derived from PitchBook, Briter Bridges and Africa: The Big Deal, as discussed in Section 2.2.



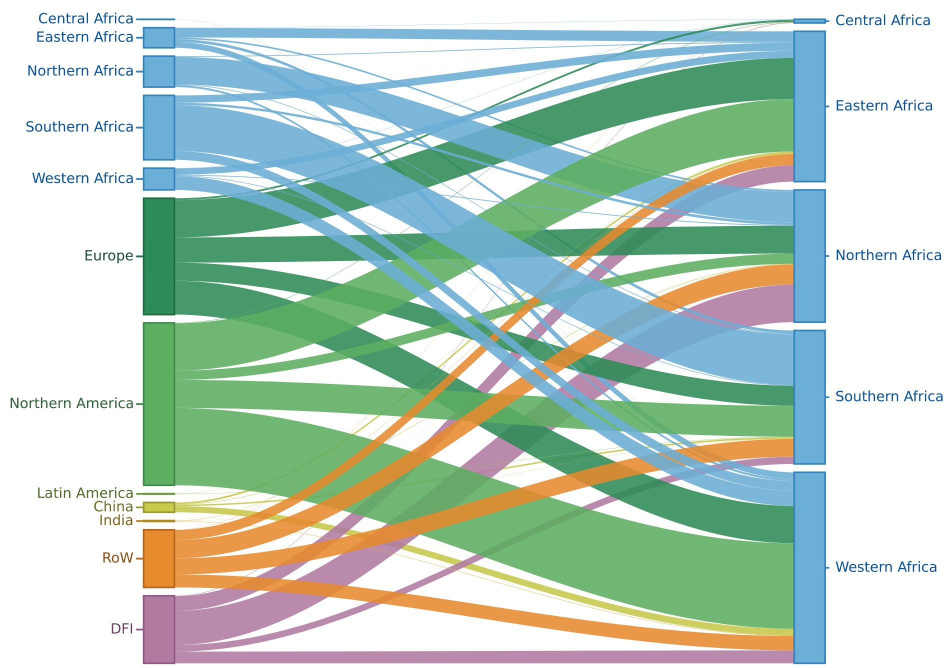

(A) Share of Funding from Foreign Investors (B) Share of Funding from Foreign Investors vs. GDP

FIGURE 7. 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 reflecting 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. Investors here refer to GPs, that is, fund managers investing directly in startups. "Foreignness" is determined using seven major regions: Africa, Northern America, Europe, Latin America, China, India, and Rest of the World (RoW). Developed Market and Emerging Market classifications follow the definitions in Section 2.3. Data on venture capital (VC) 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.



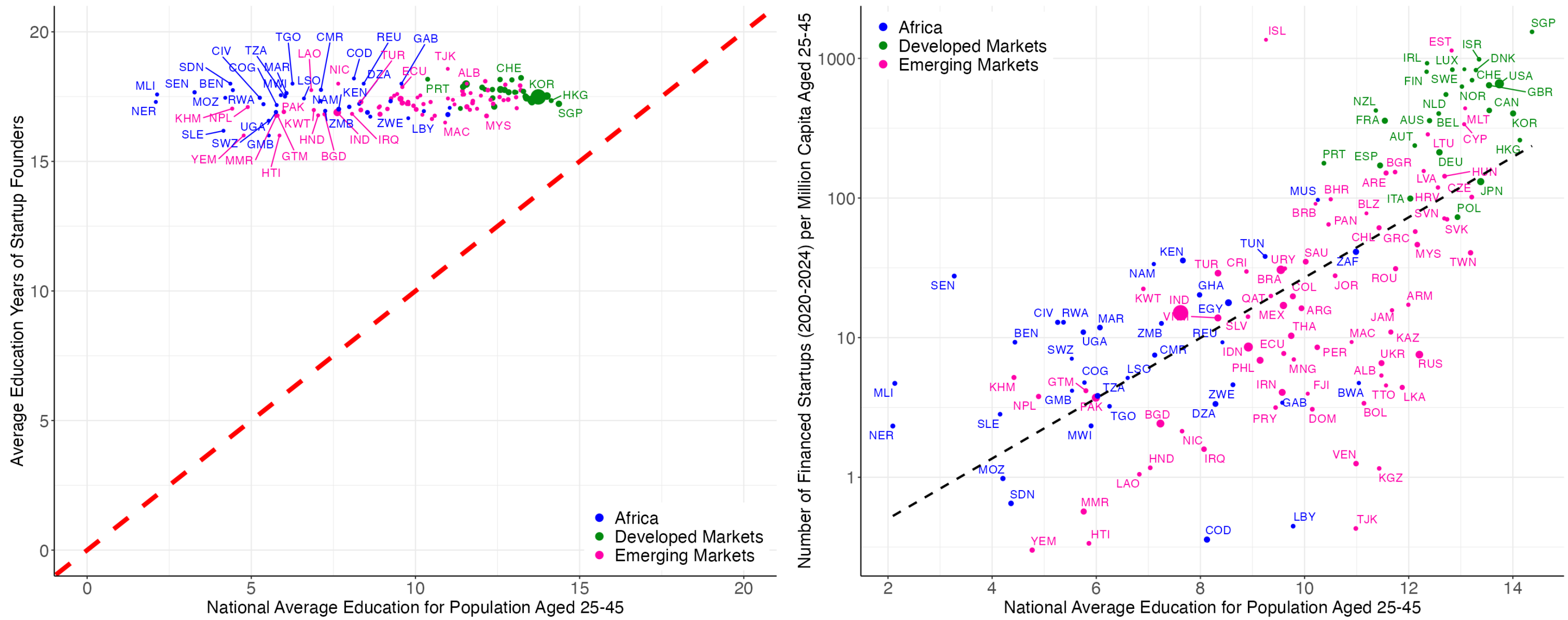

(A) By Regions




(B) By African Subregions

FIGURE 8. Who Finances Startups in Africa?

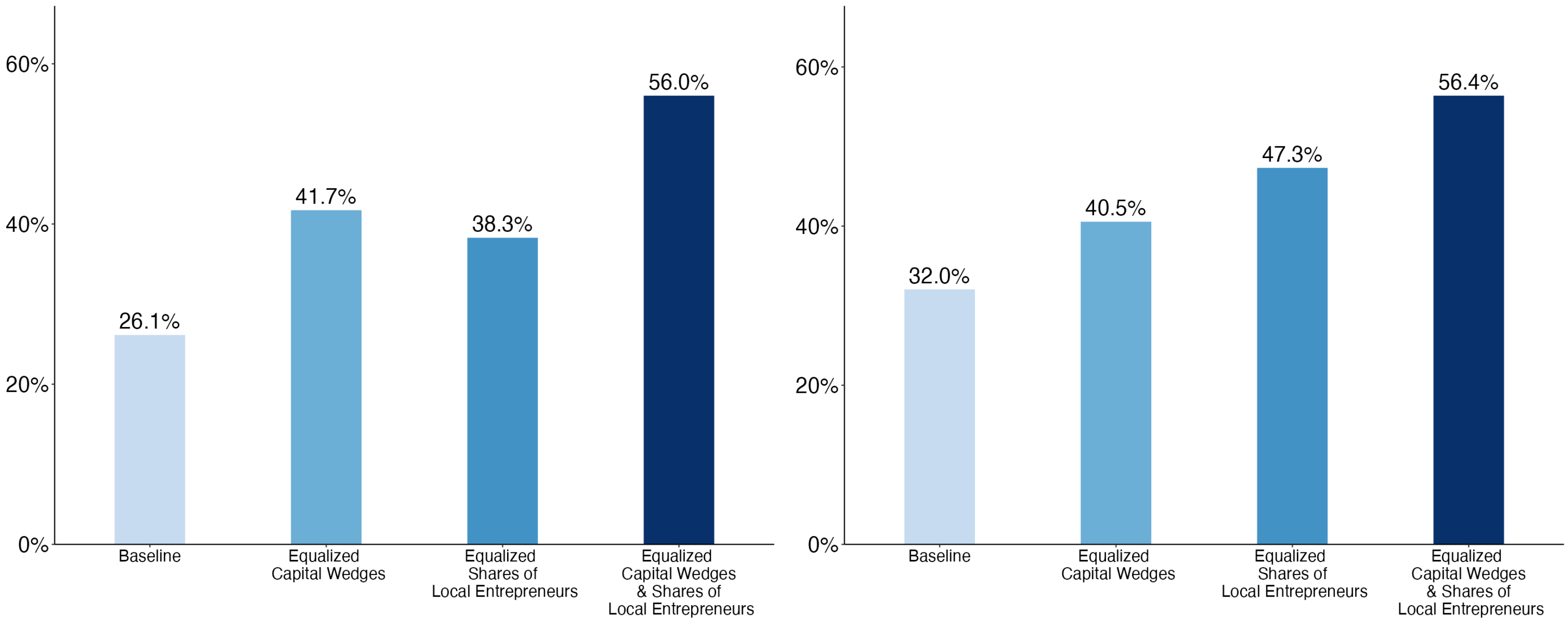
*Notes*: This figure shows the investment flows to Africa, showing the origins of capital from General Partners (GPs) to African startups using data sourced from PitchBook, Briter Bridges and Africa: The Big Deal from 2010 to 2024. The size of the flows represents the amount of funds in millions of USD. The sample includes 4,884 unique deals, corresponding to 15,207 GP-company deal pairs with non-missing deal size and GP region.




(A) Education: Startup Founders vs. National Average (B) Number of Financed Startups vs. Average Education

FIGURE 9. 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 (VC) deals are sourced from PitchBook, Briter Bridges and Africa: The Big Deal, supplemented with education records from Revelio Labs, as described in Section 2.2. Developed Market and Emerging Market classifications follow the definitions in Section 2.3. The y-axis in Panel B is log-transformed, but the labels represent the original values before log transformation to simplify interpretation.

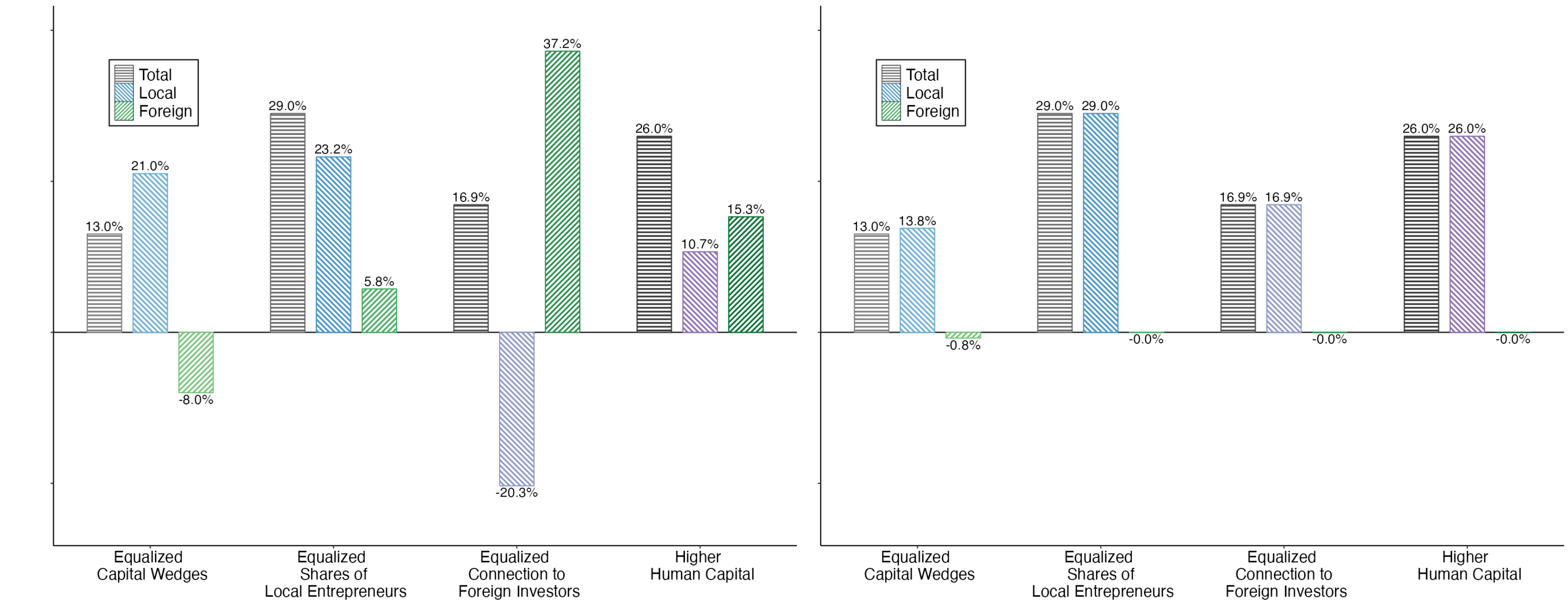



(A) Share of Local Investors

(B) Share of Local Entrepreneurs

Figure 10. 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 5.3 and Appendix A.4.3 for details on the counterfactual setup.

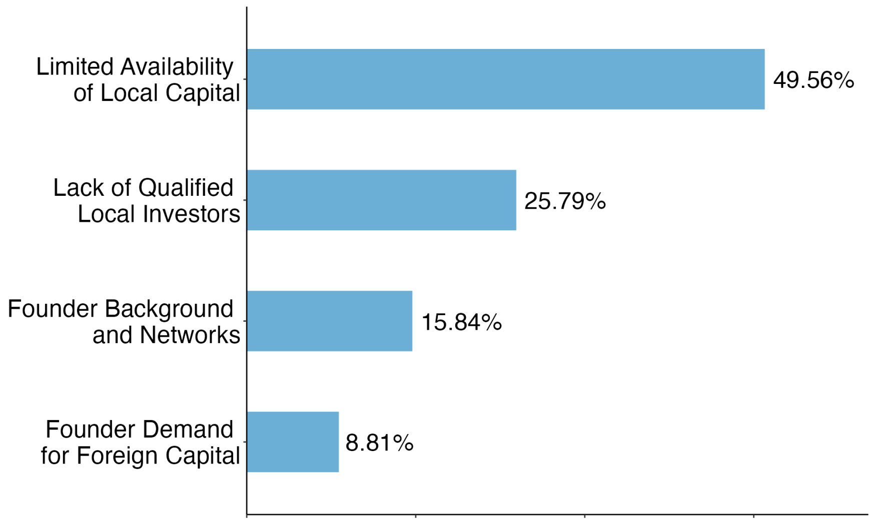



(A) By Investors' Region

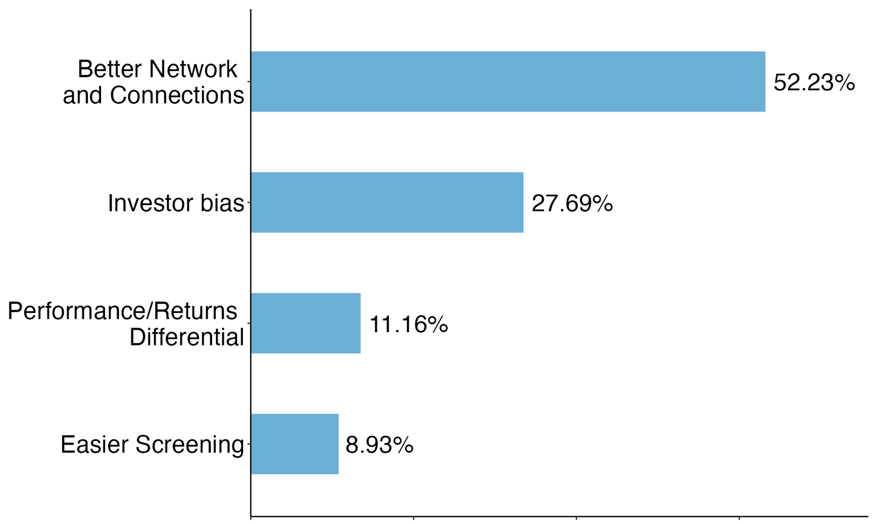
(B) By Entrepreneurs' Connection Type

FIGURE 11. 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 5.3 and Appendix A.4.3 for details on the counterfactual setup.




(A) Why Foreign Capital?




(B) Why Foreign Founders?

FIGURE 12. Survey Results on Mechanisms for Foreignness

*Notes*: This figure reports responses to survey questions on the mechanisms underlying foreign dominance in African venture capital (VC) markets. Panel A presents respondents' views on the most important explanation for why approximately 80% of total VC 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 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 male (%) | 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 |
| 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. 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). The share of founders with foreign experience is defined as the proportion of executive team members who have studied or worked outside Africa. Share of serial entrepreneurs represents the percentage of founders who have started at least one other business. Panel B summarizes firm attributes. 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) | 23.2% | 36.8% | 39.2% |
| Finance/FinTech | 11.9% | 3.8% | 3.9% |
| Manufacturing/Robotics | 10.6% | 15.9% | 11.0% |
| Health/BioTech | 7.6% | 10.8% | 15.5% |
| Media/Art/Entertainment | 6.7% | 7.4% | 7.9% |
| Retail/eCommerce | 5.8% | 3.6% | 1.9% |
| Transportation/Logistics/MobilityTech | 5.8% | 4.6% | 2.8% |
| Energy/CleanTech | 5.6% | 2.7% | 3.5% |
| Agriculture/AgriTech | 5.3% | 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 | 2.1% | 2.3% | 2.0% |
| Water/Sanitation/Waste Management | 1.4% | 0.4% | 0.5% |
| Other | 7.3% | 5.9% | 7.7% |
| **(B) Deal Types** | **Africa** | **Emerging Markets** | **Developed Markets** |
| Accelerator/Incubator | 4.5% | 0.4% | 0.8% |
| Seed Round | 34.2% | 19.5% | 29.8% |
| Early Stage VC | 23.8% | 44.2% | 31.1% |
| Later Stage VC | 17.1% | 29.0% | 27.3% |
| Growth/Expansion | 20.4% | 7.0% | 11.0% |

| **(C) Firm & Deal Characteristics** | **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 | 6.6 | 11.4 | 0.0 | 3.0 | 17.0 | 5.4 | 4.6 | 7.7 | 0.0 | 2.0 | 12.0 | 3.6 | 6.0 | 13.4 | 0.0 | 2.0 | 14.0 | 3.2 |
| Employment at the First Deal | 33.1 | 69.2 | 2.0 | 12.0 | 72.0 | 22.3 | 40.9 | 91.3 | 2.0 | 13.0 | 89.0 | 20.3 | 25.7 | 58.5 | 2.0 | 9.0 | 51.0 | 21.2 |
| Number of Founders | 4.7 | 18.9 | 1.0 | 3.0 | 8.0 | 28.7 | 4.8 | 7.1 | 1.0 | 3.0 | 9.0 | 27.1 | 5.2 | 10.6 | 1.0 | 3.0 | 10.0 | 28.1 |
| Share of Female Founders | 0.2 | 0.3 | 0.0 | 0.0 | 0.6 | 28.7 | 0.2 | 0.3 | 0.0 | 0.0 | 0.5 | 27.1 | 0.2 | 0.3 | 0.0 | 0.0 | 0.5 | 28.1 |
| Total Deal size per firm (in millions USD) | 6.2 | 21.8 | 0.0 | 0.1 | 11.3 | 0.0 | 15.0 | 49.3 | 0.0 | 0.5 | 30.3 | 0.0 | 15.0 | 45.7 | 0.0 | 1.3 | 31.5 | 0.0 |
| 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) | 6.9 | 19.5 | 0.1 | 0.9 | 15.0 | 37.3 | 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 Investors per Deal | 2.6 | 3.5 | 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 VC financing between 2010 and 2024, based on data from PitchBook, Africa: The Big Deal, and Briter Bridges. Employment at the First Deal is constructed from the final Revelio Labs company-year employee panel and measured in the firm's first-deal year. The rows Number of Founders and Share of Female Founders are constructed using final founder data from Revelio Labs; all other rows use final company- and deal-level VC data only. Employment at the First Deal, Total Deal size per firm, and Deal Size are winsorized at the 99th percentile within Africa, Emerging Markets, and Developed Markets. The sample covers 5,470 unique companies and 8,751 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 Market and Emerging Market classifications follow the definitions in Section 2.3.

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 | 36.3 | 45.1 | 33.3 | 27.8 | 18.9 |
| Family and friends | 18.1 | 19.0 | 20.7 | 15.6 | 12.0 |
| Bank loans | 13.3 | 8.6 | 15.5 | 15.2 | 25.2 |
| Angel or VCs | 12.0 | 7.2 | 10.9 | 18.4 | 25.5 |
| Government funded or backed loans | 7.1 | 7.3 | 7.7 | 6.7 | 5.4 |
| Others (Grants, Crowdfunding, etc.) | 13.1 | 12.8 | 11.9 | 16.3 | 12.9 |
| Share of Respondents | 65.5% | 30.8% | 16.9% | 10.4% | 7.5% |

(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 | 78.2 | 78.7 | 80.0 | 78.1 | 71.2 |
| Access to markets | 33.1 | 35.0 | 33.2 | 30.0 | 28.2 |
| Access to good infrastructure | 27.3 | 28.3 | 28.4 | 26.7 | 20.6 |
| Lack of qualified and skilled managers | 14.3 | 11.9 | 14.6 | 16.7 | 21.3 |
| Lack of other qualified and skilled labor | 12.2 | 12.1 | 11.3 | 13.9 | 12.5 |
| Business regulations | 11.5 | 11.5 | 10.4 | 10.8 | 15.7 |
| Other | 1.8 | 2.0 | 1.3 | 2.0 | 1.7 |
| Share of Respondents | 98.8% | 49.1% | 24.8% | 14.4% | 10.5% |

*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 was shown only to respondents who indicated that they had sought funding during the past three years, and it was optional for respondents in the second survey round. Panel B summarizes the most binding obstacles preventing business growth, based on answers to the multi-select question: "What are the most binding obstacles preventing your business from growing?" This question was also optional for respondents in the second round. Column (1) reports the share of respondents across each choice. Columns (2) to (5) report the shares within four size groups split by number of employees, with the average number of employees in each group reported in parentheses. The last row reports the share of respondents who answered each question. The total number of respondents answering the first question is 2,911, with 1,367, 750, 461, and 333 respondents in the four employee bins, respectively. The total number answering the second question is 4,392, with 2,183, 1,104, 640, and 465 respondents in the four employee bins, respectively.

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** | 21.5 | 50.8 | 73.5 | 46.8 | 58.4 | 67.7 |
| N Africa | 15.9 | 68.4 | 69.6 | 42.8 | 58.9 | 67.1 |
| E Africa | 24.8 | 42.5 | 80.2 | 56.1 | 60.1 | 71.2 |
| C Africa | 23.9 | 47.9 | 47.4 | 36.7 | 52.0 | 56.4 |
| W Africa | 22.3 | 34.8 | 76.5 | 51.8 | 64.0 | 73.6 |
| S Africa | 22.1 | 62.8 | 71.8 | 37.0 | 50.6 | 59.6 |
| **Europe** | 21.1 | 87.0 | 68.8 | 21.4 | 32.2 | 40.4 |
| **Northern America** | 21.3 | 76.4 | 78.5 | 17.9 | 25.7 | 31.6 |
| **Latin America** | 17.4 | 38.0 | 67.2 | 35.0 | 32.3 | 48.3 |
| **India** | 15.3 | 9.1 | 76.3 | 19.2 | 28.6 | 36.2 |
| **RoW** | 20.2 | 54.0 | 71.8 | 38.1 | 44.9 | 56.4 |

| 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** | 34.9 | 42.8 | 53.2 | 24.5 | 26.2 | 35.2 |
| N Africa | 30.5 | 77.9 | 52.3 | 20.4 | 21.3 | 30.9 |
| E Africa | 37.2 | 22.2 | 57.7 | 23.1 | 22.0 | 30.3 |
| C Africa | 34.5 | 40.8 | 48.2 | 35.0 | 32.2 | 45.6 |
| W Africa | 32.4 | 26.2 | 60.0 | 25.2 | 26.5 | 35.9 |
| S Africa | 39.8 | 43.1 | 43.5 | 28.7 | 33.8 | 42.2 |
| **Europe** | 39.9 | 77.6 | 50.4 | 23.5 | 28.9 | 36.0 |
| **Northern America** | 41.6 | 65.0 | 57.5 | 23.3 | 28.5 | 34.4 |
| **Latin America** | 40.3 | 38.2 | 23.5 | 9.6 | 9.5 | 15.2 |
| **India** | 22.7 | 6.6 | 67.9 | 5.9 | 7.7 | 11.0 |
| **RoW** | 35.1 | 41.7 | 55.2 | 30.0 | 30.6 | 40.6 |

*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.2.2; (3) have attained college-level education; (4) have foreign education experience; (5) have foreign work experience; and (6) have foreign education or work experience. Columns (3)–(6) are constructed using founders' or employees' education and work experience measured prior to the startup's first recorded VC deal or, for employees, prior to joining the startup. "Foreignness" is determined using seven major regions: Africa, Northern America, Europe, Latin America, China, India, and the Rest of the World (RoW).

Table 5. Founder-Investor Connections Shape Capital Flows

| | Prob. making 1+ deals | | | Total Funds (USD mln) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Same Investor and Founder Edu Country | 0.077*** | | 0.065*** | 1.156*** | | 0.988*** |
| | (0.002) | | (0.002) | (0.110) | | (0.111) |
| Same Investor and Founder Exp Country | | 0.079*** | 0.066*** | | 1.111*** | 0.912*** |
| | | (0.002) | (0.002) | | (0.099) | (0.100) |
| Log(Distance Investor-Company) | -0.005*** | -0.004*** | -0.004*** | -0.274*** | -0.272*** | -0.272*** |
| | (0.000) | (0.000) | (0.000) | (0.009) | (0.009) | (0.009) |
| Observations | 5850260 | 5850260 | 5850260 | 5850260 | 5850260 | 5850260 |
| Mean Dep. Var. | 0.022 | 0.022 | 0.022 | 0.316 | 0.316 | 0.316 |
| Startup 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 |
| Deal 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 VC 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 5.2.1 describes the empirical specification in detail. The underlying data consist of all possible founder–investor country pairs constructed from VC deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges during 2010–2024, supplemented with education and work experience data of founders obtained from Revelio Labs. The sample is restricted to potential matches between African founders and investors from non-African countries that have at least 5 VC deal–investor pair records in African VC deals during 2010–2024, as recorded in PitchBook+. We obtain pairwise country-distance measures from GeoDist, accessed on July 3, 2024. 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 | 0.025* | -0.005 | 0.020** | -0.035*** | 6.195*** | -0.039** | -0.013*** | -0.004 | 0.001 | 2.292 |
| | (0.014) | (0.004) | (0.010) | (0.012) | (1.311) | (0.016) | (0.005) | (0.011) | (0.015) | (1.789) |
| Foreign Startup | -0.005 | 0.012*** | 0.009 | -0.072*** | 2.511*** | -0.021 | 0.006 | -0.012 | -0.033* | -0.553 |
| | (0.012) | (0.004) | (0.007) | (0.012) | (0.674) | (0.017) | (0.005) | (0.012) | (0.018) | (1.525) |
| Unique Firms | 5352 | 5352 | 5352 | 5352 | 3985 | 5352 | 5352 | 5352 | 5352 | 3985 |
| Number of Events | 1103 | 63 | 328 | 833 | - | 1103 | 63 | 328 | 833 | - |
| Mean DV | 0.206 | 0.012 | 0.061 | 0.156 | 5.273 | 0.206 | 0.012 | 0.061 | 0.156 | 5.273 |
| 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 | 0.310 | 0.110 | 0.142 | 0.137 | 0.187 | 0.339 | 0.131 | 0.161 | 0.157 | 0.345 |

*Notes*: This table compares startup performance across local startups, foreign startups, and foreign-connected startups. A "foreign-connected startup" is defined as a company with at least one founder whose education or work experience, measured at the time of receiving the first VC deal, took place in the same country as a future foreign investor. A "foreign startup" is defined as a company with at least one founder who had foreign education or foreign work experience, also measured at the time of receiving the first VC deal. Section 5.2.2 describes the empirical specification in detail. Columns (1)-(5) report unconditional, Columns (6)-(10) report conditional performances. Control variables include number of investors at the first deal, share of foreign investors at first deal, logarithm of deal size at the first deal, log employment at the first deal, and the number of founders. The underlying data consist of all established startups that have received VC financing in 2010-2024, as recorded in PitchBook, Africa: The Big Deal, and Briter Bridges, supplemented with education and work experience data of founders obtained from Revelio Labs. 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) | 0.075*** | 0.154** | | |
| | (0.024) | (0.071) | | |
| instrument (count) | | | 0.072*** | 0.381*** |
| | | | (0.018) | (0.093) |
| Year FE | Yes | No | Yes | No |
| Country FE | Yes | No | Yes | No |
| Sector FE | Yes | No | Yes | No |
| Year-Sector FE | No | Yes | No | Yes |
| 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 | 0.474 | 0.668 | 0.655 | 0.797 |

*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 VC deals as outcome measures, while Columns (3)–(4) use the total number of VC deals. The causal effects are estimated by proxying foreign capital supply shocks with Bartik-style shift–share instruments. Section 5.2.3 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

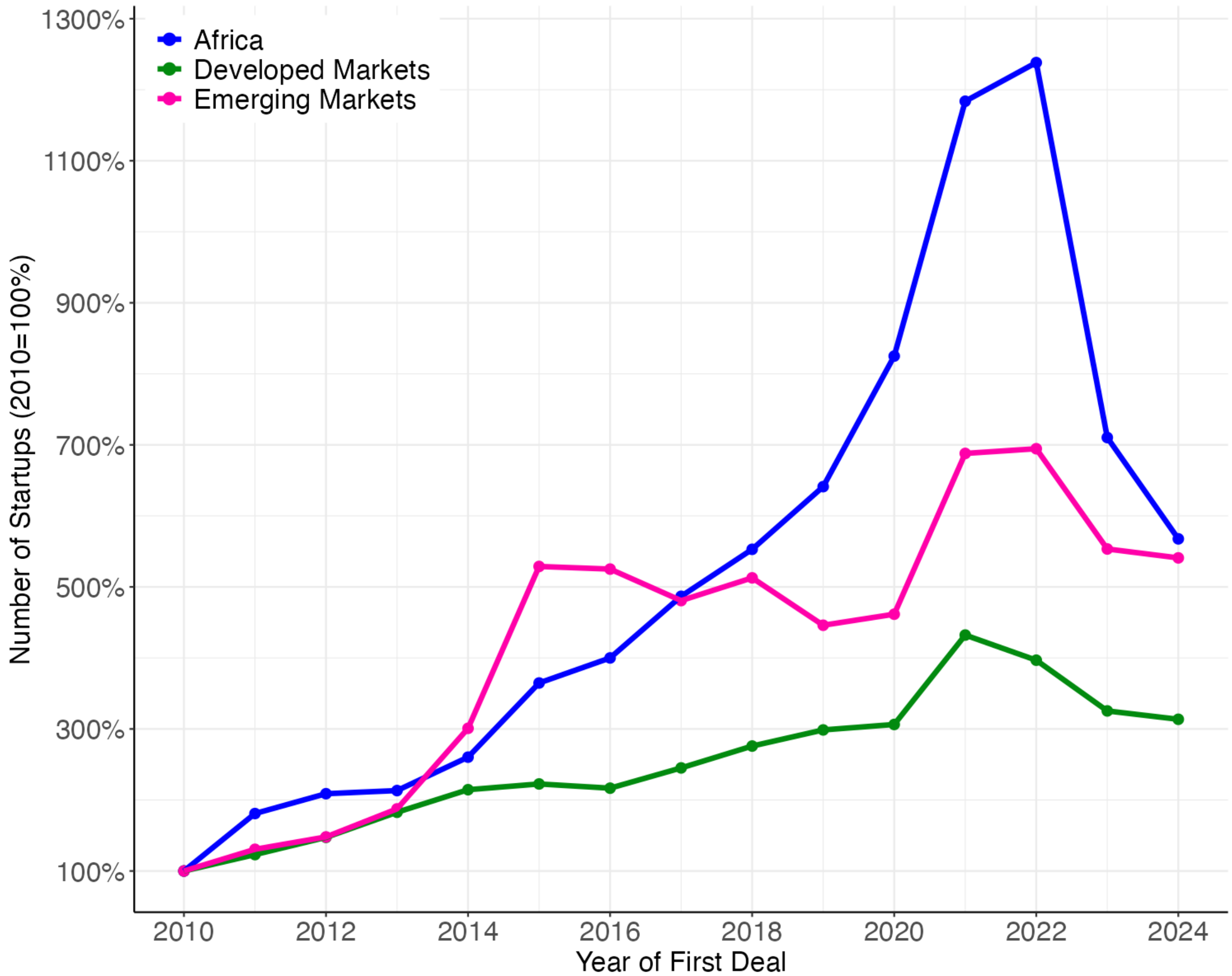



Figure A1. Number of New Startups

*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 5,470 companies in Africa, 65,821 in Emerging Markets, and 193,715 in Developed Markets. Developed Market and Emerging Market classifications follow the definitions in Section 2.3.

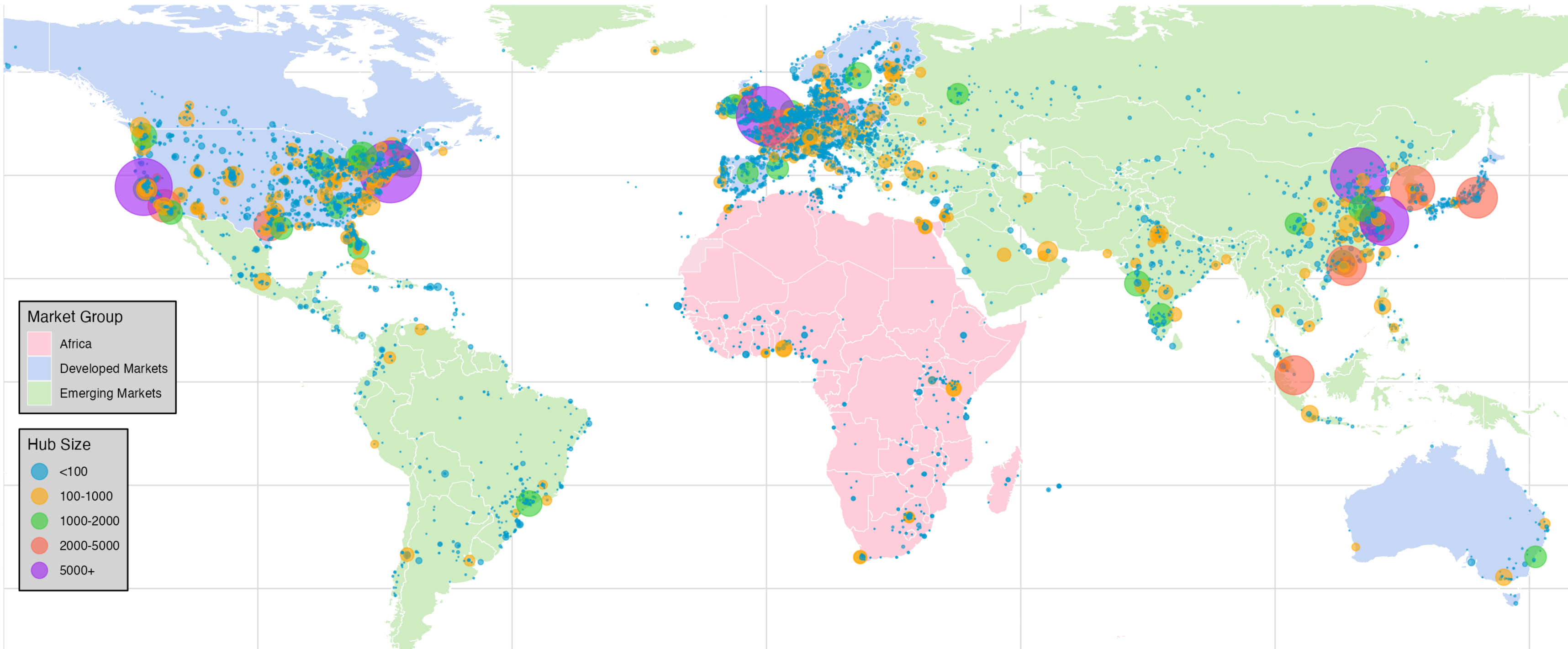
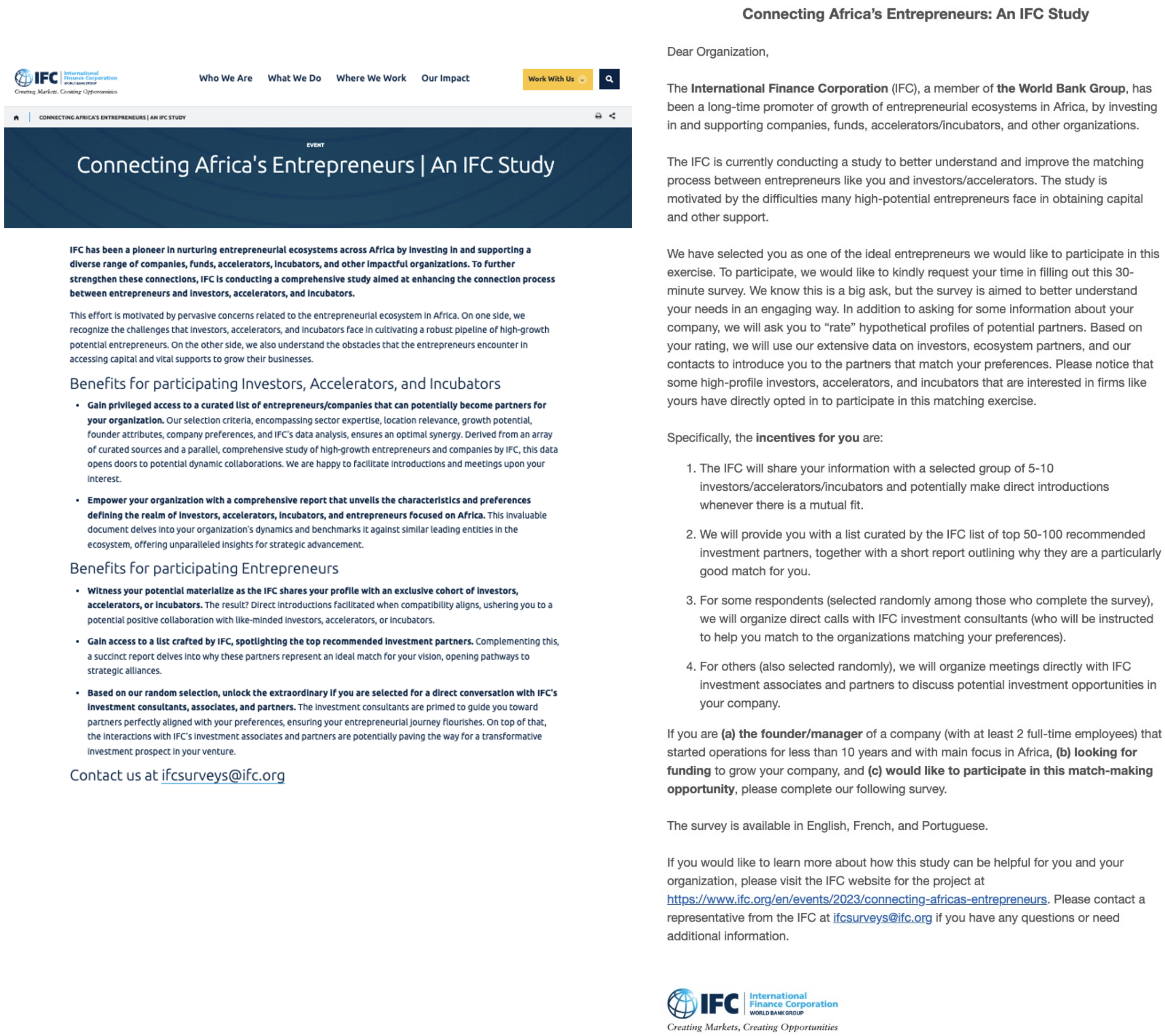



FIGURE A2. Global Startup Distribution

*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 5,470 companies in Africa, 65,821 in Emerging Markets, and 193,715 in Developed Markets. Developed Market and Emerging Market classifications follow the definitions in Section 2.3. Each circle represents a city, and its size corresponds to the number of startups located in that city.



Who We Are What We Do Where We Work Our Impact Work With Us

CONNECTING AFRICA'S ENTREPRENEURS | AN IFC STUDY

EVENT

# Connecting Africa's Entrepreneurs | An IFC Study

**IFC has been a pioneer in nurturing entrepreneurial ecosystems across Africa by investing in and supporting a diverse range of companies, funds, accelerators, incubators, and other impactful organizations. To further strengthen these connections, IFC is conducting a comprehensive study aimed at enhancing the connection process between entrepreneurs and investors, accelerators, and incubators.**

This effort is motivated by pervasive concerns related to the entrepreneurial ecosystem in Africa. On one side, we recognize the challenges that investors, accelerators, and incubators face in cultivating a robust pipeline of high-growth potential entrepreneurs. On the other side, we also understand the obstacles that the entrepreneurs encounter in accessing capital and vital supports to grow their businesses.

## Benefits for participating Investors, Accelerators, and Incubators

- **Gain privileged access to a curated list of entrepreneurs/companies that can potentially become partners for your organization.** Our selection criteria, encompassing sector expertise, location relevance, growth potential, founder attributes, company preferences, and IFC's data analysis, ensures an optimal synergy. Derived from an array of curated sources and a parallel, comprehensive study of high-growth entrepreneurs and companies by IFC, this data opens doors to potential dynamic collaborations. We are happy to facilitate introductions and meetings upon your interest.
- **Empower your organization with a comprehensive report that unveils the characteristics and preferences defining the realm of investors, accelerators, incubators, and entrepreneurs focused on Africa.** This invaluable document delves into your organization's dynamics and benchmarks it against similar leading entities in the ecosystem, offering unparalleled insights for strategic advancement.

## Benefits for participating Entrepreneurs

- **Witness your potential materialize as the IFC shares your profile with an exclusive cohort of investors, accelerators, or incubators.** The result? Direct introductions facilitated when compatibility aligns, ushering you to a potential positive collaboration with like-minded investors, accelerators, or incubators.
- **Gain access to a list crafted by IFC, spotlighting the top recommended investment partners.** Complementing this, a succinct report delves into why these partners represent an ideal match for your vision, opening pathways to strategic alliances.
- **Based on our random selection, unlock the extraordinary if you are selected for a direct conversation with IFC's investment consultants, associates, and partners.** The investment consultants are primed to guide you toward partners perfectly aligned with your preferences, ensuring your entrepreneurial journey flourishes. On top of that, the interactions with IFC's investment associates and partners are potentially paving the way for a transformative investment prospect in your venture.

Contact us at ifcsurveys@ifc.org

**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-profile 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.

(A) Official Advertisement on the IFC's Website (B) First Page of Survey

FIGURE A3. 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 A4. Examples of Synthetic Profiles

*Notes*: This figure shows two examples of synthetic profiles of investment opportunities. 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.3.1.

**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.**

Figure A5. Script for Profile Rating Instructions

*Notes*: This figure displays the screenshot of the survey page shown to respondents that explains the instructions for rating profiles.

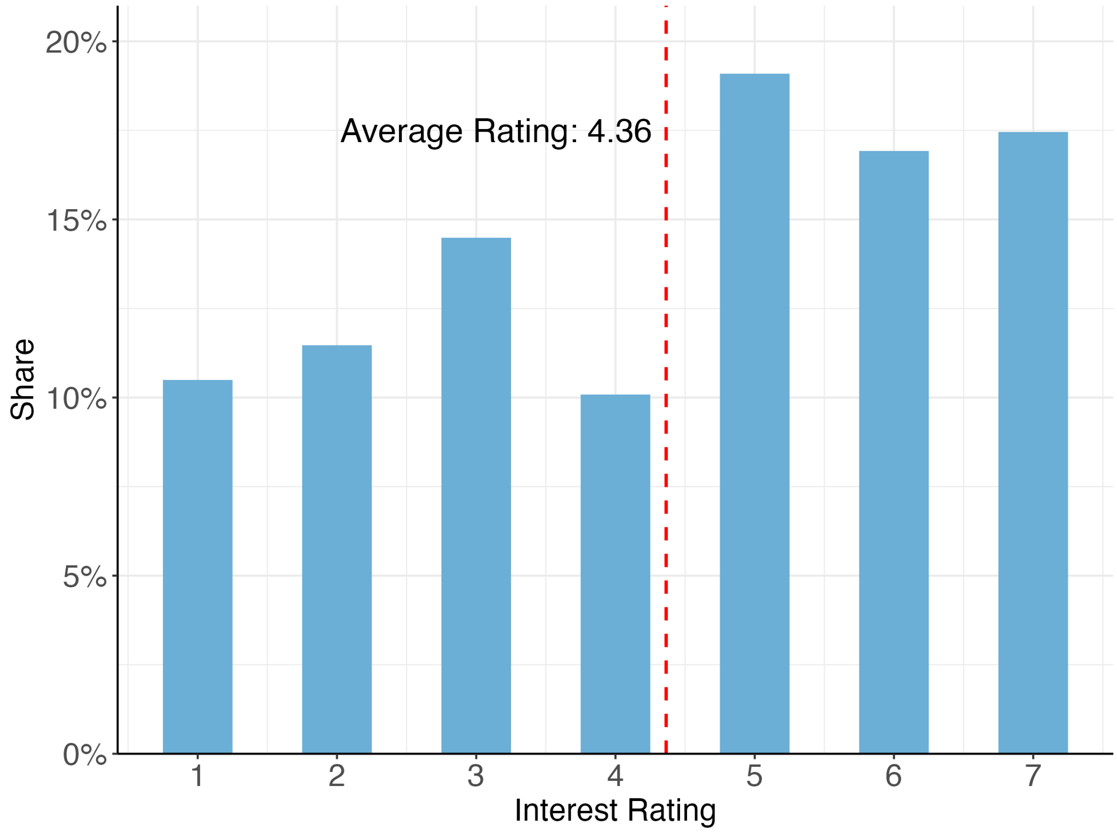
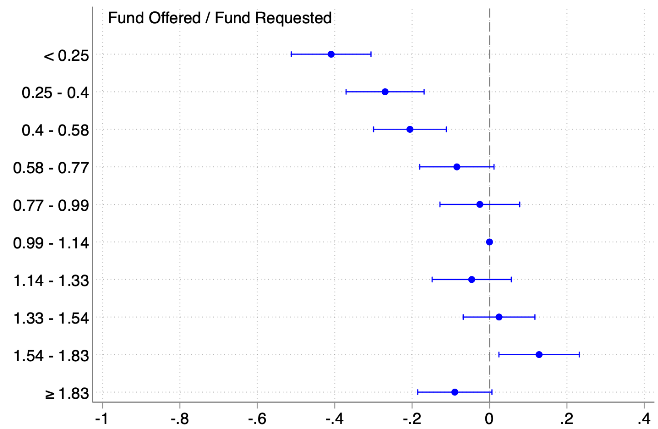
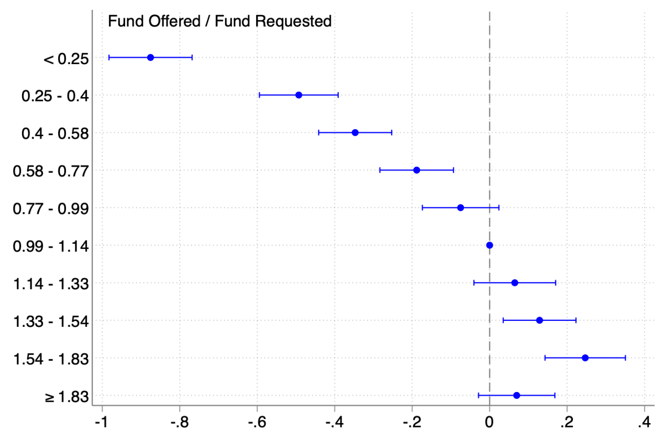



Figure A6. Distribution of Interest Ratings for Investment Opportunities

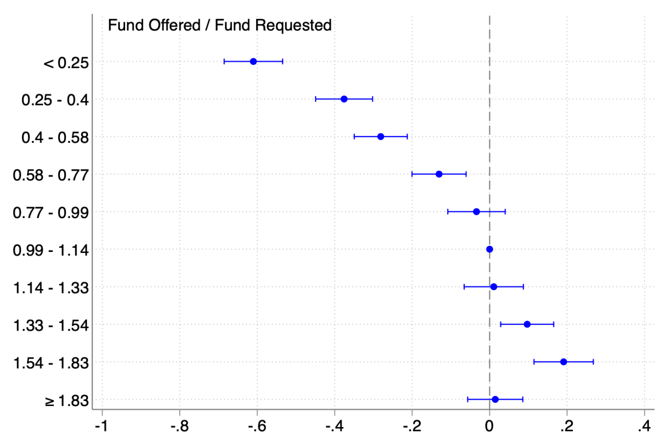
*Notes*: This figure shows the distribution of respondents' interest ratings for synthetic profiles of investment opportunities, which serve as the dependent variable in estimating equation 3.1. The red vertical line indicates the mean rating.




(A) Debt



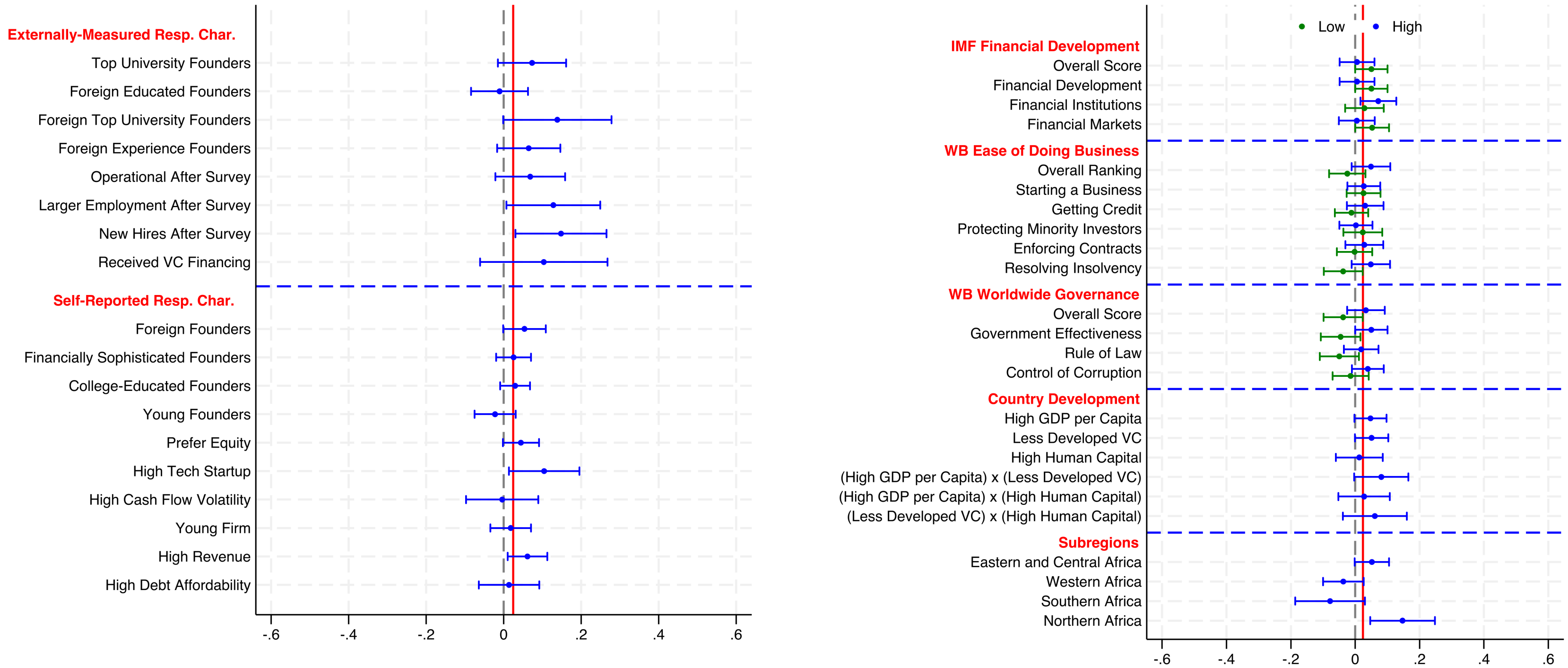

(B) Equity




(C) Equity + Debt

Figure A7. Relative Preference for Investment Amount

*Notes*: This figure shows respondents' relative preferences over investment amount, normalized by the amount of funding they are seeking. Panel A presents results for synthetic equity-financing profiles, Panel B for debt-financing profiles, and Panel C for both financing types combined. The estimates are obtained by replacing the "Large Investment" indicator with 10 bins defined by the ratio of funds offered to funds requested. "Fund Offered" refers to the investment amount shown in the synthetic profiles, while "Fund Requested" is defined as the median of the distribution of investment amounts shown to each respondent, constructed to be consistent with the funding range that the respondent reports currently seeking in the filtering questions asked before showing the synthetic investment opportunities. The fund offered/fund requested ratio is partitioned into 10 bins based on deciles of its empirical distribution in the experiment. All intervals are left-closed and right-open.

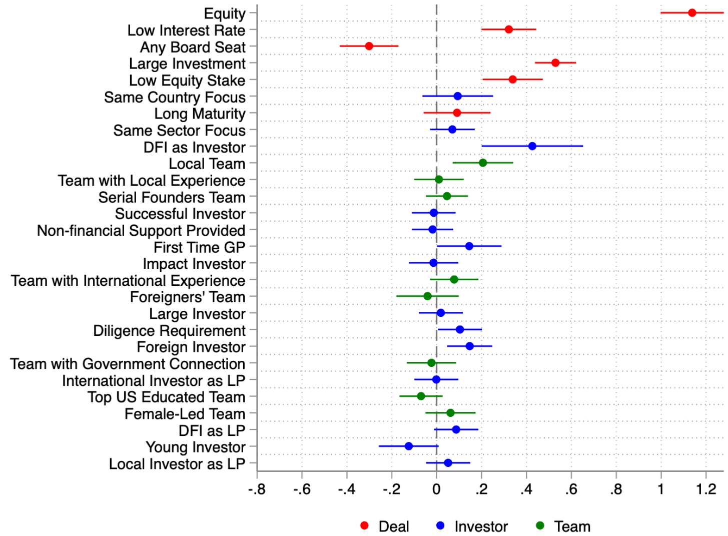



(A) Respondent Characteristics

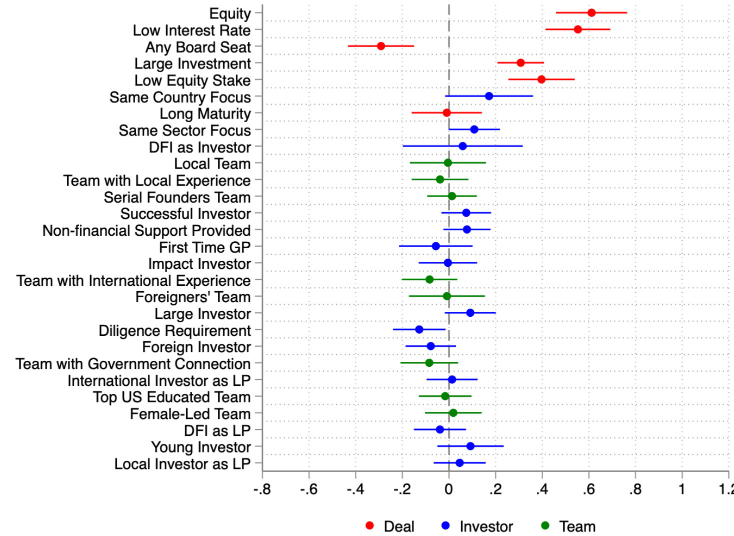
(B) Country Characteristics

FIGURE A8. Startup Preferences for Foreign Investor: Heterogeneity

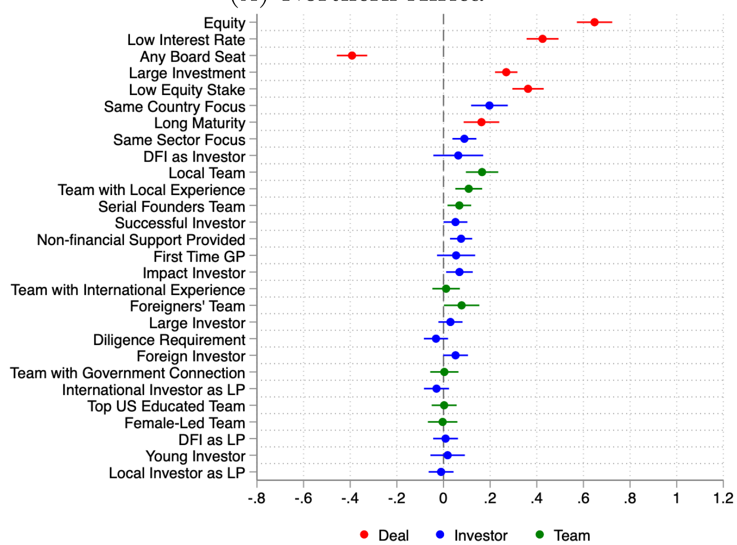
*Notes*: This figure reports startups' preferences for *Foreign Investor* across heterogeneity groups. Panel A reports heterogeneity by profile characteristics and respondent characteristics, while Panel B reports country-level heterogeneity. Red vertical lines indicate the baseline coefficient estimated in the full sample. "Externally Measured Resp. Char." are constructed by matching respondents to external commercial datasets, including PitchBook+ and Revelio Labs. "Self-Reported Resp. Char." are constructed from respondents' survey answers. Country characteristics include subregions (defined according to the UN geoscheme), country development measures, and external indices, including the IMF Financial Development Index, the World Bank Ease of Doing Business Rankings, and the World Bank Worldwide Governance Indicators. The "High" and "Low" groups denote respondents located in countries above the top tercile and below the bottom tercile of the sample distribution, respectively. Detailed definitions of all heterogeneity groups are provided in Appendix A.3.2.



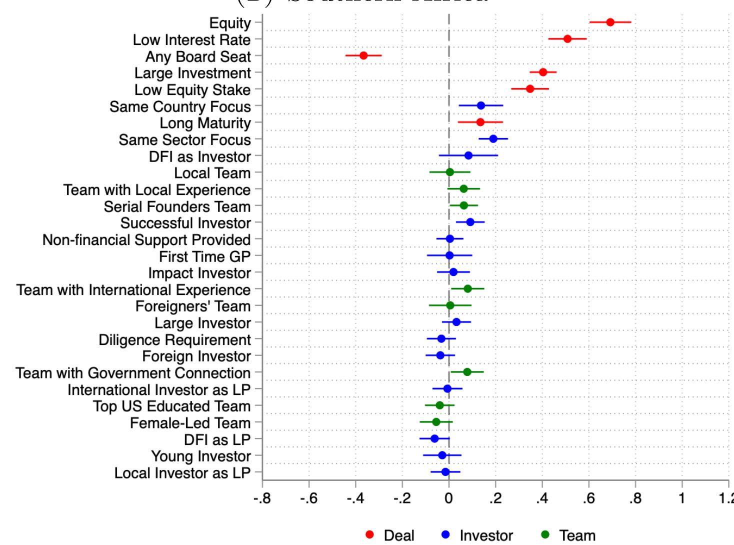

(A) Northern Africa




(B) Southern Africa




(C) Eastern & Central Africa




(D) Western Africa

FIGURE A9. Heterogeneity Analysis: Startup Preferences by Region

*Notes*: This figure summarizes startups' preferences for investment attributes featured in the synthetic profiles of investment opportunities, as captured by the coefficients $\beta_k$ in Equation 3.1, shown separately by African subregion. Subregions are defined according to the UN geoscheme. 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 3.

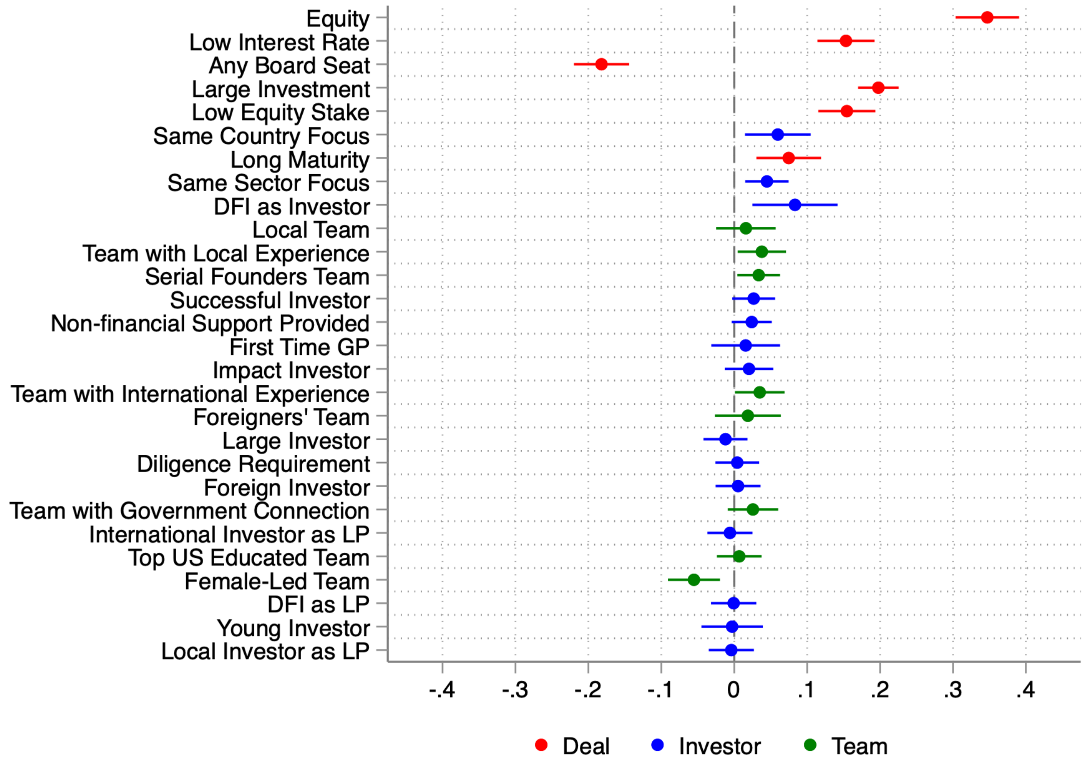
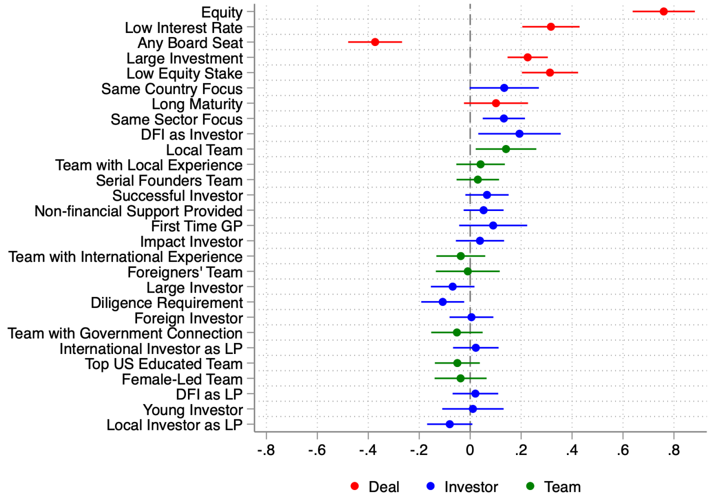
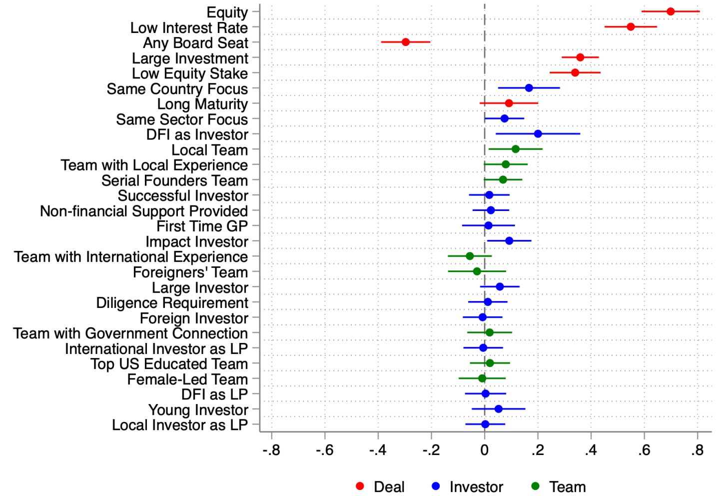



FIGURE A10. Preferences for Investor and Financing Characteristics, Controlling for Perceived Likelihood

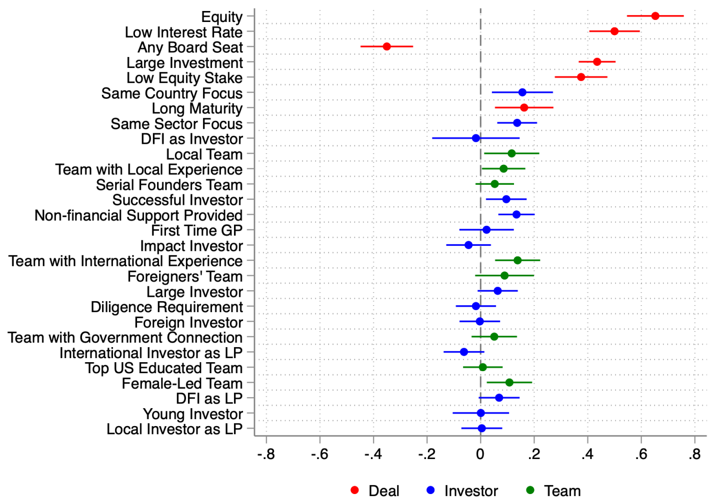
*Notes*: This figure summarizes startups' preferences for investment attributes featured in the synthetic profiles of investment opportunities, as captured by $\beta_k$ in Equation 3.1. The estimates additionally control for respondents' perceived likelihood of receiving the investment opportunity (see Section 3.2.4 for details on the likelihood rating). 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 3.



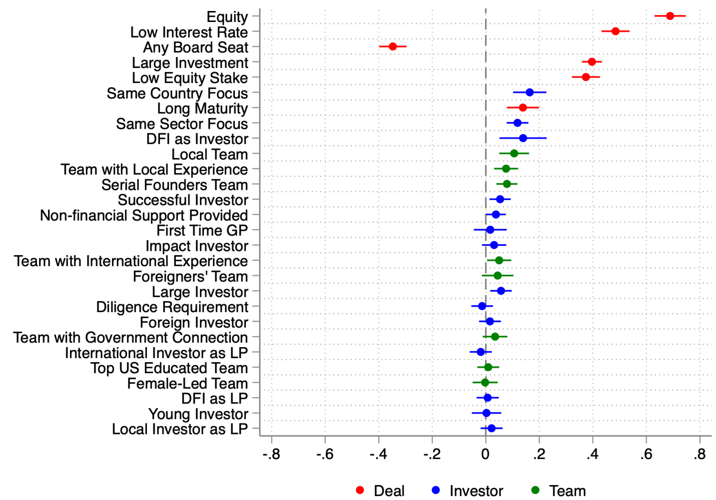

(A) Profiles with Highlighted "Deal" Characteristics




(B) Profiles with Highlighted "Investor" Characteristics



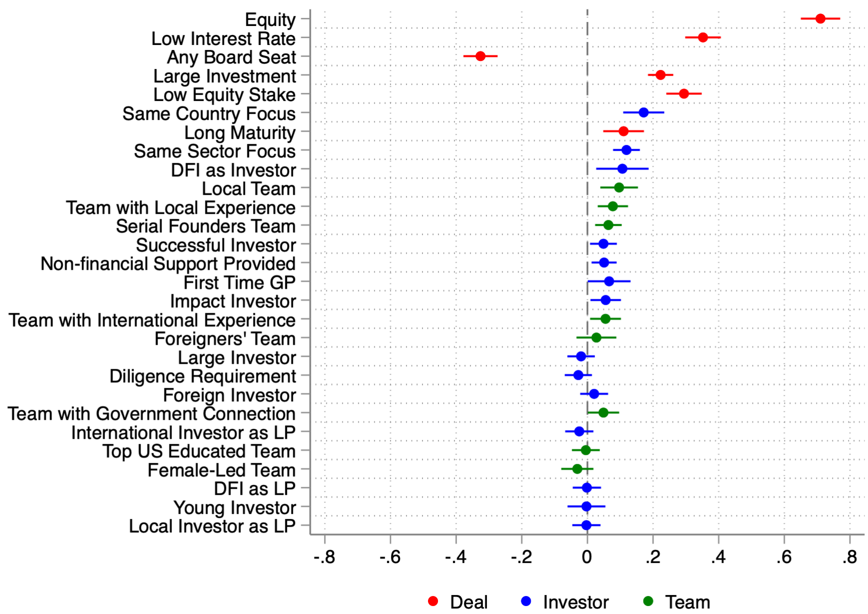

(C) Profiles with Highlighted "Team" Characteristics



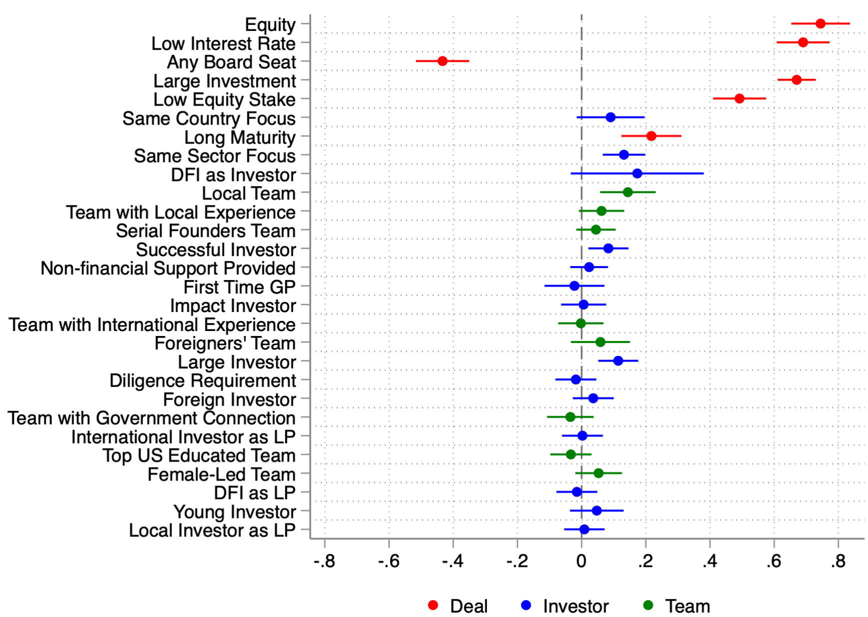

(D) Profiles with Highlighted Investor HQ Location

Figure A11. Startup Preferences across Profiles with Different Highlighted Components

*Notes*: This figure shows startups' preferences for all investment attributes across different subsets of profiles, defined by which profile component is highlighted in color (blue or green rather than the default black text). Panel A reports estimates using profiles in which the "Deal" characteristics are highlighted. Panel B reports estimates using profiles in which the "Investor" characteristics are highlighted. Panel C reports estimates using profiles in which the "Team" characteristics are highlighted. Panel D reports estimates using profiles in which the investor's headquarters location and geographic preferences are highlighted.



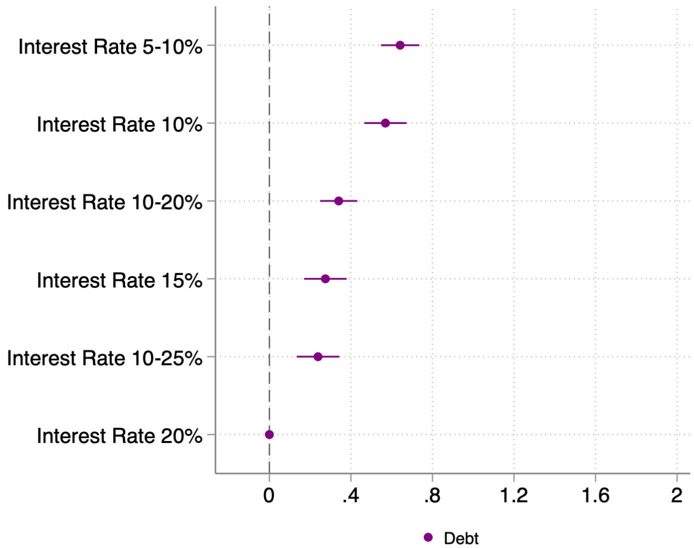

(A) First Round



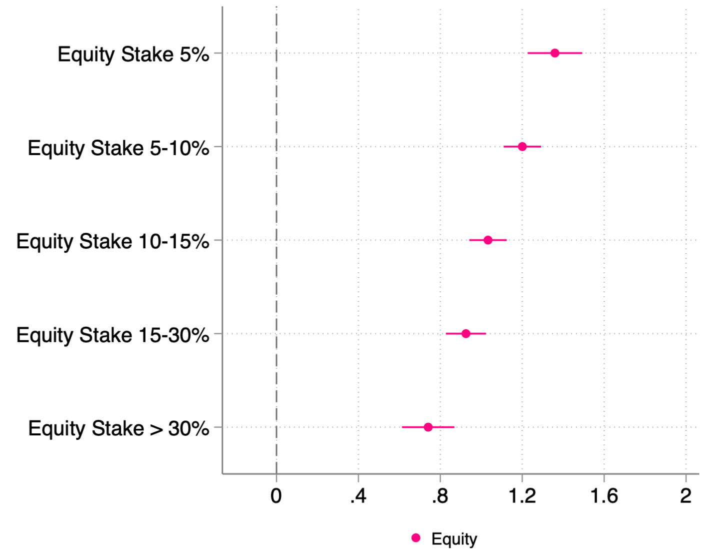

(B) Second Round

FIGURE A12. Heterogeneity Analysis: Startup Preferences by Survey Round

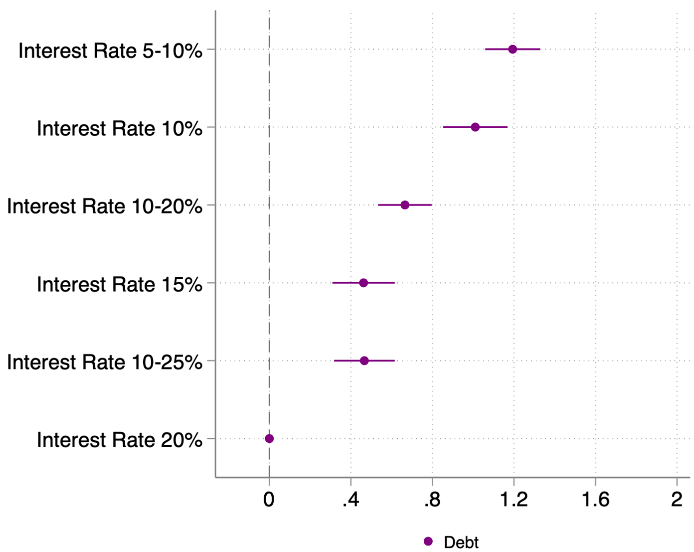
*Notes*: This figure summarizes startups' preferences for investment attributes featured in the synthetic profiles of investment opportunities, as captured by $\beta_k$ in Equation 3.1, shown separately for the two survey rounds. The figure also reports 95% confidence intervals for each attribute. Attributes 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 3.



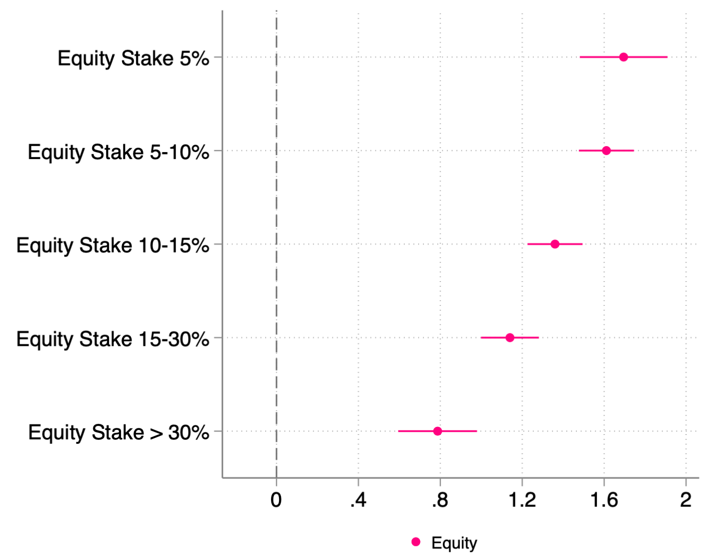

(A) Preference for Debt, First Round




(B) Preference for Equity, First Round



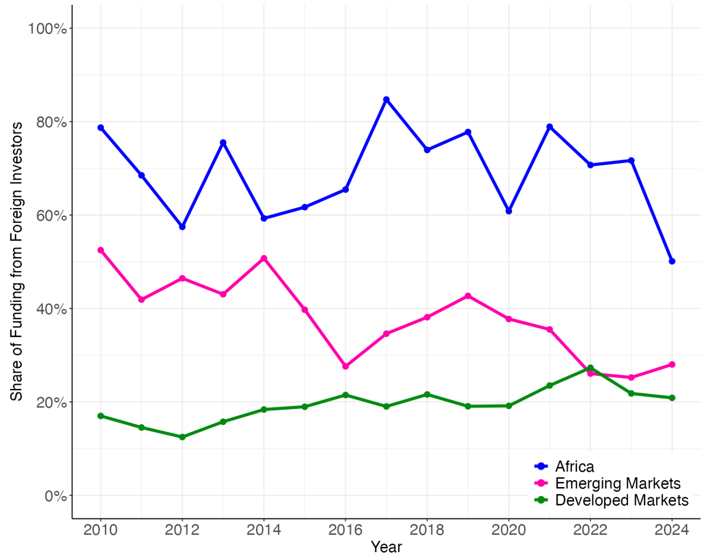

(C) Preference for Debt, Second Round



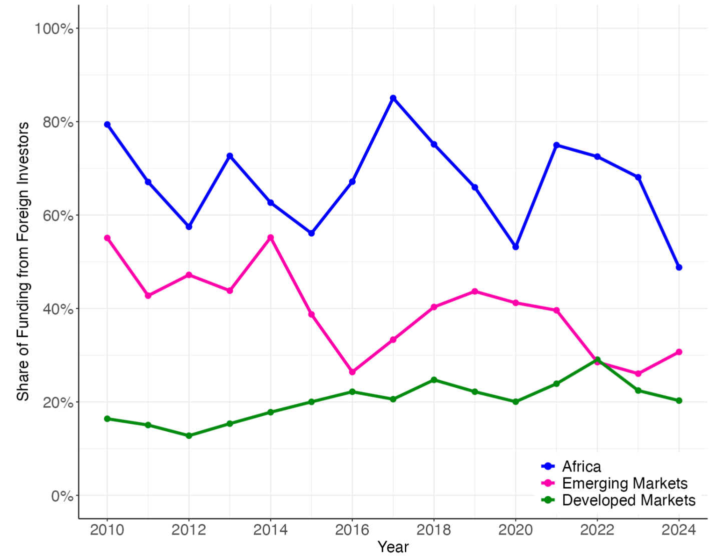

(D) Preference for Equity, Second Round

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

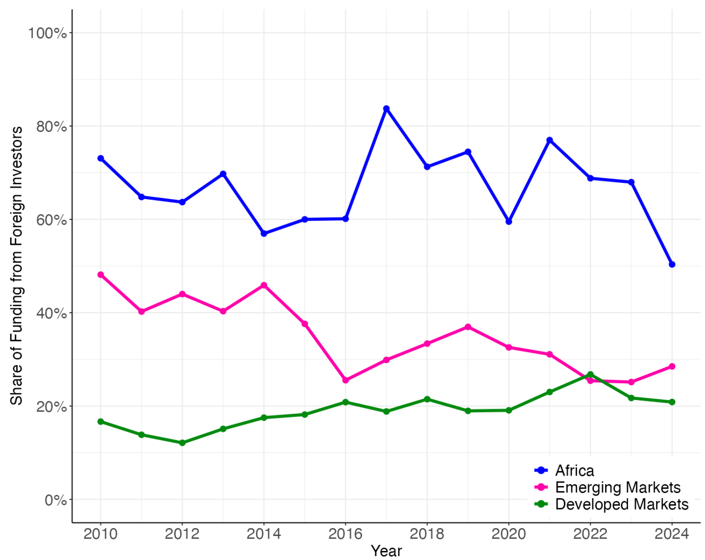
*Notes*: This figure reports the result shown in Figure 4 separately for two survey rounds. Panels A and C present relative preferences for debt, split by different interest rates. Panels B and D present relative preferences for equity, split by different equity stake requirements. We modified the specification of Equation 3.1 by replacing the indicator for *Equity*, *LowInterestRate* and *LowEquityStake* with six indicators for debt financing split by different *InterestRate*, and five indicators for equity financing split by different *EquityStake*. *InterestRate* denotes the annual interest rate associated with the debt financing in the synthetic investment opportunity, while *EquityStake* denotes the share of equity required in exchange for equity financing.



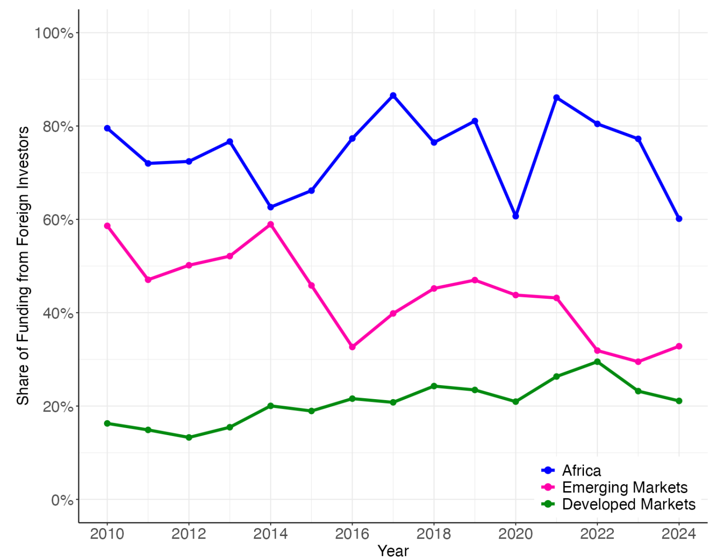

(A) Evenly Split Deal Size Across Investors




(B) Assign Foreignness By Lead Investor



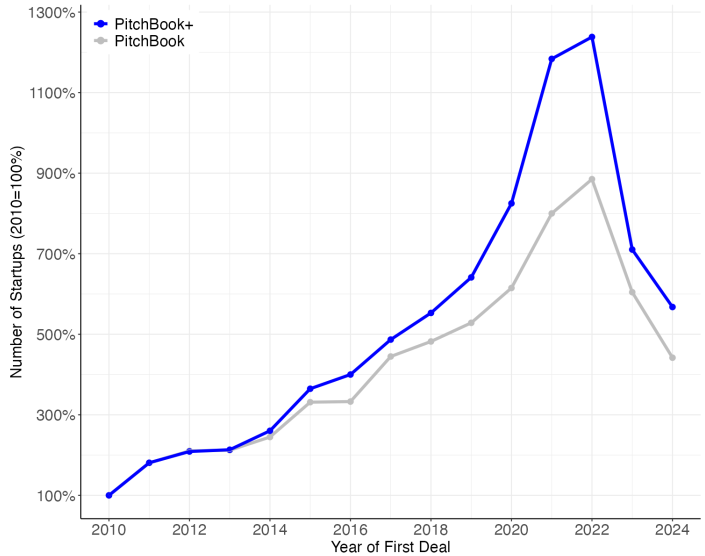

(C) Impute Missing Deal Size



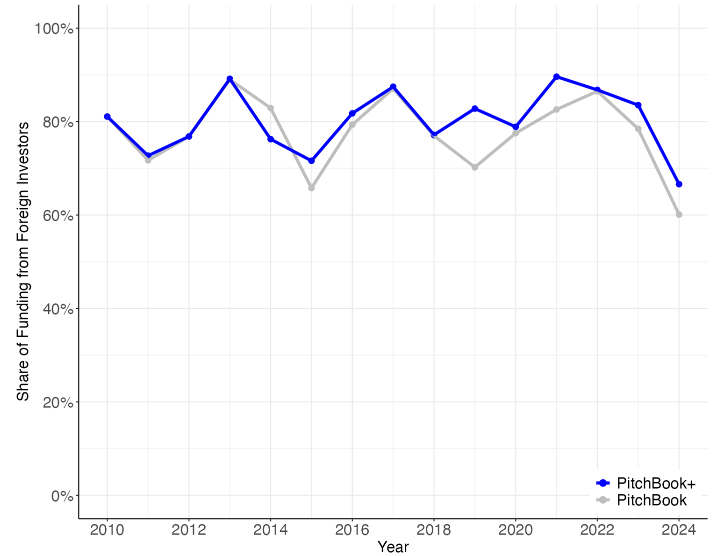

(D) Weight Deal Size By Investor Size

Figure A14. Dominance of Foreign Capital: Robustness Checks

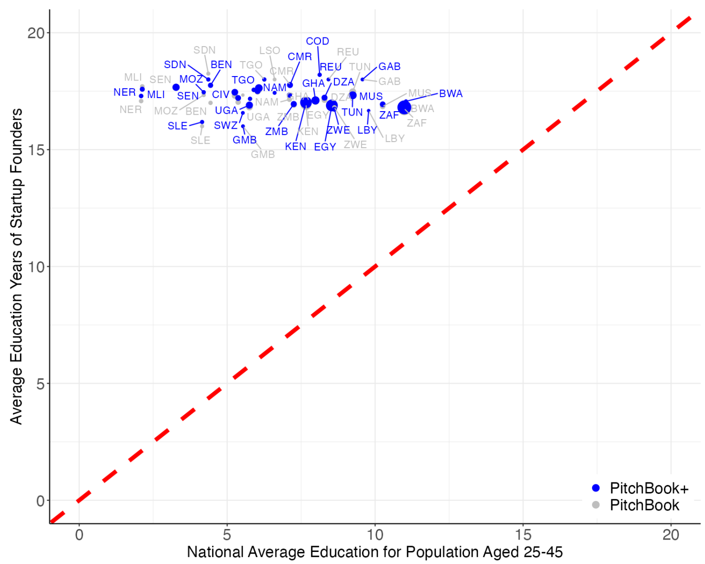
*Notes*: This figure presents robustness checks for the dominance of foreign capital in Africa shown in Figure 7 Panel A, by allocating deal size to participating investors using different methods. Panel A allocates each deal's size equally across all participating investors. Panel B allocates deal size 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. Developed Market and Emerging Market classifications follow the definitions in Section 2.3. Investor "foreignness" is defined using seven regions: Africa, Northern America, Europe, Latin America, China, India, and Rest of the World (RoW).



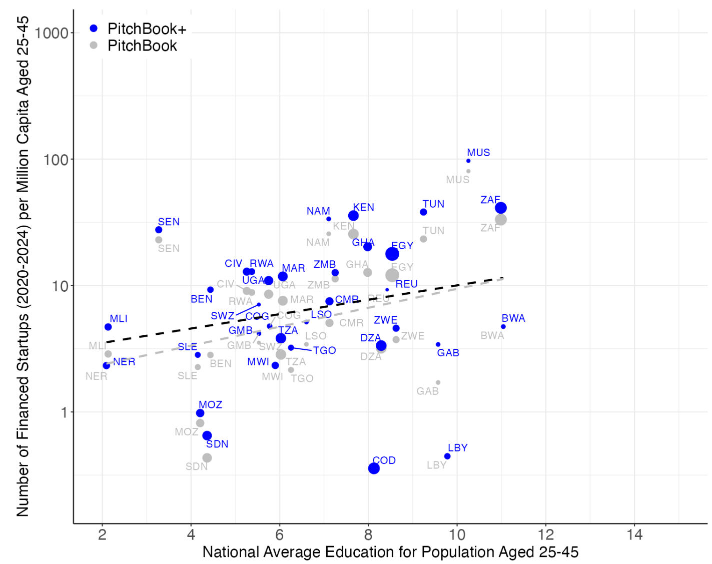

(A) Number of New Startups




(B) Share of Funding from Foreign Investors




(C) Education: Startup Founders vs. National Average




(D) N. Financed Startups vs. Average Education

Figure A15. Descriptive Facts Comparing PitchBook and PitchBook+

*Notes*: This figure presents descriptive statistics on established startups in Africa, comparing results based on PitchBook+ and PitchBook data. Panel A presents the number of firms receiving their first deal each year from 2010 to 2024. Panel B shows the share of total deal amounts with at least one investor from outside of Africa. Panel C 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 D 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 of panel D is log-transformed, but the labels represent the original values before log transformation to simplify interpretation.

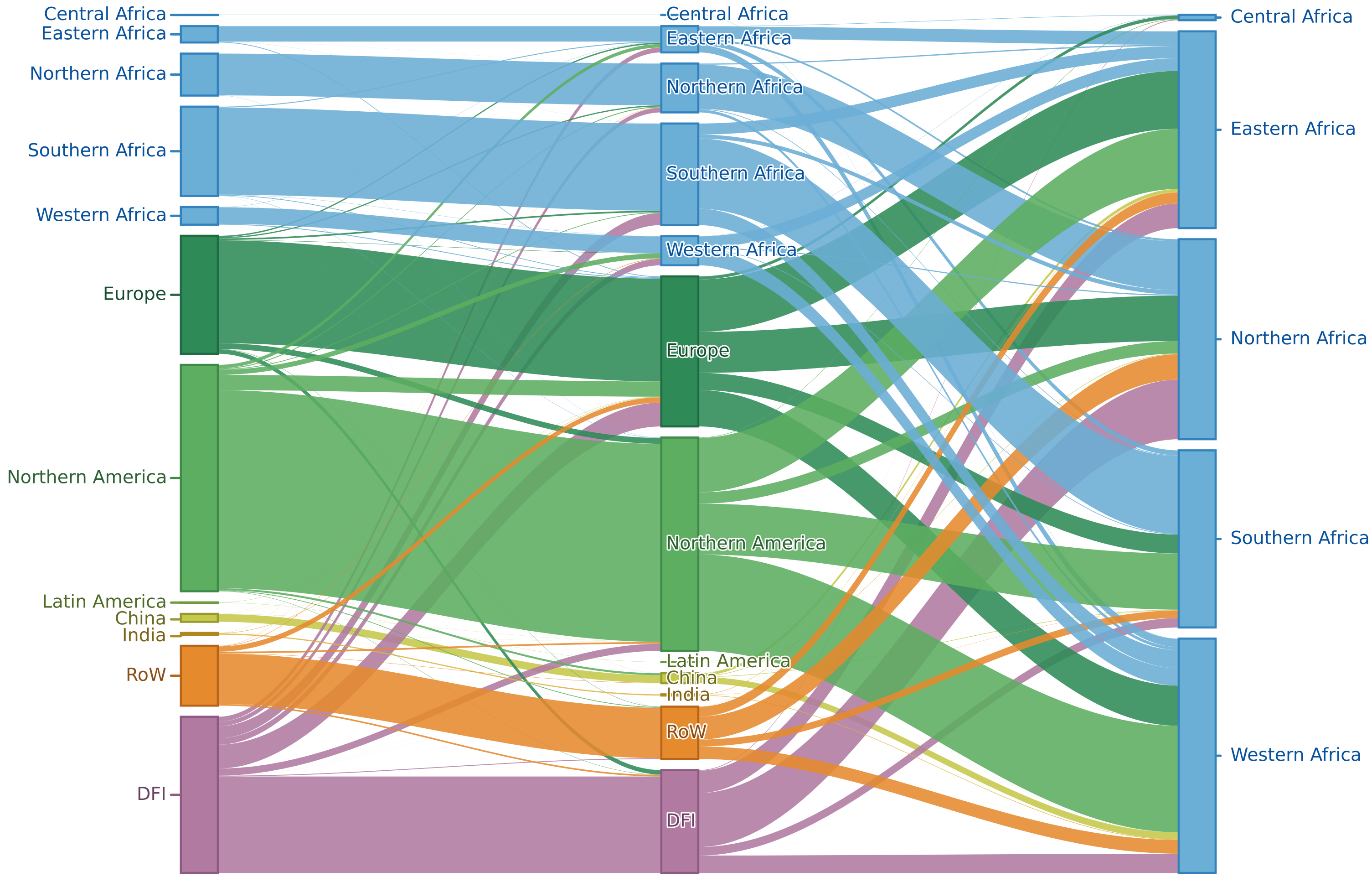
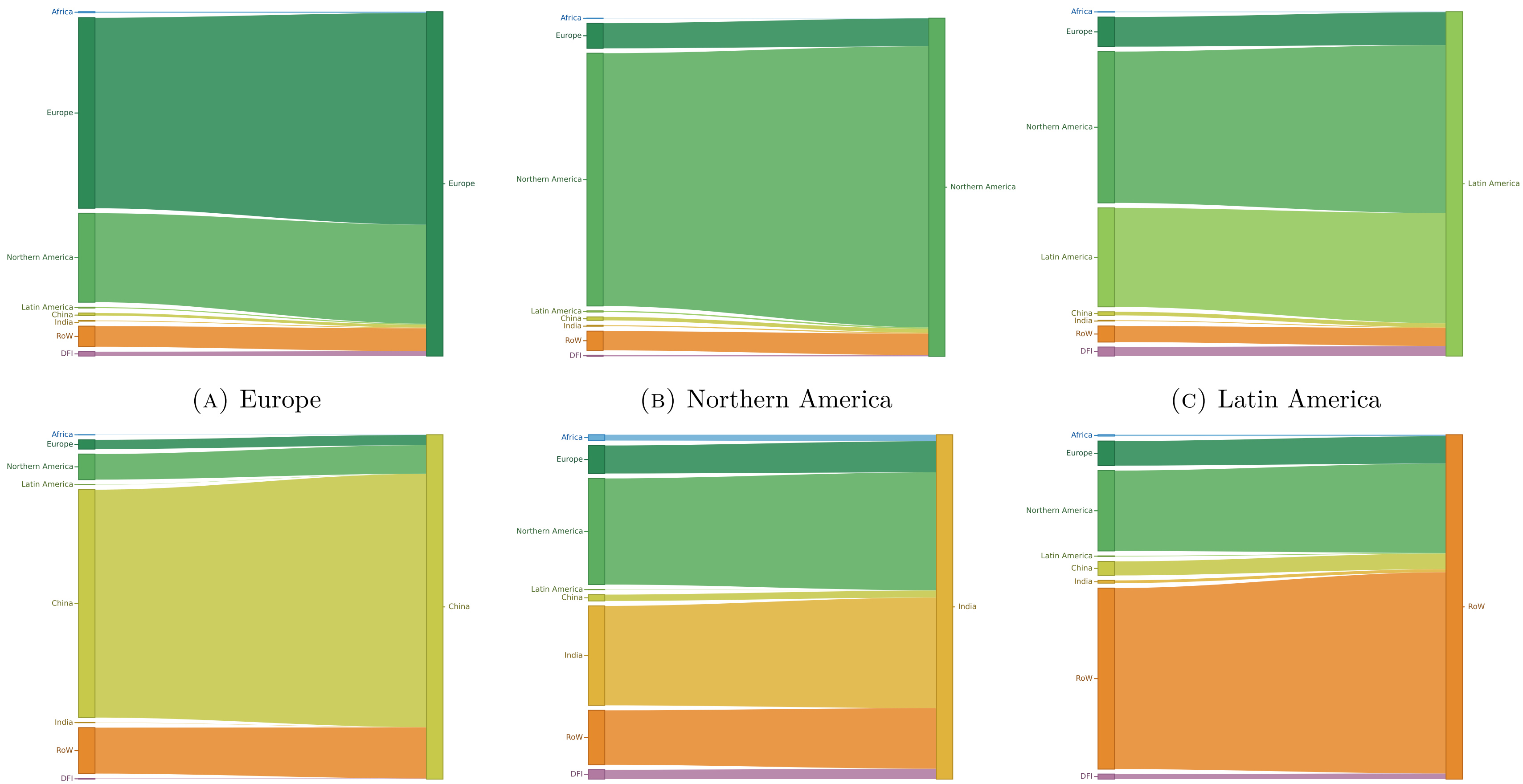



FIGURE A16. Who Finances Startups in Africa? LP to GP to Company

*Notes*: This figure presents the origins of capital from Limited Partners (LPs) and Development Finance Institutions (DFIs), channeled through General Partners (GPs) to African startups, using PitchBook data from 2010 to 2024, with destinations divided into five African subregions. Flow size reflects funding amounts in millions of U.S. dollars. When GP information is available but LP information is missing, we infer LP identity from the associated GP. The sample includes 2,869 unique deals, corresponding to 14,739 LP-GP-company deal pairs with non-missing deal size, GP region, and LP region.

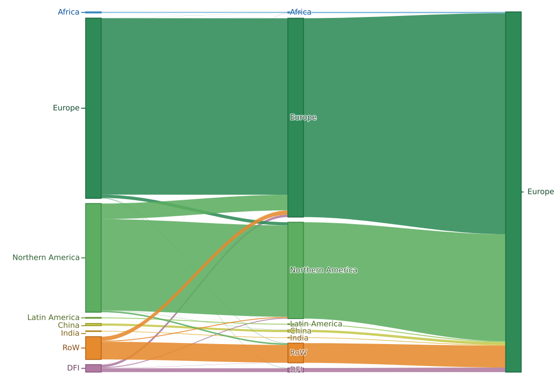



(A) Europe (B) Northern America (C) Latin America

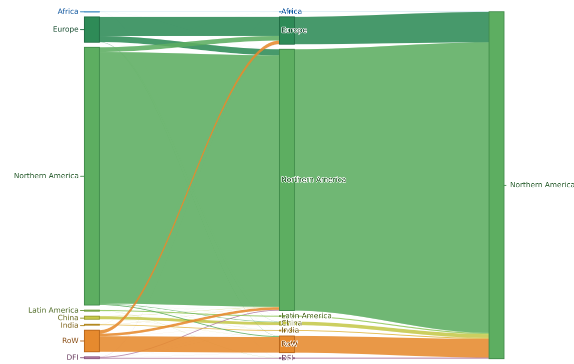
(D) China (E) India (F) Rest of the World

FIGURE A17. Who Finances Startups in Other Regions?

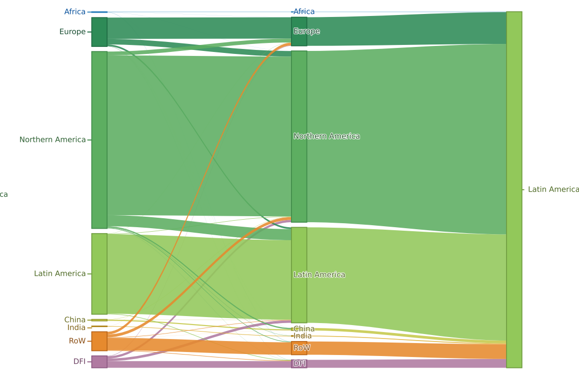
*Notes*: This figure shows the investment flows from General Partners (GP) to established startups in other regions of the world (Europe, Northern America, Latin America, China, India, and the Rest of the World) using PitchBook data. The size of the flows reflects the amount of funds in millions of USD. The sample includes 72,348 unique deals in Europe (114,170 in Northern America, 5,228 in Latin America, 27,706 in China, 12,378 in India, and 32,833 in the Rest of the World). These correspond to 205,070 GP-company deal pairs with non-missing deal size and GP region in Europe (492,408 in Northern America, 17,846 in Latin America, 70,121 in China, 44,026 in India, and 124,703 in the Rest of the World).



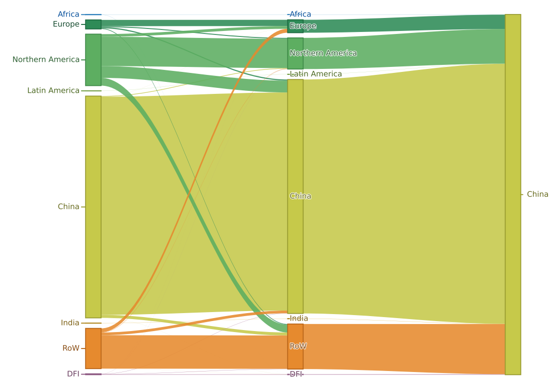

(A) Europe



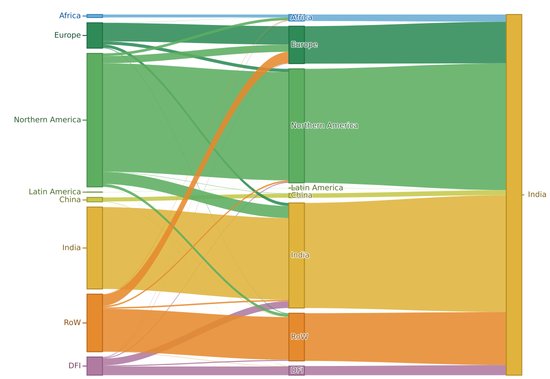

(B) Northern America



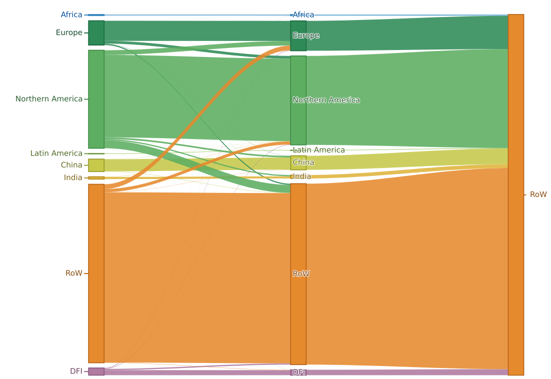

(C) Latin America




(D) China




(E) India




(F) Rest of the World

FIGURE A18. 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. The sample includes 72,347 unique deals in Europe (114,167 in Northern America, 5,228 in Latin America, 27,704 in China, 12,376 in India, and 32,829 in the Rest of the World). These correspond to 338,686 LP-GP-company deal pairs with non-missing deal size, GP region and LP region in Europe (1,002,716 in Northern America, 26,690 in Latin America, 127,251 in China, 80,907 in India, and 167,063 in the Rest of the World).

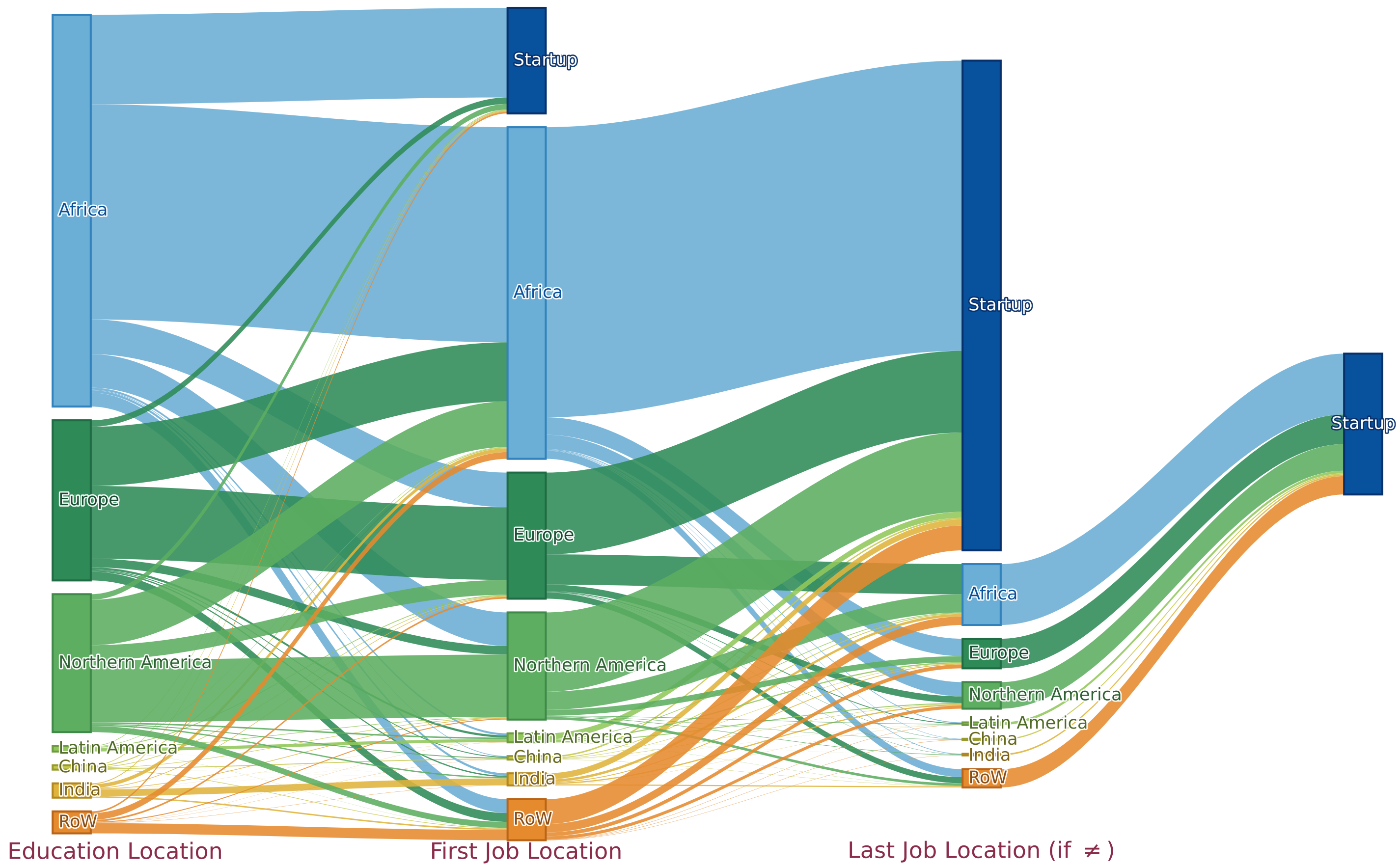
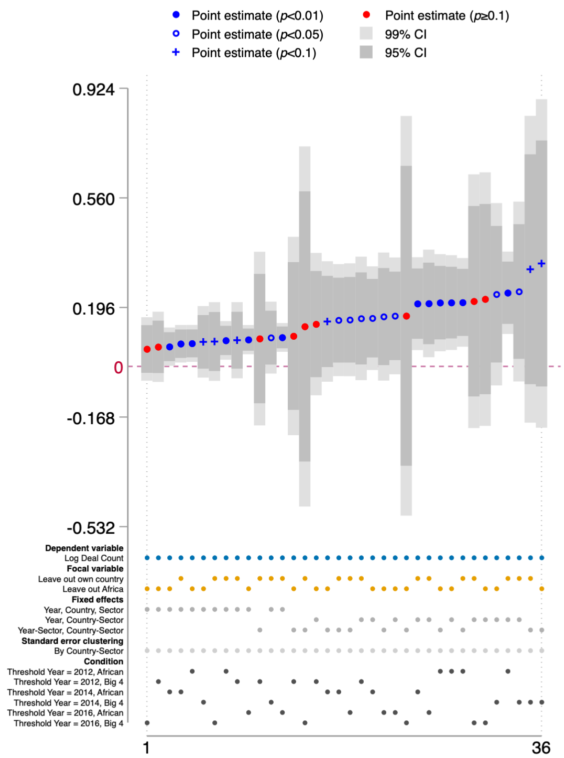
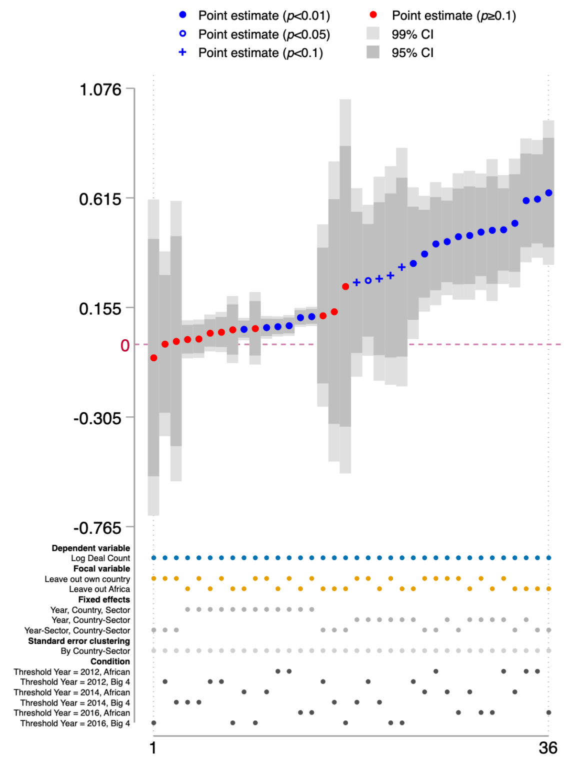



Figure A19. Typical Job Trajectory of African Startup Founders

*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 A20. Robustness to "Leave-Out" Means, Fixed Effects and Alternative Samples

*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), constructed using leave-out own-country and leave-out Africa shifters; (ii) three fixed effects structures (year FE + country FE + sector FE, year FE + country-sector FE, and year-sector FE + 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 4: Kenya, Egypt, Nigeria, and South Africa). 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 5.2.3 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 | 1,098 | 5,470 |
| Deals | 6,293 | 2,458 | 8,751 |
| Investors | 4,986 | 1,333 | 6,319 |
| **B. Deal Year** | | | |
| 2010-2014 | 12.38% | 1.34% | 9.28% |
| 2015-2019 | 30.34% | 20.55% | 27.59% |
| 2020-2024 | 57.29% | 78.11% | 63.14% |
| **C. Deal Size** | | | |
| USD 0-100K | 14.25% | 10.04% | 12.71% |
| USD 100K-250K | 11.95% | 31.30% | 20.48% |
| USD 250K-1M | 21.34% | 21.88% | 21.74% |
| USD 1M-2.5M | 16.37% | 12.37% | 14.44% |
| USD 2.5M-10M | 19.98% | 14.65% | 17.44% |
| USD >10M | 16.12% | 9.75% | 13.19% |
| **Panel D. Company Sector** | | | |
| Information Technology (IT/SaaS/AI) | 27.42% | 6.19% | 23.16% |
| Manufacturing/Robotics | 12.37% | 3.46% | 10.59% |
| Finance/FinTech | 8.74% | 24.50% | 11.90% |
| Health/BioTech | 7.16% | 9.11% | 7.55% |
| Media/Art/Entertainment | 6.79% | 6.38% | 6.71% |
| Energy/CleanTech | 5.54% | 5.65% | 5.56% |
| Transportation/Logistics/MobilityTech | 5.08% | 8.65% | 5.80% |
| Retail/eCommerce | 5.10% | 8.47% | 5.78% |
| Agriculture/AgriTech | 4.92% | 6.92% | 5.32% |
| Real Estate/Construction | 3.55% | 0.46% | 2.93% |
| Education/EdTech | 3.41% | 6.10% | 3.95% |
| Hospitality/Smart Hospitality Solutions | 2.38% | 0.82% | 2.07% |
| Water/Sanitation/Waste Management | 1.24% | 1.91% | 1.37% |
| Other | 6.31% | 11.38% | 7.33% |
| **Panel E. Company Country** | | | |
| South Africa | 23.42% | 16.30% | 21.99% |
| Nigeria | 15.48% | 21.58% | 16.71% |
| Egypt | 11.51% | 14.94% | 12.19% |
| Kenya | 11.25% | 13.75% | 11.76% |
| Other Countries | 38.33% | 33.42% | 37.35% |

*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. Survey Representativeness

| | Survey | Average | N. Startups | N. VC Deals | $ VC Deals | GDP | Population |
|---|---|---|---|---|---|---|---|
| Nigeria | 20.8% | 17.1% | 16.3% | 16.4% | 24.7% | 12.7% | 15.4% |
| Kenya | 17.8% | 9.9% | 14.8% | 15.1% | 12.1% | 3.8% | 3.7% |
| South Africa | 10.2% | 15.4% | 18.5% | 18.6% | 22.3% | 13.2% | 4.3% |
| Uganda | 9.7% | 2.1% | 2.6% | 2.7% | 0.3% | 1.7% | 3.3% |
| Egypt | 6.4% | 12.5% | 13.8% | 13.8% | 13.2% | 13.8% | 7.7% |
| Ghana | 4.5% | 3.4% | 3.7% | 3.5% | 4.6% | 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% | 4.9% | 4.6% | 4.3% | 8.2% | 5.0% | 2.5% |
| Cameroon | 2.3% | 1.7% | 2.3% | 2.2% | 0.4% | 1.7% | 1.9% |
| Tanzania | 1.9% | 2.2% | 1.7% | 1.6% | 0.3% | 2.8% | 4.5% |
| Côte d'Ivoire | 1.5% | 2.3% | 2.4% | 2.7% | 1.4% | 2.8% | 2.1% |
| Tunisia | 1.4% | 1.4% | 2.0% | 2.2% | 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% | 2.2% | 0.8% | 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% | 2.7% | 2.6% | 0.5% | 1.1% | 1.2% |
| Zambia | 0.8% | 0.9% | 1.0% | 0.9% | 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% | 4.0% | 1.1% | 1.2% | 3.4% | 5.6% | 8.7% |
| Burkina Faso | 0.5% | 0.6% | 0.3% | 0.3% | 0.2% | 0.7% | 1.6% |
| Mauritius | 0.4% | 1.1% | 0.7% | 0.6% | 3.7% | 0.5% | 0.1% |
| Angola | 0.4% | 1.2% | 0.3% | 0.3% | 0.1% | 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% | 0.2% | 0.1% | 0.1% | 0.0% | 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% | 2.6% | 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% | 0.6% | 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% | 0.2% | 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% | 0.5% | 0.9% | 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% | 1.7% | 1.7% | 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 VC 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. VC Deals" refers to the total number of VC deals recorded in PitchBook+ in 2024. "$ VC Deals" is the aggregate dollar value of VC deals recorded in PitchBook+ in 2024. "GDP" is country-level total GDP in 2024, and "Population" is total population in 2024.

# Table A3. Description of Randomized Profile Components

| Component | Variable | Options |
|---|---|---|
| Investor Name (1) | NA | **1. Investor Name (Early-Stage) (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. Investor Name (Later-Stage) (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 (1) [Round 1] | ***Large Investment:***<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 (1) [Round 2] | ***Large Investment:***<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 headquarters 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 A3 (cont.): Description of Randomized Profile Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| Target<br>(1) | ***Same Country Focus:***<br>**1 if the investor focuses exclusively on the respondent's country [5].** | **1 Global (0.2)**<br>Global<br>Emerging Markets<br>Africa | **2 Africa 1 (0.4)**<br>Subregion of Africa where the respondent is located. | **3 Africa 2 (0.2)**<br>Subregion of Africa where the respondent is located and the adjacent subregion. | **4 Country 3 (0.1)**<br>The country where the respondent is located and its two neighboring countries. |
| | | **5 Self (0.1)**<br>Country where the respondent is located. | | | |
| Finance Type<br>(1) | ***Equity:***<br>**1 if the investor finances startups with equity. [2].** | **1 Debt (0.5)**<br>Debt | | **2 Equity (0.5)**<br>Equity | |
| Board Seat Requirement<br>(0.5) | ***Any Board Seat:***<br>**1 if the investor requires any board seat [2-3].** | **1. No Board Seat (0.15)**<br>No seats | **2. Small Board Seat (0.45)**<br>One; Two; 10%; 15%; 20%; 25% | **3. Large Board Seat (0.40)**<br>35%; 40%; 50% | |
| Interest Rate<br>(1)<br>[Appears only if Finance Type is Debt.] | ***Low Interest Rate:***<br>**1 if interest rate is lower than 15%.** | **1. Interest Rate (1)**<br>5-10; 10; 12; 15; 20; 10-25; 5-10; 10-20 | | | |
| Maturity<br>(0.5)<br>[Appears only if Finance Type is Debt.] | ***Long Maturity:***<br>**1 if the maturity is longer than 3 years.** | **1. Maturity (1)**<br>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<br>(0.7)<br>[Round 1, in millions USD] | ***Large Investor:***<br>**1 if AUM is larger than group median (cutoffs are 9.5m, 22.5m, 55m for AMO1/2/3 respectively)** | **1. AMO1**<br>1; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13; 14; 15; 16; 17 | **2. AMO2**<br>18; 19; 20; 21; 22; 23; 24; 25; 26; 27 | **3. AMO3**<br>30; 35; 40; 45; 50; 60; 70; 80; 90; 100 | |
| AUM<br>(0.7)<br>[Round 2, in millions USD] | ***Large Investor:***<br>**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**<br>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**<br>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**<br>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**<br>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**<br>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<br>(0.7)<br>[Each profile can have 1 to 3 LP(s), with the same probability] | ***International Investor as LP:***<br>**1 if international LP, except for DFIs [2].**<br><br>***DFI as LP:***<br>**1 if DFI as LP [3].**<br><br>***Local Investor as LP:***<br>**1 if institutions in Africa as LP, except for DFIs [4].** | **1. Institutional Investor (0.1)**<br>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)**<br>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)**<br>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)**<br>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<br>(0.3) | ***First Time GP:***<br>**1 if New Fund [1].** | **1 New Fund (0.4)**<br>First fund; 1st fund | | **2 Old Fund (0.6)**<br>2nd fund; 3rd fund; 4th fund; 5th fund | |
| Professional Team Size<br>(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+ | |

# Table A3 (cont.): Description of Randomized Profile Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| 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 | | | |
| 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 | |

Table A3 (cont.): Description of Randomized Profile Components

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| 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].**<br><br>***Local Team***<br>**1 if all team member are African. [5]**<br><br>***Foreigners' Team***<br>**1 if all team members are foreigners. [6]** | **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 |
| | | **5. Local Team (if names of all team members are African-sounded)**<br>Key people born and raised in the respondent's country | **6. Foreign Team (if names of all team members are Western-sounded)**<br>Key people born and raised in the US; Key people born and raised in Europe | | |

*Notes*: This table summarizes the details used to construct investor profiles. Column (1) lists the profile components, with the probability that each component appears in an investment partner profile reported in parentheses. Additional notes are provided in brackets. Column (2) lists the specific variables in *italics*, as discussed in Appendix Table A5, together with the conditions determined by the randomly drawn text in Column (3). Column (3) reports all textual options under each profile component, with the conditional probability of each option being shown reported in parentheses. For each selected option, one of the corresponding text snippets is then drawn with equal probability. See Appendix A.3.1 for more details.

# Table A4. 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) [Round 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 (1) [Round 2] | ***Large Investment:*** **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 headquarters 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:*** **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.** | **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 | | | |

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

| Component | Variable | Options | | | |
|---|---|---|---|---|---|
| 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 | | | |
| 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. Medium (0.5)** 15; 17; 20; 21; 22; 23; 24; 25 | | **2. Large (0.5)** 25; 30; 35; 37; 40; 50 | |
| Fund Return (0.5) | ***Successful Investor:*** **1 if high return [1].** | **1. High (0.75)** 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)** 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:*** **1 if large exits [2].** | **1. Small Exits (0.5) (only if "Fund Return" is Neutral or not showed)** 1;1;2;2;3;4 | | **2. Large Exits (0.5) (only if "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 | |
| 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. (0.25)** 1 | **2. (0.5)** 2 | **3. (0.25)** 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 | |

## Table A4 (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].**<br><br>***Local Team***<br>**1 if all team member are African. [5]**<br><br>***Foreigners' Team***<br>**1 if all team members are foreigners. [6]** | **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 |
| | | **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 members are foreigners)**<br>Key people born and raised in the US; Key people born and raised in Europe | | |

*Notes*: This table summarizes the details used to construct DFI profiles. Column (1) lists the profile components, with the probability that each component appears in an investment partner profile reported in parentheses. Additional notes are provided in brackets. Column (2) lists the specific variables in *italics*, as discussed in Appendix Table A5, together with the conditions determined by the randomly drawn text in Column (3). Column (3) reports all textual options under each profile component, with the conditional probability of each option being shown reported in parentheses. For each selected option, one of the corresponding text snippets is then drawn with equal probability. See Appendix A.3.1 for more details.

Table A5. Variables in Synthetic Profiles

| Variables | Description |
|---|---|
| Equity | =1 if the investment opportunity is an equity investment. |
| 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 Investment | =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 experience. |
| 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 headquarters is located in China, UAE, Brazil, USA or Europe. |
| Team with Intl. Experience | =1 if the investor shows international experience. |
| 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 returns or successful 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 first manager is 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 synthetic profiles of investment opportunities with their definitions. See Appendix Tables A3 and A4 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 A6. Reasons Why Early-Stage Startups Prefer Debt or Equity

(a) Why Prefer Equity Investments?

| | Count | Share (%) |
|---|---|---|
| Cashflow and financial flexibility (no interests payments) | 1121 | 49.0% |
| Investors have incentives to help | 906 | 39.6% |
| Access to investors' expertise, guidance, and networks | 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% |

(b) 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% |

*Notes:* Panel A (Panel B) reports reasons why survey respondents prefer equity over debt (debt over equity). 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 a multi-select question.

# 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 Investment | 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 profiles of investment opportunities. 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) Sector | (3) Country | (4) Country × Sector | (5) Sector | (6) Country | (7) Country × Sector |
| Equity | 0.718*** | 0.826*** | 0.777*** | 0.826*** | 0.809*** | 0.783*** | 0.816*** |
| | (0.026) | (0.033) | (0.033) | (0.044) | (0.032) | (0.032) | (0.041) |
| Low Interest Rate | 0.443*** | 0.438*** | 0.461*** | 0.464*** | 0.444*** | 0.460*** | 0.461*** |
| | (0.023) | (0.030) | (0.029) | (0.041) | (0.028) | (0.028) | (0.038) |
| Any Board Seat | -0.358*** | -0.380*** | -0.343*** | -0.315*** | -0.385*** | -0.346*** | -0.333*** |
| | (0.023) | (0.029) | (0.029) | (0.039) | (0.028) | (0.028) | (0.036) |
| Large Investment | 0.352*** | 0.384*** | 0.419*** | 0.425*** | 0.389*** | 0.421*** | 0.440*** |
| | (0.017) | (0.021) | (0.021) | (0.029) | (0.020) | (0.020) | (0.027) |
| Low Equity Stake | 0.350*** | 0.381*** | 0.358*** | 0.386*** | 0.382*** | 0.357*** | 0.394*** |
| | (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*** | 0.146*** | 0.142*** | 0.162*** |
| | (0.027) | (0.036) | (0.035) | (0.054) | (0.034) | (0.034) | (0.049) |
| Long Maturity | 0.133*** | 0.137*** | 0.110*** | 0.111** | 0.138*** | 0.110*** | 0.116*** |
| | (0.026) | (0.034) | (0.033) | (0.044) | (0.033) | (0.032) | (0.042) |
| Same Sector Focus | 0.123*** | 0.073*** | 0.127*** | 0.065** | 0.074*** | 0.127*** | 0.075** |
| | (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* | 0.121** | 0.171*** | 0.119** |
| | (0.038) | (0.050) | (0.050) | (0.063) | (0.047) | (0.048) | (0.059) |
| Local Team | 0.105*** | 0.126*** | 0.119*** | 0.099** | 0.116*** | 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* | 0.066*** | 0.055** | 0.053* |
| | (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*** | 0.080*** | 0.065*** | 0.084*** |
| | (0.017) | (0.022) | (0.022) | (0.030) | (0.021) | (0.021) | (0.028) |
| Successful Investor | 0.058*** | 0.037 | 0.059*** | 0.050 | 0.038* | 0.059*** | 0.055* |
| | (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 | 0.047** | 0.033 | 0.033 |
| | (0.016) | (0.021) | (0.021) | (0.029) | (0.020) | (0.020) | (0.027) |
| First Time GP | 0.043 | 0.034 | 0.037 | 0.051 | 0.034 | 0.039 | 0.054 |
| | (0.027) | (0.035) | (0.034) | (0.049) | (0.033) | (0.033) | (0.046) |
| Impact Investor | 0.042** | 0.032 | 0.040 | 0.020 | 0.031 | 0.043* | 0.029 |
| | (0.020) | (0.026) | (0.025) | (0.033) | (0.025) | (0.025) | (0.031) |
| Team with International Experience | 0.037* | 0.015 | 0.023 | 0.004 | 0.016 | 0.026 | 0.002 |
| | (0.020) | (0.026) | (0.025) | (0.034) | (0.025) | (0.025) | (0.032) |
| Foreigners' Team | 0.034 | 0.035 | 0.019 | 0.062 | 0.039 | 0.018 | 0.061 |
| | (0.026) | (0.033) | (0.033) | (0.046) | (0.032) | (0.032) | (0.042) |
| Large Investor | 0.034* | 0.039* | 0.053** | 0.045 | 0.043* | 0.049** | 0.046* |
| | (0.018) | (0.023) | (0.022) | (0.029) | (0.022) | (0.022) | (0.028) |
| Diligence Requirement | -0.025 | -0.005 | -0.022 | -0.036 | -0.006 | -0.020 | -0.027 |
| | (0.018) | (0.023) | (0.022) | (0.032) | (0.022) | (0.022) | (0.029) |
| Foreign Investor | 0.024 | 0.052** | 0.027 | 0.058* | 0.043* | 0.029 | 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 | 0.013 | 0.025 |
| | (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 | -0.014 |
| | (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 | 0.004 |
| | (0.018) | (0.023) | (0.023) | (0.032) | (0.022) | (0.022) | (0.030) |
| Female-Led Team | -0.008 | 0.015 | -0.007 | -0.057 | 0.010 | -0.008 | -0.050 |
| | (0.021) | (0.027) | (0.026) | (0.036) | (0.025) | (0.025) | (0.034) |
| DFI as LP | -0.007 | -0.018 | -0.007 | -0.018 | -0.022 | -0.006 | -0.019 |
| | (0.018) | (0.024) | (0.023) | (0.031) | (0.022) | (0.023) | (0.029) |
| Young Investor | 0.007 | -0.005 | 0.013 | 0.009 | -0.007 | 0.011 | -0.001 |
| | (0.024) | (0.031) | (0.031) | (0.042) | (0.030) | (0.030) | (0.039) |
| Local Investor as LP | 0.003 | 0.009 | 0.010 | 0.018 | 0.016 | 0.011 | 0.021 |
| | (0.018) | (0.023) | (0.023) | (0.030) | (0.022) | (0.022) | (0.028) |
| Observations | 45475 | 45475 | 43350 | 40345 | 45475 | 44855 | 40695 |
| 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 profiles of investment opportunities. 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 VC 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. Relocating Company Headquarters: Comparing PitchBook+ with LinkedIn

(a) Unweighted

| PitchBook+ HQ | LinkedIn-imputed HQ | | | | | | |
|---|---|---|---|---|---|---|---|
| | Africa | Northern America | Europe | Latin America | India | RoW | Total |
| Africa | 83.67 | 4.94 | 5.48 | 1.16 | 1.36 | 3.39 | 100.00 |
| Northern America | 1.06 | 83.67 | 4.90 | 2.02 | 3.50 | 4.85 | 100.00 |
| Europe | 1.50 | 4.03 | 87.28 | 1.79 | 1.64 | 3.76 | 100.00 |
| Latin America | 0.51 | 2.79 | 2.66 | 91.68 | 0.62 | 1.74 | 100.00 |
| India | 0.40 | 1.73 | 1.40 | 0.41 | 94.51 | 1.56 | 100.00 |
| RoW | 1.63 | 7.45 | 7.08 | 2.36 | 3.51 | 77.97 | 100.00 |

(b) Weighted by Firm Size

| PitchBook+ HQ | LinkedIn-imputed HQ | | | | | | |
|---|---|---|---|---|---|---|---|
| | Africa | Northern America | Europe | Latin America | India | RoW | Total |
| Africa | 51.76 | 33.47 | 12.63 | 0.29 | 0.48 | 1.36 | 100.00 |
| Northern America | 0.48 | 81.66 | 4.03 | 1.62 | 5.91 | 6.30 | 100.00 |
| Europe | 1.28 | 4.71 | 83.63 | 2.24 | 2.22 | 5.91 | 100.00 |
| Latin America | 0.30 | 0.25 | 0.28 | 97.75 | 0.16 | 1.26 | 100.00 |
| India | 0.04 | 0.33 | 0.09 | 0.08 | 99.38 | 0.08 | 100.00 |
| RoW | 0.91 | 5.56 | 4.02 | 0.94 | 5.91 | 82.65 | 100.00 |

*Notes:* This table reports the distribution of LinkedIn-imputed headquarters for PitchBook+ companies in each region. PitchBook+ headquarters are defined as the company headquarters reported in PitchBook, Africa: The Big Deal, and Briter Bridges. LinkedIn-imputed headquarters are defined as the region in which the largest share of a firm's current employees in 2024 are located. Panel A reports the unweighted distribution across firms. Panel B reports the distribution weighted by firm size, measured using the number of employees observed in Revelio Labs in 2024.

Table A10. Currency of VC Deals in Africa

| | All Deal | Foreign Deal | Local Deal |
|---|---|---|---|
| Foreign currency | 56.2% | 67.2% | 43.6% |
| Local currency | 43.8% | 32.8% | 56.4% |
| *Foreign Currency* | | | |
| US Dollars (USD) | 51.6% | 61.2% | 40.6% |
| Euros (EUR) | 3.1% | 4.1% | 2.0% |
| British Pounds (GBP) | 0.6% | 0.8% | 0.4% |
| Other foreign currency | 0.9% | 1.1% | 0.6% |
| *Local Currency* | | | |
| South African Rand (ZAR) | 14.3% | 6.8% | 23.0% |
| Nigerian naira (NGN) | 6.2% | 5.8% | 6.6% |
| Kenyan shilling (KES) | 4.4% | 5.3% | 3.5% |
| Egyptian pound (EGP) | 4.3% | 3.7% | 4.9% |
| Other local currency | 14.6% | 11.2% | 18.5% |

*Notes:* This table displays the distribution of deal currencies, using data on VC deals in Africa recorded in PitchBook from 2010 to 2024. The missing rate for deal currency information in this sample is less than 0.02%. Local currencies refer to currencies used by African countries, while foreign currencies refer to currencies used by countries outside Africa. A deal is classified as foreign if at least one investor (with non-missing location information) is based outside Africa. A deal is classified as local if all investors are based within Africa (or if investor location information is missing).

Table A11. Heterogeneity Analysis: Foreign Capital Supply Shocks Affect Startup Activity by Local vs. Foreign Startups

| | Africa | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Log Deal Size | | | | Log Deal Count | | | |
| | Local | | Foreign | | Local | | Foreign | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| instrument (size) | 0.024** | 0.044 | 0.058** | 0.158** | | | | |
| | (0.012) | (0.049) | (0.024) | (0.063) | | | | |
| instrument (count) | | | | | 0.032*** | 0.068 | 0.056*** | 0.418*** |
| | | | | | (0.010) | (0.055) | (0.018) | (0.089) |
| Year FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Country FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Sector FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Year-Sector FE | No | Yes | No | Yes | No | Yes | No | Yes |
| 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 | 0.192 | 0.406 | 0.467 | 0.671 | 0.399 | 0.585 | 0.633 | 0.790 |

*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 has education or work experience outside Africa, measured at the time of receiving their first VC deal. Columns (1)–(4) use the total U.S. dollar value of VC deals as outcome measures, while Columns (5)–(8) use the number of VC deals. The causal effects are estimated by proxying foreign capital supply shocks with Bartik-style shift–share instruments. See Section 5.2.3 for details on the empirical specification and the construction of the shift–share instruments.

Table A12. Observed Capital Flow $n_{c,x}$ and Solved Capital Wedge $r_{c,x}$

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

| | Investor Origin $x$ | | | |
|---|---|---|---|---|
| Company Region $c$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 18.9% | 38.7% | 33.3% | 9.1% |
| Western Africa | 20.5% | 45.9% | 22.2% | 11.4% |
| Northern Africa | 27.1% | 20.1% | 37.2% | 15.6% |
| Southern Africa | 41.6% | 24.1% | 19.3% | 15.0% |
| 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 $r_{c,x}$ (Row-Normalized to Local = 1)

| | Investor Origin $x$ | | | |
|---|---|---|---|---|
| Company Region $c$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 1.00 | 0.53 | 0.62 | 0.97 |
| Western Africa | 1.00 | 0.57 | 1.05 | 0.97 |
| Northern Africa | 1.00 | 0.72 | 0.69 | 1.03 |
| Southern Africa | 1.00 | 1.06 | 1.44 | 0.93 |
| Northern America | 4.04 | 1.00 | 2.18 | 2.16 |
| Europe | 2.66 | 0.93 | 1.00 | 1.85 |
| RoW | 1.91 | 0.90 | 1.84 | 1.00 |

*Notes:* This table reports the observed capital flows $n_{c,x}$ used as calibration targets and the equilibrium capital wedges $r_{c,x}$ that match 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 $n_{c,x}$ from the deal-size-weighted number of financed startups in region $c$ backed by investors from origin $x$, based on deals recorded in PitchBook, Africa: The Big Deal, and Briter Bridges in 2010-2024. See Section 5.2.4 and Appendix A.4.2 for details on the calibration targets and estimation procedure.

Table A13. Observed/Latent Entrepreneurs by Connection Region

(a) Observed Financed Entrepreneurs by Connection Region $n_c^k$

| | Connection Region $k$ | | | |
|---|---|---|---|---|
| Company Region $c$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 31.0% | 26.7% | 29.0% | 13.3% |
| Western Africa | 26.4% | 29.2% | 31.2% | 13.2% |
| Northern Africa | 32.9% | 15.6% | 32.3% | 19.2% |
| Southern Africa | 40.4% | 23.2% | 26.1% | 10.3% |
| Northern America | 1.3% | 68.4% | 15.3% | 15.0% |
| Europe | 2.4% | 22.3% | 59.6% | 15.6% |
| RoW | 1.6% | 23.9% | 18.8% | 55.7% |

(b) Solved Latent Entrepreneurs by Connection Region $e_c^k$

| | Connection Region $k$ | | | |
|---|---|---|---|---|
| Company Region $c$ | Africa | Northern America | Europe | RoW |
| Eastern & Central Africa | 42.1% | 17.6% | 22.8% | 17.5% |
| Western Africa | 30.3% | 17.6% | 37.5% | 14.7% |
| Northern Africa | 39.3% | 12.4% | 24.6% | 23.6% |
| Southern Africa | 35.0% | 21.5% | 35.4% | 8.2% |
| Northern America | 2.2% | 49.3% | 24.6% | 23.9% |
| Europe | 4.6% | 17.7% | 51.6% | 26.1% |
| RoW | 2.7% | 18.2% | 31.1% | 48.0% |

*Notes:* This table reports the observed entrepreneur distribution by connection type $n_c^k$ used as calibration targets, and the equilibrium latent entrepreneur mass $e_c^k$ that matches the data. Each row is normalized to sum to 1 in both panels. We construct $n_c^k$ from founders of financed startups in region $c$, 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, measured at the time of receiving their first VC deal, from Revelio Labs. See Section 5.2.4 and Appendix A.4.2 for details on the calibration targets and estimation procedure.

## Appendix A.2. Data Sources and Treatment

A.2.1. **Data Matching and Consolidation.** This subsection details our methodology for matching and harmonizing PitchBook, Briter Bridges, and Africa: The Big Deal.

*Data Matching.* We conduct data matching at three levels: companies, deals, and investors. At each level, we first consolidate Briter Bridges and Africa: The Big Deal into an intermediate BB–AfricaTBD dataset, and then merge PitchBook with this combined dataset.

At the company and investor levels, we begin with strict matching based on names and websites after basic text standardization. We then manually review all unmatched cases to identify potential missed matches using all available identifiers, including company name, legal name, former name, and website. Conditional on company-level matches, we perform deal-level matching within matched companies, starting with exact matching on deal dates and then manually reviewing remaining unmatched deals using deal size, 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. When overlapping or conflicting information is available across datasets, we retain the version reported by the highest-priority source.[44]

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

A.2.2. **Data Treatments.** This subsection outlines the data treatments applied in the construction and processing of specific variables used in this paper.

[44]This preference ranking applies only to overlapping or competing information across datasets. If a data point appears exclusively in a lower-priority dataset, we retain that observation.

*Education and Location in Revelio Labs.* To impute individuals' educational attainment, we run a program that parses degree-related information from each individual's profile in Revelio Labs' LinkedIn data. The program searches for keywords associated with degree completion across multiple languages and uses these to assign degree categories such as high school, bachelor's, master's, and PhD. For example, if "M.Sc." appears in the text string, the individual is assigned a master's degree. An individual can be assigned more than one degree category, such as bachelor's, master's, and PhD.

We obtain location information for each entity in Revelio Labs' LinkedIn data, such as a company or a school, from self-reported location fields and map these to OpenStreetMap to retrieve latitude and longitude coordinates. This allows us to identify the country of a company's headquarters as well as the locations of an individual's work and education history.

*Identifying Employees and Founders.* We run a program on the job-description variable for each individual in Revelio Labs' LinkedIn data and search for keywords in different languages 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 improve identification accuracy. Specifically, we inspect all African startups present in PitchBook, Africa: The Big Deal, and Briter Bridges. For companies not matched by the automated procedure, we conduct manual searches within Revelio Labs. When founders are not identified automatically, we conduct additional searches for founder information in both Revelio Labs and external online sources.

*Improving the Quality of Revelio Labs Classifications.* According to Revelio Labs' methodology (Revelio Labs' classification), gender is predicted using a classification algorithm trained on first names from U.S. Social Security Administration data, while race is predicted using first name, last name, and geographic location in models trained on U.S. Census data. To address potential misclassification, we manually inspect LinkedIn profile photos for a sample of founders to validate gender and ethnicity. Specifically, we review and, where necessary, correct the gender and race classifications for all African founders, as well as for founders from a random sample of 500 companies in other regions. Based on this visual verification, we update the gender and ethnicity labels accordingly. In cases where a LinkedIn profile photo is missing or does not allow for a definitive manual classification, we retain the original Revelio Labs classification.

## Appendix A.3. Additional Details on Startup Survey

This section provides additional details on the startup survey, including the construction of the synthetic profiles, and the definition of heterogeneity groups.

A.3.1. **Profile Design.** The two survey rounds use the same profile design and are drawn from an identical underlying pool of hypothetical profiles. Appendix Tables A3 and A4 describe all profile components and text options from which the analysis variables are constructed. These tables report every possible way in which a given component and its corresponding options may appear in the text of a synthetic profile. For each component, some text realizations correspond to some specific dummy variable taking the value 1 in the regression.

To illustrate the process, consider the "Subtitle" component in Appendix Table A3. In the first column, the value 0.5 in parentheses below the component name "Subtitle" indicates that this component appears in a given synthetic investment partner profile with probability 0.5; that is, 50% of synthetic profiles include a subtitle, while the other 50% do not. The third column, "Options", lists all possible text options for this component, grouped by category, together with the conditional probability that each category is selected. In this example, conditional on a profile including a subtitle, there is a 30% probability that the subtitle is drawn from group "1. Established Year, Young", a 20% probability that it is drawn from group "2. Established Year, Old", and a 50% probability that it is drawn from group "3. Impact Investor". Within each group, one specific text option is selected with equal probability.

The second column shows how the selected option is mapped into the dummy variables used in the estimation. Specifically, the numbers in the brackets after each dummy variable indicate the correspondence between specific categories and the relevant dummy variable. In this example, two dummy variables are involved. If the selected subtitle comes from group "1. Established Year, Young", the profile is coded as 1 for *Young Investor*. If the selected subtitle comes from group "3. Impact Investor", the profile is coded as 1 for *Impact Investor*.

The general structure of a synthetic profile is as follows.

*Basic Information of Investment Partners.* At the top of the investment partner profiles, we include basic information related to the investment partners and their preferences. For investment partner profiles, components that always appear include the firm's name, the location of their headquarters, and their geographical preferences. In some investment partner 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.

*Team Members.* Below the part of "Basic Information and Investment Preferences", we present team members of the investment partners. We randomize the number of team members shown, which can be 1, 2, or 3 for investment partner profiles. We consistently show prior work 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) the team's experience in Africa, (ii) their international experience, (iii) connections to 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.

*Investment Characteristics.* For each profile shown to respondents, we assign equal probability to *equity* and *debt* financing. The supplemental financing information then varies by financing type. If the profile features an equity investment, we randomize the exact equity stake required.[45] If the profile features a debt investment, we randomize the interest rate and, for some profiles, also include information on debt maturity. For both financing types, we always include and randomize the investment amount.[46] We report the ticket-size distributions used in survey rounds 1 and 2 separately. For robustness purposes, the second round design uses a finer set of investment-amount bins and, overall, smaller ticket sizes, implying a leftward shift in the distribution relative to round 1. Some profiles also report the number of board seats required.

[45] The range of equity stakes is consistent with the range the respondent indicated being willing to give up in the filtering questions before the profiles are shown.

[46] The range of investment amounts shown is consistent with the financing range indicated by the respondent in the filtering questions before the profiles are shown.

*Fund Characteristics.* In certain investment partner profiles, we include key characteristics that may not directly relate to the financing type, but give additional background information about an investment partner to the respondent. These characteristics range from financial details, such as the size of assets under management (AUM), the investment partner'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.* Investment partner profiles may also include information on an investment partner's past performance. The indicators used to capture the past performance of an investment partner range from measures of investment quantity, such as the number of prior investments and successful investments, to measures of investment quality, such as a textual summary of the average returns generated on previous investments.

*Additional Non-Financial Support.* Finally, at the bottom of a investment partner profile, we might also highlight the additional non-financial support provided by investment partners. 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.

A.3.2. **Definition of Heterogeneity Groups.** This subsection provides detailed definitions of the heterogeneity groups used in the analysis in Section 3.3.

A.3.2.1. *Externally-Measured Respondent Characteristics.* We match survey respondents to PitchBook+ and Revelio Labs records available through April 2026. These data capture outcomes observed 2.5 years after the first survey round and 6 months after the second survey round. For founder education and work-experience measures, we restrict attention to records dated before the respondent completed the survey.

*"Top University Founders"* are respondents with an education record from either (i) a top-100 university worldwide, (ii) a top-10 university in Africa, or (iii) the highest-ranked university in an African country.[47] *"Foreign Educated Founders"* are respondents with at least one education record outside Africa. *"Foreign Top University Founders"* are respondents with an education record from a top-100 university outside Africa. *"Foreign Experience Founders"* are respondents with at least one work-experience record outside Africa. *"Operational After Survey"* denotes respondents with an active current-employee

[47]For university rankings, we use the QS World University Rankings 2026 for the global top 100, and UNIRANKS Verified Universities 2026 for the Africa top 10 and country-level top university lists.

record on LinkedIn as of April 2026. *"Larger Employment After Survey"* denotes respondents whose number of current employees reported on LinkedIn as of April 2026 exceeds the number of employees reported at the time of the survey. *"New Hires After Survey"* denotes respondents with employees who joined after the survey, measured through April 2026. *"Received VC Financing"* denotes respondents with VC financing records in PitchBook+ through April 2026.

A.3.2.2. *Self-Reported Respondent Characteristics.* Self-reported respondent characteristics are constructed from respondents' answers to survey questions. *"Foreign Founders"* is defined as respondents with self-reported education or work experience outside Africa. *"Financially Sophisticated Founders"* refers to respondents who self-assessed their financial proficiency at 7 or above on a 1–10 scale. *"College-Educated Founders"* refers to respondents who report having completed college education. *"Young Founders"* refers to respondents with age below the sample median. *"Prefer Equity"* denotes respondents who self-report a preference for equity financing over debt financing. *"High 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). *"High Revenue"* indicates firms with revenue 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%.

A.3.2.3. *Country Development.* We use several measures to proxy for country development. *"High GDP Per Capita"* indicates that the respondent's country had GDP per capita in 2024 above the median of our sample. *"Less Developed VC"* indicates that the respondent's country had VC 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).

## 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 four steps.

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

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

An investor supplying one unit of capital is matched with probability

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

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

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

Free entry implies

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

which rearranges to

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

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

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

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

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

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

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

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

$$\bar{\tau}_{c,x}\lambda^k_{c,x}\left(\frac{s_{c,x}}{d_{c,x}}\right)^{\eta}.$$

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

$$\mu^k_{c,x} = \frac{\left(\bar{\tau}_{c,x}\lambda^k_{c,x}\left(\frac{s_{c,x}}{d_{c,x}}\right)^{\eta}\right)^{\sigma}}{\sum_{y\in\mathbb{X}}\left(\bar{\tau}_{c,y}\lambda^k_{c,y}\left(\frac{s_{c,y}}{d_{c,y}}\right)^{\eta}\right)^{\sigma} + \left(\bar{\tau}_{c,d}\right)^{\sigma}}.$$

*Step 4: The number of equity-financed startups.*

Entrepreneurs of type $k$ in destination $c$ have mass $e^k_c$. A fraction $\mu^k_{c,x}$ searches in market $(c, x)$ and contributes $\lambda^k_{c,x}\mu^k_{c,x}e^k_c$ units of effective demand. Each such demand unit is financed with probability

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

Hence

$$n^k_{c,x} = e^k_c\mu^k_{c,x}\lambda^k_{c,x}\left(\frac{s_{c,x}}{d_{c,x}}\right)^{\eta}.$$

Using the results derived in Step 1,

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

so

$$n^k_{c,x} = \left(\frac{\beta E[z_{c,x}]}{r_{c,x}}\right)^{\frac{\eta}{1-\eta}}\lambda^k_{c,x}\mu^k_{c,x}e^k_c.$$

This proves the lemma. ■

A.4.1.2. *Proof of Lemma 2.* Before proving the result, define

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

Proof. Start from Lemma 1. Aggregating over entrepreneur types,

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

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

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

Hence

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

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

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

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

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

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

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

This proves the lemma. ■

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

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

Proof. Start again from Lemma 1. For entrepreneur type $k$,

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

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

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

Hence

$$\frac{n^f_c}{n^\ell_c} = \frac{e^f_c}{e^\ell_c} \cdot \frac{\sum_{x\in\mathbb{X}} A_{c,x}\omega^f_{c,x}}{\sum_{x\in\mathbb{X}} A_{c,x}\omega^\ell_{c,x}}.$$

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

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

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

$$\frac{n^f_c}{n^\ell_c} = \frac{e^f_c}{e^\ell_c} \cdot \frac{\mathbb{E}_x[A_{c,x}]\,\mathbb{E}_x[\omega^f_{c,x}] + \mathrm{Cov}_x(A_{c,x}, \omega^f_{c,x})}{\mathbb{E}_x[A_{c,x}]\,\mathbb{E}_x[\omega^\ell_{c,x}] + \mathrm{Cov}_x(A_{c,x}, \omega^\ell_{c,x})}.$$

This proves the lemma. ■

A.4.2. **Calibration Details.**

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

- $\bar{\tau}_{c,d} = 0$ for all $c$, 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 $n_{c,x} = s^\eta_{c,x} d^{1-\eta}_{c,x}$;
- $\bar{\tau}_{c,x} = 1$ for all $(c, x)$, so entrepreneurs have homogeneous preferences over investors from all origins;
- $E[z^k_c] = 1$ for all $(c, k)$, so there is no difference in project returns across entrepreneur connection types;
- $\lambda^k_{c,x} = \lambda$ if $k = x$, and $\lambda^k_{c,x} = 1$ otherwise, so connection advantages are concentrated on the diagonal.

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

$$c \in \mathbb{C} = \{\text{Eastern \& Central Africa, Western Africa, Southern Africa, Northern Africa, Europe, Northern America, RoW}\},$$

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.[48]

[48] We exclude China from "RoW" in the destination-region set $\mathbb{C}$ because limited LinkedIn coverage there prevents us from reliably recovering founder information. However, we retain China in "RoW" for the exposure-type/investor-origin region set $\mathbb{X}$, allowing founders of established startups in other regions to have exposure to China (proxied by education or work experience records, as detailed below in Section A.4.2.3) or to receive capital from Chinese investors.

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 $c$ by investor origin $x$, denoted $n_{c,x}$, and the number of equity-financed startups in destination $c$ by entrepreneur type $k$, denoted $n_c^k$.

To construct $n_{c,x}$, we start from VC 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 $n_{c,x,t}$ for each year and then take annual averages to obtain $n_{c,x}$.

To construct $n_c^k$, 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 $w_c^k$ denote the share of founders in destination $c$ who belong to type $k$, with $\sum_{k \in \mathbb{X}} w_c^k = 1$. We then define

$$n_c^k := w_c^k \cdot N_c = w_c^k \cdot \sum_{x \in \mathbb{X}} n_{c,x}.$$

This construction guarantees that $\sum_{k \in \mathbb{X}} n_c^k = \sum_{x \in \mathbb{X}} n_{c,x}$, 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 $c$, conditional on $(\sigma, \lambda)$, parameters $\{\beta, \eta, \lambda_{c,x}^k, \bar{\tau}_{c,x}, \bar{\tau}_{c,d}, E[z_c^k]\}$ are externally calibrated and the counts $\{n_c^k, n_{c,x}\}$ are observed. Then, using the equilibrium characterized in the proof of Lemma 1, the system is square in $\{e_c^k, r_{c,x}, s_{c,x}, d_{c,x}, E[z_{c,x}], \mu_{c,x}^k\}$, which allows us to recover the latent entrepreneur masses $e_c^k$ and capital wedges $r_{c,x}$ together with the associated equilibrium parameters.

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

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

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 $n_{c,x,t}^k$ under the perturbed capital wedge.

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

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

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

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

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 Tables 7 and 5. The best-fitting values we obtain are $\sigma = 3.904$ and $\lambda = 2.235$.

A.4.3. **Details on the Counterfactuals.** This subsection describes the counterfactual exercises in Section 5.3.

A.4.3.1. *Equalizing Capital Wedges.* Appendix Table A12 reports the capital-wedge matrix $r_{c,x}$ 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 Northern American-investor wedge matches the corresponding ratio observed in Europe.

A.4.3.2. *Equalizing Shares of Local Entrepreneurs.* Appendix Table A13 reports the latent entrepreneur-mass distribution $e^k_c$. 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 Connection to Foreign Investors.* 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 entrepreneurs unchanged.

A.4.3.4. *Higher Human Capital.* Figure 9 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:

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

The four African education groups are defined using average years of schooling for the population aged 25–45, based on Barro and Lee (2013); the cutoffs correspond to quartiles of this distribution. 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 $e_c^k$ 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.