Frontier Technology in Frontier Markets: Financing Global AI Entrepreneurship*

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Abstract

Does the global diffusion of artificial intelligence extend to the creation and financing of the firms that build it? Using a novel dataset of 116,795 startups founded between 2015 and 2022 across 172 countries, we link company descriptions and financing histories to the employment and education records of founders, early employees, and potential investors. We document a stark divergence between the real and financial sides of global AI entrepreneurship. On the real side, AI startups everywhere display the hallmarks of a general-purpose technology: in every world region, they target more customer sectors than comparable non-AI startups and are more likely to sell horizontal products that apply across industries. Moreover, following the release of ChatGPT, startups whose baseline tasks were more amenable to AI expanded the breadth of their work activities and commercial staffing. Yet the financing advantage that such scalable businesses command is sharply localized. AI startups raise 151 percent more annual capital than non-AI peers in North America and 181 percent more in the Middle East, compared with 42 percent more in East Asia, 16 percent more in Europe, and no detectable premium in Africa, Latin America, or South Asia. Accounting for targeted customer markets, founder credentials, early-team human capital, and local investor characteristics explains part of the gap in Latin America but leaves the broader global divide intact. In Africa, half of all AI funding goes to basic compute and data-center infrastructure; excluding these providers reveals that African AI product startups raise 57 percent *less* than non-AI peers. These patterns provide an early warning that AI may reach users around the world without building firms around the world.

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1 Introduction

Will artificial intelligence narrow or widen the income gap between rich and poor countries? The history of earlier general-purpose technologies gives reason for concern. Over the past two centuries, the lags with which developing countries adopted new technologies shrank, but the intensity with which they used those technologies, and their incomes, diverged (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Theoretical models warn that AI could follow a similar or even more polarizing path: when a new technology substitutes for labor or requires deep stocks of complementary capital, advanced economies capture the lion's share of the gains while developing economies risk losing their comparative advantage in tradable tasks (Korinek and Stiglitz, 2021; Alonso et al., 2022; Cazzaniga et al., 2024).

Because the aggregate productivity effects of AI will take years to materialize in national accounts, economists have turned to early warning indicators such as occupational employment shifts in the United States (Brynjolfsson et al., 2025a) and cross-country disparities in the usage of large language models (Appel et al., 2025; Sajadieh et al., 2026). Yet usage statistics capture only the consumption of AI tools built elsewhere. For developing and emerging economies to capture the rents, high-skill employment, and spillovers of technological change, they must also build and scale firms that produce AI and adapt it to local markets (Kalyani et al., 2025). Because venture financing and entry decisions are inherently forward-looking, the capital markets that back new ventures offer an early, high-stakes signal of where the supply side of the global AI economy is taking root (Bena et al., 2026).

This paper studies the global geography of AI entrepreneurship through the lens of startup financing. We define AI firms as startups that develop or sell AI products at any layer of the supply chain (applications, models, data tools, infrastructure, or compute) rather than firms whose employees merely use AI internally. Comparing AI and non-AI startups within the same country, founding cohort, and funding year, we ask four questions. First, do AI startups around the world build broader, more scalable businesses than non-AI startups, both in the customer markets they target and in how they organize work? Second, do capital markets reward this breadth with an "AI financing premium," and is that premium uniform across world regions? Third, where the financing premium is absent, can the gap be explained by differences in customer demand, the human capital of founders and early employees, or the characteristics and networks of local investors? Finally, what do the remaining gaps imply for the complementary infrastructure and institutions required to spread the gains from AI?

To answer these questions, we assemble a global dataset covering 116,795 startups founded between 2015 and 2022 across 172 countries in seven world regions: North America, Europe and Central Asia, East Asia and the Pacific, Latin America and the Caribbean, the Middle

East, South Asia, and Africa. We combine comprehensive company and deal records from PitchBook with data from Stears to ensure deep coverage of African ventures, including startups that never raised external capital or subsequently closed. We link these firms to the employment and educational histories of 52,203 founders and 719,358 early nonfounder employees from Revelio Labs, and to investor and fund-commitment records from Preqin. Using a large language model to apply a standardized questionnaire to company descriptions and archived web pages, we identify 42,312 AI producers and map each startup's targeted customers across 99 three-digit NAICS industries and 20 broad sectors. We further link employee occupations to O*NET work activities and task-level ratings of LLM exposure (Eloundou et al., 2024) to track how startups organize their workforces over time.

Our first set of results establishes that, on the real side of the firm, AI startups everywhere exhibit the defining traits of a general-purpose technology (GPT) (Bresnahan and Trajtenberg, 1995). Across all seven regions, AI startups target significantly broader customer markets than non-AI startups founded in the same country and year—serving 0.102 more broad sectors on average and proving 16 to 23 percentage points more likely to offer horizontal products that apply across industries. These differences are not artifacts of how firms market themselves; they hold conditional on data source and description length, and they are already visible in archived business descriptions written near founding. Furthermore, when AI startups target multiple industries, they do not string together unrelated markets: holding ordinary task overlap fixed, the industries targeted by multi-sector AI firms share tasks with significantly higher suitability for AI (0.080 higher on a zero-to-one scale). AI thus enables startups in every region to build a single technological capability and redeploy it across diverse customer sectors.

This product breadth is mirrored by organizational expansion inside the firm. Realizing the returns to a GPT requires complementary adjustments in how work is organized (Brynjolfsson et al., 2021). Using a quarterly panel of roughly 63,000 startups from 2021 through 2025, we examine how firms adjusted their workforces around the public release of ChatGPT in November 2022. To avoid endogenous post-release adjustments, we measure each firm's baseline task amenability to AI in December 2021 as the AI-weighted overlap between its workforce's tasks and the average industry's task profile. Controlling for firm fixed effects, country-by-quarter shocks, and baseline firm task suitability, we show that startups with higher baseline task amenability evolved in parallel with less-amenable peers prior to late 2022, but diverged sharply afterward. Following ChatGPT's release, a one-standard-deviation higher baseline amenability is associated with 1.09 additional distinct work activities on average in 2023–2025 (rising to 1.54 by late 2025) and a 1.62 percentage point increase in the likelihood of employing commercial staff. Rather than merely displacing labor, generative

AI appears to help startups broaden their internal scope and commercialize across wider markets (Acemoglu and Restrepo, 2019).

If AI startups in every region build broader products, and if AI-amenable organizations expand their operational and commercial reach, standard theories of innovation finance predict that AI startups should command a financing premium over comparable non-AI startups (Babina et al., 2024; Hoberg and Phillips, 2025; Kim and Koning, 2026). Our second set of results shows that while an AI financing premium exists on average (AI startups raise 87 percent more annual funding than non-AI peers) its geography is highly unequal. We estimate annual funding between 2019 and 2025 using Poisson pseudo-maximum likelihood (PPML) with country-by-funding-year, country-by-founding-year, and firm-age fixed effects. Because these fixed effects absorb the aggregate supply of venture capital, macroeconomic conditions, and financial development in each country and year, our estimates isolate how investors value AI startups relative to non-AI startups operating in the same local market.

The regional divergence is striking. In North America and the Middle East, AI startups raise 151 percent and 181 percent more annual funding, respectively, than non-AI startups founded in the same country and year. In East Asia and the Pacific, the premium is 42 percent; in Europe and Central Asia, it is just 16 percent. In Africa, Latin America and the Caribbean, and South Asia, the AI financing premium vanishes entirely. Relative to North America, the AI-to-non-AI funding ratio is 54 percent lower in Europe, 63 percent lower in South Asia, 65 percent lower in Africa, and 76 percent lower in Latin America. These patterns are robust to classifying AI status from archived website descriptions near founding, mitigating concerns that successfully funded startups simply rebrand as AI firms later in life.

Why do investors give AI startups a large funding premium in North America while offering no premium at all in Africa, Latin America, and South Asia, despite AI startups building broader businesses in all of these regions? In the third part of the paper, we test three primary candidate explanations by sequentially introducing firm, worker, and investor controls on a consistent sample of 554,513 firm-years and tracking how each region's funding gap relative to North America changes.

First, we test a demand explanation: AI startups in developing regions might target customer industries with weaker global growth or lower willingness to pay for AI. Absorbing worldwide demand shocks via principal-customer-industry-by-year fixed effects and controlling for product breadth narrows the gap relative to North America only slightly (by 0.06 to 0.08 log points in Europe, East Asia, and South Asia) and leaves the gaps in Africa and Latin America unchanged.

Second, we test a human capital explanation. Venture capitalists place heavy weight on founding teams and early hires (Hsu, 2007; Bernstein et al., 2017; Choi et al., 2025). We

measure whether founders previously started another company, hold an MBA, or hold a PhD, alongside the size, prior startup experience, and university education of early nonfounder employees. While startups led by PhD founders raise 30 percent more capital, founder credentials explain less than 0.01 log points of any regional gap. Early nonfounder employees matter substantially more: larger and more educated early teams attract significantly more funding, and accounting for early-team characteristics narrows Latin America's gap relative to North America by 0.44 log points (roughly 29 percent). Yet early-team human capital does not narrow the gap for Africa or South Asia.

Third, we test a local investor explanation. Venture capital expertise and syndication networks are geographically concentrated (Chen et al., 2010; Lerner and Nanda, 2020; Colonnelli et al., 2026). For every startup and year, we construct its pool of potential VC investors (those active in the startup's country and primary industry over the preceding three years) and measure their early-stage focus (Barrot, 2017), typical round size, recent fund commitments (Kaplan and Schoar, 2005), and university alumni connections to the startup's founders (Garfinkel et al., 2026). Although startups raise substantially more capital when surrounded by early-stage-focused investors, larger-round investors, and alumni-connected VCs, controlling for these investor characteristics—and allowing their returns to differ between AI and non-AI firms—fails to narrow any regional gap. In fact, accounting for investor characteristics widens the estimated gaps for Europe and South Asia.

If customer demand, founder and worker human capital, and observable investor traits do not explain the missing AI premium in much of the world, what does? Our results point to a fourth explanation: complementary physical and institutional infrastructure. Unlike traditional software, scaling an AI startup requires intensive access to compute clusters, data centers, and reliable power, which are overwhelmingly concentrated in a few rich economies (Lehdonvirta et al., 2024; Sajadieh et al., 2026; Impink, 2026), as well as legal and financial institutions that support long-horizon, intangible-heavy equity contracts and liquid exit markets (Black and Gilson, 1998; Lerner and Schoar, 2005).

A striking pattern inside our African data points to the role of physical infrastructure. While computing and network infrastructure providers (such as data centers and cloud hosts) represent only 2 percent of AI firms and 12 percent of AI funding in North America, they account for 8 percent of AI firms and 51 percent of all AI funding in Africa. When we exclude infrastructure providers to focus on startups building AI models, tools, and applications, Africa's financing shortfall relative to North America deepens to -1.41 log points under current classifications and -1.48 log points under historical classifications: African AI product startups raise 57 percent *less* annual funding than comparable non-AI startups in the same country and year. In frontier markets, capital is flowing to build the basic physical rails of

the digital economy, while application-layer AI innovators remain starved of the financing premium their peers enjoy in North America.

For policymakers and development institutions, these findings carry a sobering message. Initiatives that focus solely on training founders, subsidizing local demand, or marginally expanding traditional venture pools are unlikely by themselves to close the global divide in AI entrepreneurship, though strengthening early technical and commercial talent pools may help in regions like Latin America. Instead, enabling local firms to capture the supply-side gains of AI as a general-purpose technology will likely require relaxing bottlenecks in compute infrastructure and technology-finance institutions. Absent these complements, the financing of global startups warns that AI may diffuse rapidly to users worldwide while concentrating firm creation and economic rents in a handful of regions.

1.1 Related literature

Our paper contributes to five literatures: the global diffusion of technologies and AI, AI as a general-purpose technology inside firms, the financing of innovation, the human capital and investor networks that shape venture capital flows, and the infrastructure and institutions on which technology ecosystems depend.

The global diffusion of AI. A foundational literature shows that while new technologies reach developing countries with shrinking adoption lags, differences in the intensity of use account for a large share of cross-country income disparities (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Even within advanced economies, the development of frontier technologies is geographically concentrated, and high-skill jobs remain anchored in pioneering hubs for decades (Kalyani et al., 2025). Theoretical work warns that labor-substituting AI may widen global inequality and erode developing countries' gains from trade (Korinek and Stiglitz, 2021; Alonso et al., 2022; Cazzaniga et al., 2024). Recent empirical work tracks AI's early diffusion through youth employment in exposed U.S. occupations (Brynjolfsson et al., 2025a), cross-country LLM usage (Appel et al., 2025; Sajadieh et al., 2026), firm entry in exposed sectors (Bena et al., 2026), and the correlation between national VC inflows and AI producer locations (Rishabh and Shreeti, 2026). We contribute a global supply-side indicator that separates investor valuation of AI from local financial depth: by comparing AI and non-AI startups within the same country and year across 172 countries, we show that while AI entrepreneurs everywhere build broad businesses, the capital market premium for doing so is restricted to a few regions.

AI as a general-purpose technology inside firms. General-purpose technologies spread across sectors through complementary innovation (Bresnahan and Trajtenberg, 1995) and require intangible organizational investments (Brynjolfsson et al., 2021), traits shared by large language models (Eloundou et al., 2024). In the United States, AI investment spurs firm growth through product innovation (Babina et al., 2024), firms expanding into related markets command higher valuations (Hoberg and Phillips, 2025), founders' scientific knowledge widens market scope (Chattopadhyay et al., 2025), and AI-native startups scale with smaller, flatter teams (Kim and Koning, 2026). Within firms, generative AI boosts worker productivity (Brynjolfsson et al., 2025b), and its net labor impact hinges on whether new tasks reinstate displaced labor (Acemoglu and Restrepo, 2019). We provide the first global micro-evidence on both the product and organizational margins: AI startups in every region target broader customer sectors connected by AI-suitable tasks, and startups with higher pre-ChatGPT task amenability expanded their distinct work activities and commercial staffing after generative AI became widely available.

Financing innovation. Venture capital finances a disproportionate share of radical innovation (Kortum and Lerner, 2000), yet concentrates on a narrow band of technologies and geographies (Lerner and Nanda, 2020). Financing conditions and the cost of experimentation govern the novelty of startups that VCs back (Nanda and Rhodes-Kropf, 2013; Ewens et al., 2018), while data-driven screening can tilt investors toward familiar archetypes (Bonelli, 2026). More broadly, financial development shapes industrial growth (King and Levine, 1993; Rajan and Zingales, 1998). We demonstrate that the financing advantage commanded by a frontier general-purpose technology varies sharply across regions even after holding local financial development and country-year funding cycles fixed.

Founders, early employees, and the geography of venture capital. Startup performance and VC backing depend heavily on founding teams (Hsu, 2007; Bernstein et al., 2017; Gompers et al., 2020), early nonfounder hires (Hellmann and Puri, 2002; Choi et al., 2025), and investor characteristics—including fund horizons (Barrot, 2017), fund size (Kaplan and Schoar, 2005), syndication networks (Sorenson and Stuart, 2001; Hochberg et al., 2007), partner experience (Sørensen, 2007; Nanda et al., 2020), geographic proximity (Chen et al., 2010; Bernstein et al., 2016; Chen and Ewens, 2025), and shared university networks (Garfinkel et al., 2026). In developing regions such as Africa, friction between local entrepreneurs and foreign investors constrains capital flows (Colonnelli et al., 2026). By linking global startup records to founder, employee, and investor histories, we show that while PhD founders, larger and more educated early teams, and connected, early-stage investors

strongly predict funding levels, they explain very little of the global divergence in the AI financing premium outside of early-team size and education in Latin America.

Infrastructure, institutions, and AI policy. Finally, we connect innovation finance to the literature on physical and institutional complements. Computing capacity and data centers are heavily concentrated in advanced economies (Lehdonvirta et al., 2024; Sajadieh et al., 2026), creating scaling bottlenecks for startups reliant on big-tech cloud providers (Impink, 2026). At the same time, venture contracting relies on liquid exit markets and legal enforcement (Black and Gilson, 1998; Lerner and Schoar, 2005). By ruling out demand, human capital, and observable investor traits—and by showing that African AI finance goes predominantly to data-center infrastructure rather than application builders—our paper highlights physical compute and institutional ecosystems as critical margins for global AI policy.

Outline. The paper proceeds as follows. Section 2 describes the data and measurement. Section 3 documents AI startups' broader customer markets and the workforce expansion associated with task amenability to AI. Section 4 estimates the AI financing premium across regions. Section 5 tests whether targeted markets, founders, early employees, and potential investors explain the regional financing gaps. Section 6 presents robustness checks—including historical classifications and the role of infrastructure providers—and discusses policy implications. Section 7 concludes.

2 Data and measurement

We combine company and financing data from PitchBook and Stears to identify AI firms, describe their customer markets, and measure their annual funding. We match these companies to employment and education histories from Revelio and to investor and fund information from Preqin. With these data, we measure the backgrounds of founders and early employees, the tasks that firms perform, and the characteristics of the investors that each startup could draw on. This section describes the sample and these measures in turn; Appendix A gives the details.

2.1 Companies and financing

We obtain companies' business activities, founding years, locations, financing, and investors from PitchBook and supplement this information with Stears data on African startups. We

match companies across sources using names, websites, aliases, and employer profiles. A company appearing in both sources enters the sample once, with financing histories combined across providers.

Our sample consists of companies founded in 2015–2022 with an identified operating country and AI classification. We determine a company's operating country from the location of its early workforce when that location is unambiguous and from company-location information otherwise (Appendix A.1). We include firms with no reported financing and firms that subsequently closed, so the sample is not limited to startups that succeeded in raising capital. The sample contains 116,795 companies in 172 countries (Table 1). Of these, 116,292 appear in PitchBook and 1,063 in Stears, with 514 appearing in both.

We group operating countries into seven regions. North America comprises Canada and the United States; Africa includes North Africa, and the Middle East grouping also includes Pakistan and Malta; China is in East Asia and the Pacific and India in South Asia (Appendix A.1). Where no confusion arises, we shorten Europe and Central Asia to Europe, East Asia and the Pacific to East Asia, and Latin America and the Caribbean to Latin America.

We measure annual financing from 2019 through 2025. We reconcile duplicate financing reports and sum the amounts raised by each firm in each year, expressed in millions of nominal U.S. dollars. We include equity, debt, grants, and other forms of financing. Annual financing is zero when a firm has no positive reported funding in that year and no financing with an unknown amount or date that could fall in it. When financing is reported, but its amount or allocation cannot be determined, annual funding is missing. We observe annual amounts for 675,923 firm-years. Appendix A.5 gives the rules for allocating financing to years and measuring coverage, and Appendix B describes the estimation samples.

2.2 AI firms and customer markets

We use a large language model to apply a common questionnaire to companies' business descriptions and other available product information. We classify a company as an AI firm if it develops or sells AI products or services at any layer of the supply chain: applications, models, data tools, infrastructure, or compute. Products under development count; internal use of AI alone does not. We identify 42,312 AI firms, or 36.2 percent of the sample. The AI share ranges from 18.4 percent in Africa to 43.6 percent in East Asia and the Pacific (Table 1).

We use the same descriptions to measure the markets that firms target. We ask whether a company's products serve customers in each of 99 three-digit NAICS industries and 20

broad sectors. We count the industries to which the classifier assigns a score of at least 0.8, a cutoff fixed in pilot checks before we examined economic outcomes, together with each broad sector that meets this cutoff directly or through one of its detailed industries (Appendix A.2). We also classify whether the product is horizontal, meaning that it applies across industries, and identify its principal customer industry at the ISIC section level.

We classify offerings as described at data collection and apply these classifications to all funding years. The financing comparisons therefore describe the funding histories of firms subsequently classified as AI or non-AI. Because a firm could begin to sell AI products after it raises capital, Section 6.1 repeats the financing comparisons with AI status measured from earlier, dated descriptions.

To examine whether customer industries share tasks suitable for AI, we combine BLS occupational employment with O*NET task profiles and the human AI-exposure ratings of Eloundou et al. (2024). For firms targeting multiple industries, we measure the suitability for AI of the tasks those industries share. Appendix A.2 describes the questionnaires, classification checks, and task measures.

Table 1: Startups across regions

Region	Countries	Startups	AI firms	AI share (%)
North America	2	40,351	14,771	36.6
Africa	47	6,125	1,128	18.4
East Asia and Pacific	21	16,837	7,338	43.6
Europe and Central Asia	52	36,464	12,626	34.6
Latin America and Caribbean	30	4,319	1,429	33.1
Middle East	16	4,307	1,844	42.8
South Asia	4	8,392	3,176	37.8
All regions	172	116,795	42,312	36.2

Notes: We count each startup founded in 2015–2022 once across PitchBook and Stears. Regions refer to operating countries.

2.3 Founders and employees

We obtain individuals' employers, employment dates, job titles, locations, skills, and education from Revelio. We match these histories to companies using employer profiles and individual identities, identifying 52,203 founder–firm pairs across 47,425 companies.

We measure founders' backgrounds through December 31 of the founding year. Adapting the founder characteristics in Hsu (2007), we use indicators for whether any matched founder previously founded another firm, completed an MBA, or completed a doctorate. We identify

previous founding from an explicit founder role at another employer and use Revelio's Doctor degree category for doctorates. An observed positive trait is sufficient for an indicator of one; a zero requires usable information on all matched founders.

We identify early employees as the people working at the firm on December 31 of the year after founding, excluding identified founders of the focal startup. We use log one plus recorded nonfounder headcount, the share with prior startup employment, and the share with a completed bachelor's degree or higher. We measure prior employment before the employee's first known joining date at the startup and education by the early-team reference date. We calculate each share among employees with usable information and control separately for coverage and missing values. Because we measure the early team at the end of the year after founding, the explanatory comparisons in Section 5 use firm-years from age two onward, and they use the same observations throughout. Appendix A.3 gives the definitions and coverage.

To examine how firms organize work, we use quarterly employment data for firms founded in 2015–2020 over 2021–2025. We use employees' occupations and the associated O*NET work activities as a proxy for the tasks performed within each firm. We measure two outcomes: task breadth, the number of distinct work activities that the firm's workforce performs, and commercial staffing, an indicator for employing at least one worker in a commercial occupation. We measure a firm's task amenability to AI adoption by the AI-weighted overlap between its December 2021 tasks and the average industry's task profile, using BLS industry employment and the human AI ratings. Amenability is high when a firm's tasks are both suitable for AI and common across industries. These organizational measures include founders. Appendix A.4 describes the task weights and the quarterly sample.

2.4 Investors

For each startup and funding year, we identify potential venture capital investors from their investments before that year. An investor enters a startup's pool if it is explicitly classified as a VC organization and financed at least one sampled company in the startup's operating country and own industry during the preceding three calendar years. We define a company's own industry by its primary PitchBook industry, which differs from the customer industries used to measure product scope. We include follow-on investments and fix pool membership before January 1, whether or not the focal startup raises funding that year. The pools therefore describe the investors that each startup could draw on, even before it has raised any financing.

We describe these investors using four characteristics. Stage focus (early-stage orientation in the tables) is the share of their classified rounds that are seed, angel, or early-stage VC.

Typical round size is the median disclosed total amount of their past rounds. We calculate both characteristics from investments in other sampled companies during the same three years, excluding the focal startup, and average across investors with observed values. Recent fund commitments measure documented VC fund commitments closed in those three years, counting each fund once. Typical round size enters as the average across these investors of the log of one plus each investor's median, and recent fund commitments as the log of one plus the average commitments of investors with observed commitments, both in USD millions (Appendix A.6).

The fourth characteristic is founders' university connections to potential investors. For each founder with an observed completed qualification, we calculate the share of pool investors, among those with at least one employee whose school we observe, that employ another graduate of the same institution at the start of the funding year, and we average across those founders. Garfinkel et al. (2026) examine founders' university connections to VC partners; our annual measure uses all observed investor employees and prior-year information, and it weights investors equally.

Empty pools, missing school histories, and unobserved stage, amount, or fund information remain missing; we retain those firm-years using the information controls described in Section 4. Appendix A.6 gives the transformations, timing, and denominators.

3 AI firms' markets and organization

A general-purpose technology applies across many sectors, and realizing its gains requires firms to reorganize how they work (Bresnahan and Trajtenberg, 1995; Brynjolfsson et al., 2021). We examine both margins. We first ask whether AI firms target broader customer markets than non-AI firms and whether the industries they serve share tasks that AI can perform. We then ask whether firms whose tasks were more amenable to AI adoption reorganized after generative AI became widely available.

3.1 Customer markets

We compare the customer markets of AI and non-AI firms founded in the same country and year. We measure customer scope by the number of broad customer sectors, an indicator for targeting multiple sectors, the number of detailed customer industries, and an indicator for a horizontal product. Because a longer description can mention more customers, and description practices can differ across data providers, we control for the length of the business

text and for the data source. For each measure of customer scope, S_i, we estimate

$$S_i = \alpha_{c(i),b(i)} + \lambda_{d(i)} + \sum_r \beta_r A_i \mathbf{1}\{r(i) = r\} + \theta_1 L_i + \theta_2 L_i^2 + \varepsilon_i, \tag{1}$$

where A_i identifies an AI firm, $c(i)$ is its operating country, $b(i)$ is its founding year, $r(i)$ is its region, $d(i)$ is its data source (PitchBook, Stears, or both), and L_i is log one plus the number of words in its business text. The coefficient β_r measures the AI–non-AI difference within region r. We estimate the equation by ordinary least squares and cluster standard errors by country. We also estimate a single AI–non-AI difference across all seven regions.

AI firms target customers in more sectors than non-AI firms in every region (Figure 1a). The differences range from 0.059 sectors in Latin America and the Caribbean to 0.133 in Africa. AI firms are also 16–23 percentage points more likely to have horizontal products in every region (Figure 1b). In the full company sample, 48.8 percent of AI firms and 30.2 percent of non-AI firms have such products.

Across all regions, AI firms target 0.102 more broad sectors and 0.054 more detailed industries, and they are 1.8 percentage points more likely to target multiple sectors (Table 2). By region, the differences in the probability of targeting multiple sectors are imprecise in Latin America and the Middle East, and the difference in the number of detailed industries is imprecise in Latin America (Table B11).

Table 2: Customer scope of AI and non-AI firms

	Customer sectors (1)	Multiple sectors (2)	Customer industries (3)
AI firm	0.102***	0.018***	0.054***
	(0.004)	(0.002)	(0.003)
Country clusters	172	172	172
Observations	116,787	116,787	116,787
Country-by-founding-year fixed effects	✓	✓	✓
Data source fixed effects	✓	✓	✓
Text length controls	✓	✓	✓

Notes: We estimate overall AI–non-AI differences by OLS using equation (1). Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Broader markets could simply reflect firms that list unrelated customers. If AI allows a firm to redeploy one capability across industries, however, AI firms should target industries that share tasks AI can perform. We therefore compare the AI suitability of the tasks shared by firms' customer industries, holding fixed how much those industries' tasks overlap. The

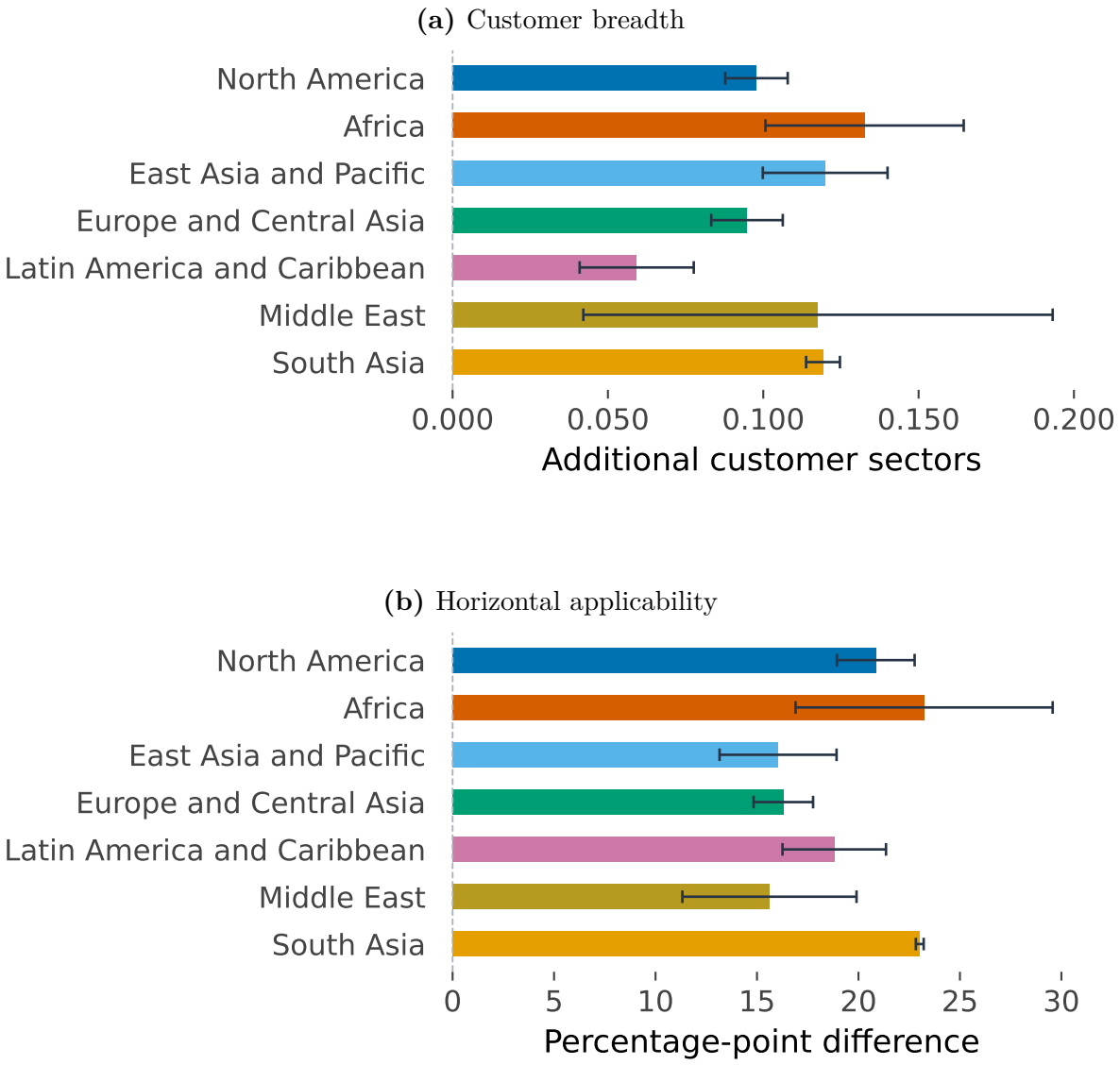


Figure 1: AI firms' customer markets across regions

Notes: We estimate AI–non-AI differences using equation (1). Customer scope counts targeted sectors out of 20; horizontal-product differences are in percentage points. Intervals are 95 percent confidence intervals clustered by country.

measure requires at least two customer industries with task profiles, so at our main threshold it is available for only 1,708 firms. Among them, AI firms target industries whose shared tasks are more suitable for AI: the difference is 0.080 on the zero-to-one suitability scale (Table B12). When we assign customer industries at the lower score threshold of 0.5, which makes the measure available for 32,300 firms, the difference is 0.035. Among firms that target several industries, AI firms thus sell to industries that make different products but perform related activities that AI can carry out.

3.2 Organizational changes

The public release of ChatGPT in November 2022 (2022Q4) made generative AI widely available. We use this release to examine whether firms whose tasks were more amenable to AI adoption subsequently expanded the range of their work activities and their commercial staffing. We follow firms founded in 2015–2020 from 2021Q1 through 2025Q4 and measure initial task amenability in December 2021, nearly a year before the release, so that it does not reflect firms' responses to it. Let Z_i denote this measure, standardized to have unit variance. For quarterly organizational outcome W_{iq}, we estimate

$$W_{iq} = \alpha_i + \lambda_{c(i),q} + \eta_{b(i),q} + \sum_{s \neq q_0} \delta_s Z_i \mathbf{1}\{q = s\} + \sum_s B_i' \gamma_s \mathbf{1}\{q = s\} + u_{iq}, \tag{2}$$

where q_0 is 2022Q3, the reference quarter before the release. Firm fixed effects absorb permanent differences across firms, and country-by-quarter and founding-cohort-by-quarter fixed effects absorb local shocks and life-cycle dynamics. The initial characteristics B_i are ordinary task affinity, the mean AI suitability of the firm's own tasks, log employment, task coverage, the number of countries represented among employees, and an indicator for missing country information. Interacting these characteristics with quarter indicators allows firms with different initial characteristics to follow different trends. Because the controls include both the AI suitability of a firm's own tasks and their overlap with other industries' tasks, the coefficients δ_s compare firms whose AI-suitable tasks are more or less common across industries. The identifying assumption is that, absent generative AI, firms with more and less amenable tasks would have evolved in parallel; the coefficients for the quarters before the release allow us to assess it. Under this assumption, δ_s measures how the arrival of generative AI changed firms with more amenable tasks relative to firms with less amenable tasks. Because we do not observe which firms used AI, it does not measure the effect of adopting AI. We cluster standard errors by country. Appendix A.4 defines task amenability and the outcomes.

Firms with more amenable tasks expanded the range of their work activities after the release (Figure 2). Among 63,020 firms, a one-standard-deviation difference in initial task amenability is associated with 1.09 additional work activities on average in 2023–2025 relative to 2022Q3, and the difference rises to 1.54 activities by 2025Q4. Before the release, we do not detect differential changes in task breadth: no pre-release coefficient is statistically significant, and we cannot reject that they are jointly zero ($p = 0.367$).

To illustrate what this looks like inside a firm, we compare two small health-technology companies in our sample below.

- *Health Cost IQ*, is an American company that analyzes costs for self-insured health plans, had tasks that were highly amenable to AI (93rd percentile). Its amenability came from customer-facing paperwork and communication that AI handles well and that many industries share. This includes: Prepare documentation for contracts, applications, or permits (2584); Respond to customer problems or inquiries (ONET Task ID: 2580); Explain technical details of products or services (ONET Task ID: 4580); Develop business or marketing plans (ONET Task ID: 951). The number of distinct work activities they covered was 56 throughout 2022 and expanded to 88 by the end of 2025. New activities included: Analyze business or financial data (ONET Task ID: 21824); Develop scientific or mathematical theories or models (ONET Task ID: 21837); Develop financial or business plans (ONET Task ID: 21251); Advise others on products or services (ONET Task ID: 8114); Write material for artistic or commercial purposes (ONET Task ID: 20554).

- *Vitomy*, on the other hand, is a German company that makes a coaching app for health, had work that was not very amenable to AI (19th percentile). Its two largest activities were Communicate with others about specifications or project details (ONET Task ID: 21673) and Design computer or information systems or applications (ONET Task ID: 21667), alongside work such as Test performance of computer or information systems (ONET Task ID: 21706). AI tools help with this kind of work, but it is very specific to software design, so few other industries share it. This company covered 51 distinct work activities throughout 2022, and the same 51 persisted by the end of 2025.

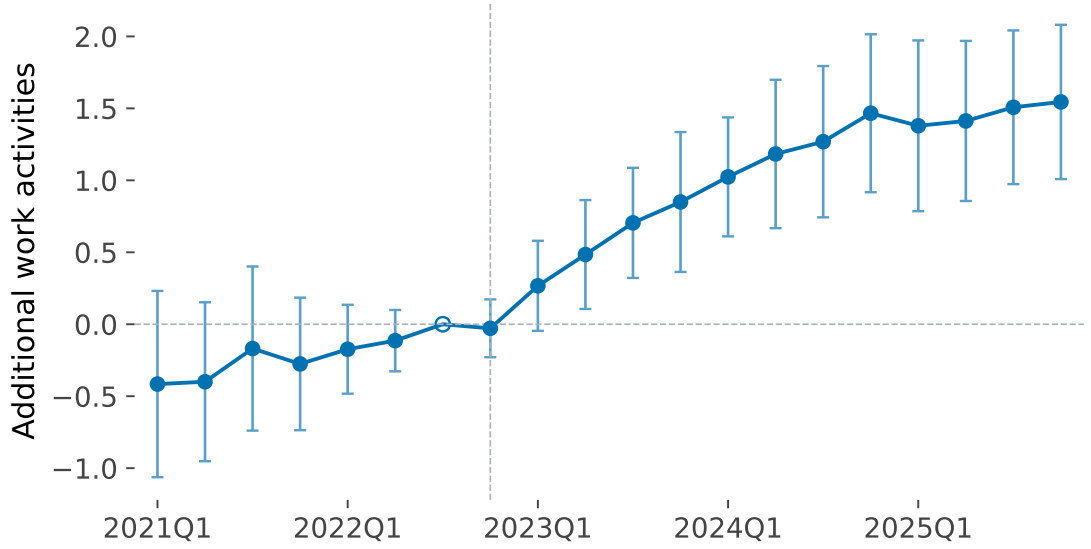


Figure 2: Task amenability to AI adoption and work activities

Notes: The figure plots the coefficients δ_s from equation (2): the difference in the number of work activities between firms one standard deviation apart in December 2021 task amenability, relative to 2022Q3. The sample includes AI and non-AI firms. Intervals are 95 percent confidence intervals clustered by country. Dashed lines mark zero and 2022Q4. The p-value for the joint test that all prerelease coefficients are zero is 0.367.

Firms with more amenable tasks also became more likely to employ commercial staff (Figure 3). Among 62,894 firms, the same difference in initial task amenability is associated with a 1.62 percentage point higher probability of employing any commercial staff on average in 2023–2025. For this outcome, the prerelease coefficients show some movement (joint $p = 0.092$), so we interpret it with more caution. Table B13 reports the quarterly coefficients for both outcomes.

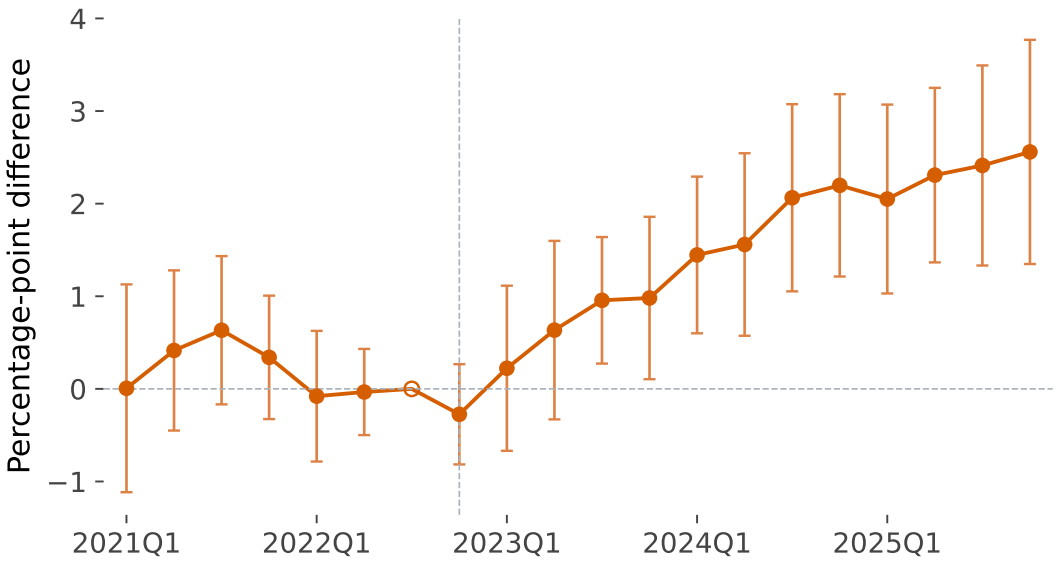


Figure 3: Task amenability to AI adoption and commercial staffing

Notes: The figure plots the coefficients δ_s from equation (2): the difference in the probability of employing commercial staff, in percentage points, between firms one standard deviation apart in December 2021 task amenability, relative to 2022Q3. The sample includes AI and non-AI firms. Intervals are 95 percent confidence intervals clustered by country. Dashed lines mark zero and 2022Q4. The p-value for the joint test that all prerelease coefficients are zero is 0.092.

A before–after comparison that uses 2022Q4–2025Q4 as the post period yields 1.22 additional activities and a 1.29 percentage point increase in commercial staffing (Table B14). These estimates describe how firms reorganized after the release, not the effect of adopting AI. Their direction suggests that AI adds activities within firms rather than only automating existing ones, the margin on which new tasks reinstate labor (Acemoglu and Restrepo, 2019).

Together, these results show that AI firms target broader markets than other firms and that task amenability to AI is associated with broader organizations. In every region, AI firms target more customer sectors and more often sell horizontal products. When they target several industries, those industries also share tasks that AI can perform, so a capability built for one customer can serve the next. Among the startups founded in 2015–2020 whose workforces we follow, AI and non-AI alike, those whose tasks were more amenable to AI also expanded their activities and their commercial staff once generative AI became available. Such businesses can scale across markets, and the complementary investments they require must be financed. If investors value this potential, AI firms should raise more funding than comparable non-AI firms. We next examine whether they do and whether the premium is the same across regions.

4 The AI financing premium

We compare the annual funding of AI and non-AI firms that operate in the same market at the same time. For firm i, founded in year $b(i)$ and operating in country $c(i)$, we estimate the conditional mean

$$\mathbb{E}[Y_{it} \mid A_i, Q_{it}, \text{FE}] = \exp\Big\{\alpha_{c(i),t} + \eta_{c(i),b(i)} + \tau_{a(i,t)} + \beta A_i + Q_{it}'\pi\Big\}, \tag{3}$$

where Y_{it} is annual funding in USD millions in year $t = 2019, \ldots, 2025$ and $a(i,t)$ is firm age. The country-by-funding-year effects $\alpha_{c(i),t}$ hold fixed everything that startups in a country share in a given year, including local demand, macroeconomic conditions, the depth of the financial system, and the stage of the funding cycle. The country-by-founding-year effects $\eta_{c(i),b(i)}$ compare firms founded in the same country and year, and the categorical firm-age effects $\tau_{a(i,t)}$ absorb life-cycle patterns in funding. The coefficient β therefore measures how much more AI firms raise than non-AI firms in the same market, not how much capital each market supplies. The corresponding percentage premium is $100[\exp(\beta) - 1]$.

The vector Q_{it} contains what we call the information controls: indicators for missing characteristics, founder matches, employee and investor coverage, and text length. We also interact AI status with indicators for missing investor information and calculate AI premia with those missingness indicators set to zero. The premia therefore describe firm-years for which potential-investor information is observed. Outside Africa, stage and round-size information is less often available for AI firms: in the explanatory sample of Section 5, for example, the stage focus and typical round size of potential investors are observed for 60.0 percent of North American AI firm-years and 93.7 percent of North American non-AI firm-years. In Africa, the pattern reverses: 48.8 and 45.1 percent of AI firm-years against 32.9 and 31.9 percent of non-AI firm-years (Table A5). When we add investor characteristics in Section 5, we also evaluate premia at common investor reference values across regions.

We estimate the conditional mean by Poisson pseudo-maximum likelihood (PPML) (Santos Silva and Tenreyro, 2006), which accommodates the many firm-years with zero funding and yields coefficients that measure proportional differences in expected funding. The overall and regional comparisons use 672,906 firm-years from 114,621 firms in 163 countries. We cluster standard errors by country. Appendix B describes the estimation samples and reports the explanatory comparisons of Section 5 with standard errors clustered by firm.

AI firms receive 87 percent more annual funding than non-AI firms in the same country, founding cohort, and funding year (Figure 4; Table B1, column 1).

This average combines very different regional premia. To measure them, we estimate a North American premium and each other region's difference from it:

$$\mathbb{E}[Y_{it} \mid A_i, Q_{it}, r(i), \mathrm{FE}] = \exp\Big\{\alpha_{c(i),t} + \eta_{c(i),b(i)} + \tau_{a(i,t)} + \beta_{NA} A_i + \sum_{r \neq NA} \kappa_r A_i \mathbf{1}\{r(i) = r\} + Q_{it}'\pi\Big\}. \tag{4}$$

Within region r, the AI-to-non-AI funding ratio is $\exp(\beta_{NA}+\kappa_r)$. Relative to North America's ratio, the percentage difference is $100[\exp(\kappa_r) - 1]$. The country-by-year effects absorb the region main effects, so κ_r compares the AI premium within region r with the AI premium within North America.

AI firms have the largest financing advantages in North America and the Middle East, where they receive 151 and 181 percent more annual funding than non-AI firms. They receive 16 percent more in Europe and Central Asia and 42 percent more in East Asia and the Pacific. In Africa, Latin America and the Caribbean, and South Asia, we do not detect a premium: the estimated AI–non-AI differences are negative and not statistically significant.

Relative to North America, the AI-to-non-AI funding ratio is 65 percent lower in Africa, 76 percent lower in Latin America, and 63 percent lower in South Asia. It is also 54 percent lower in Europe and Central Asia and 44 percent lower in East Asia and the Pacific. Each of these five differences is statistically significant, so we reject that the regional premia are equal (Table B1, column 2). The estimated Middle Eastern ratio is 12 percent higher than North America's, but the difference is not statistically significant.

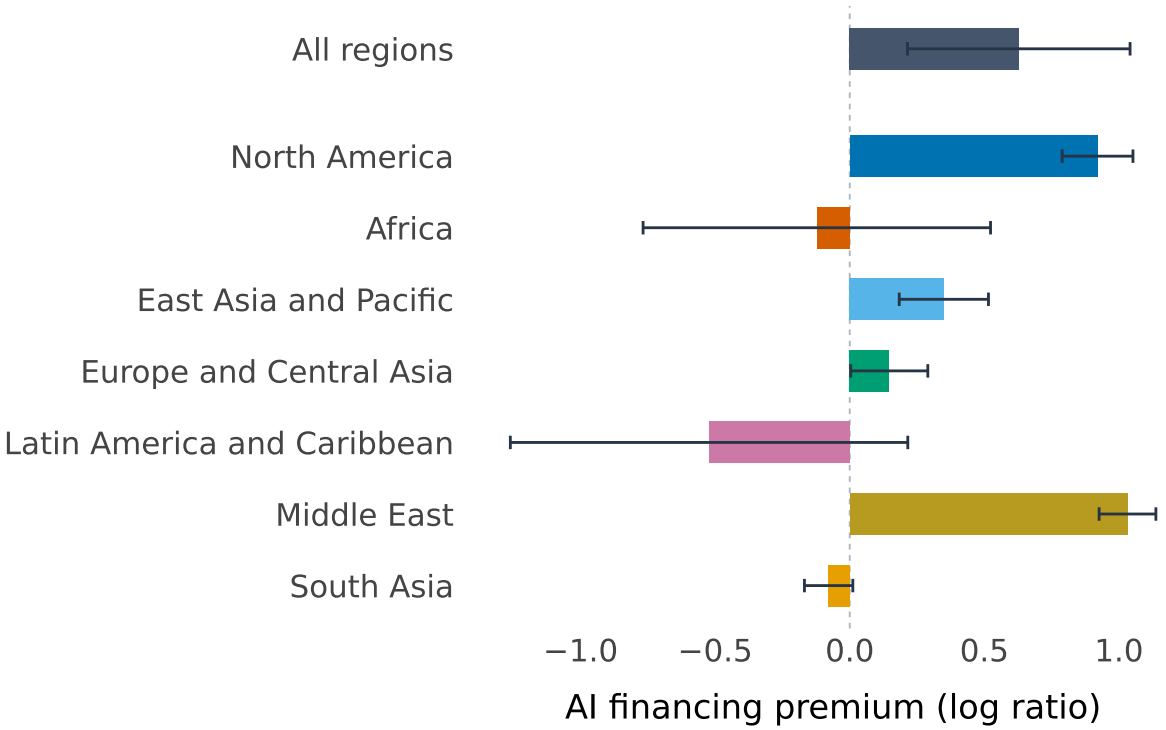


Figure 4: The AI financing premium across regions

Notes: We estimate overall and regional log funding ratios for AI relative to non-AI firms using equations (3) and (4) on the same sample. Intervals are 95 percent confidence intervals clustered by country.

The financing advantage that a general-purpose technology should command is thus concentrated in a few regions. It is absent in Africa, Latin America, and South Asia, where AI firms, as everywhere else, target broader markets than non-AI firms. The next section asks what explains this geography.

5 Explaining regional differences

Why do AI firms command a premium in some regions but not in others? The gaps could arise if AI firms in different regions target different markets, are led by founders with different backgrounds, hire different early teams, or can draw on different investors. We examine these explanations by adding each set of characteristics in turn and tracking how each region's AI premium relative to North America's changes. We build on the technology-by-group comparisons in Bloom et al. (2012, Table 6, columns 2 and 4) and the display of conditional gaps in Chetty et al. (2020, Figure VIII), adapting these approaches to estimate regional AI premia by PPML.

All five specifications use the same 554,513 firm-years from firms aged two and older, so changes across specifications reflect the added characteristics rather than changes in the sample. Restricting the broad financing sample to these firm-years leaves the regional premia close to those in Section 4 (Table B2). Every specification, starting with the Baseline, which estimates equation (4) on these firm-years, also includes what we call the expanded information controls: the information controls of Section 4 plus availability and coverage controls for the founder, employee, and investor characteristics that we add later. We evaluate the AI premia at a common reference profile of these controls.

The expanded controls change the levels of the premia substantially. On the same firm-years, North America's AI premium is 0.93 log points with the information controls of Section 4 (Table B2, column 2) but 0.04 log points and not statistically significant in the Baseline specification (Table 3, column 1), and it remains statistically insignificant in all five specifications. Africa's gap narrows from -1.03 to -0.51 log points and is no longer statistically significant ($p = 0.108$), while the other gaps change by at most 0.13 log points. Because the levels of the premia depend on these controls, we focus on how each region's gap relative to North America changes as we add characteristics.

The sequence adds four sets of characteristics. We first add principal-customer-industry-by-year effects, horizontal applicability, and log one plus the number of detailed customer industries (Demand). Next we add founders' previous founding experience, MBA attainment, and doctorate attainment (Founders). We then add log one plus nonfounder headcount and the shares of early employees with prior startup employment and with bachelor's-or-higher education (Employees). Finally, we add the four potential-investor characteristics and their interactions with AI status (Investors), which allows stage focus, typical round size, recent fund commitments, and university connections to have different associations with funding for AI and non-AI firms. Section 2 defines these characteristics. With D_i, F_i, and E_i denoting the market, founder, and employee characteristics and I_{it} the investor characteristics, the final conditional mean is

$$\begin{aligned}\mu_{it} = \exp\Big\{&\alpha_{c(i),t} + \eta_{c(i),b(i)} + \tau_{a(i,t)} + \psi_{j(i),t} + \beta_{NA}A_i + \sum_{r\neq NA}\kappa_r A_i \mathbf{1}\{r(i)=r\} \\ &+ D_i'\delta + F_i'\phi + E_i'\omega + (I_{it}-\overline{I})'\rho + A_i(I_{it}-\overline{I})'\gamma + Q_{it}'\pi\Big\}.\end{aligned} \tag{5}$$

Here $j(i)$ is the principal customer industry, Q_{it} now contains the expanded information controls, and $\overline{I}$ contains the means of the observed investor characteristics in the common sample. For non-AI firms, the slope on an investor characteristic is ρ; for AI firms, it is $\rho + \gamma$, so γ measures the difference between the two slopes. Because we center each investor characteristic at its mean, the regional premia $\beta_{NA} + \kappa_r$ are evaluated at the same investor

characteristics in every region. We use the same units for each main effect and its AI interaction and report coefficients on shares per ten-percentage-point increase. The fixed effects absorb any exactly redundant information controls.

For each region, the change in its gap between adjacent specifications measures how much the added characteristics account for that region's difference from North America. Because adjacent specifications use the same observations, we compute standard errors for these changes from their joint country-clustered covariance (Appendix B). We test whether the seven regional premia are equal and whether the six gaps change jointly as we add each set of characteristics (Table 3). Table B3 reports the individual changes and their standard errors, and Figure 5 plots each region's gap across the five specifications.

5.1 Targeted markets

If AI firms in some regions target markets with weaker demand, accounting for targeted markets should narrow their gaps. Our comparisons already absorb conditions common to all startups in a country and year. The Demand specification also absorbs worldwide changes in funding across the principal customer industries that startups target, and it controls for the horizontal applicability and breadth of their products. These controls narrow the gaps relative to North America modestly: by 0.058 log points for Europe and Central Asia, 0.081 for East Asia and the Pacific, and 0.057 for South Asia (Table B3). The changes for Africa, Latin America, and the Middle East are imprecise. We reject the hypothesis that all six gaps remain unchanged, but every gap that is statistically significant in the Baseline specification remains so. Within customer industries and years, neither horizontal applicability nor customer breadth has a statistically significant association with funding (Table B5).

5.2 Founders and early employees

Investors place great weight on founding teams (Gompers et al., 2020; Bernstein et al., 2017), so regional differences in founders could account for regional differences in the AI premium. Adding founders' previous founding experience, MBA attainment, and doctorate attainment changes each regional gap by less than 0.01 log points, and we do not reject that all six gaps remain unchanged ($p = 0.219$). These traits are observed for only 12 to 18 percent of the firms in this sample (Appendix A.3), and the indicators for missing founder information enter every specification, so this step can change the gaps only through that minority of firms. Of the three credentials, only a doctorate is associated with more funding: in the final specification, firms with a founder who holds a doctorate receive 30 percent more annual

funding, while the estimated associations with previous founding and an MBA are negative and imprecise (Table B6).

Early employees matter more. Adding the size, prior startup experience, and education of early nonfounder employees narrows Latin America's gap relative to North America from 1.54 to 1.10 log points. This change of 0.44 log points is the largest in the sequence and is statistically significant. South Asia's gap widens by 0.054 log points, and the other changes, including Africa's, are imprecise. We reject the hypothesis that all six gaps remain unchanged.

Firms with larger early teams and more educated employees receive more funding (Table B7). In the final specification, the coefficient on log one plus nonfounder headcount is 1.18, so expected funding rises slightly more than proportionally with one plus the size of the early team. A ten-percentage-point increase in the share of employees with a bachelor's degree or higher is associated with 8 percent more funding. The same increase in the share with prior startup employment is associated with 5 percent more funding, but the confidence interval includes both lower and higher funding.

5.3 Investors

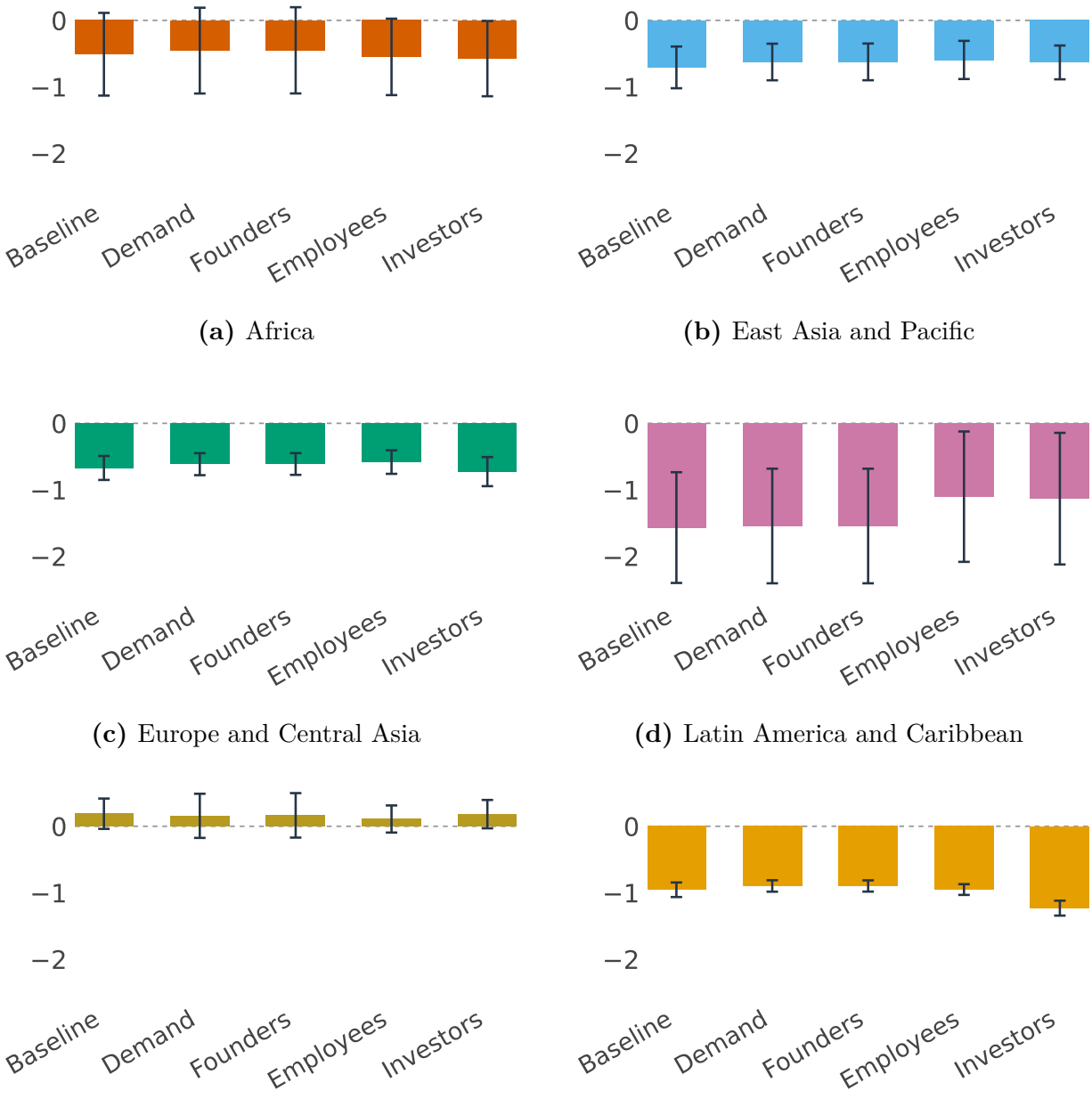
Venture capital, and the experience and networks of the investors who provide it, are concentrated in a few places (Chen et al., 2010; Lerner and Nanda, 2020). If AI firms in some regions can draw only on investors that are less able to evaluate or finance AI businesses, accounting for potential investors should narrow their gaps. It does not. When we add the four investor characteristics and their interactions with AI status, Europe's gap relative to North America widens by 0.14 log points and South Asia's by 0.28, and the Middle East's positive difference increases by 0.073 log points. The changes for Africa, Latin America, and East Asia are imprecise. We reject the hypothesis that all six gaps remain unchanged.

The investor characteristics are nonetheless strongly associated with funding. AI and non-AI firms receive more annual funding when their potential investors focus more on early-stage companies, participate in larger rounds, and share more university connections with their founders (Tables B9 and B10). A ten-percentage-point increase in stage focus is associated with 23 percent more funding for non-AI firms and 14 percent more for AI firms; this difference is not statistically significant at the five percent level ($p = 0.051$). A one-unit increase in the typical-round-size measure, the average across potential investors of the log of one plus each investor's median round size in USD millions, is associated with 1.11 log points more funding for non-AI firms and 0.56 for AI firms; the difference between these slopes is statistically significant (Table B8). A ten-percentage-point increase in university connections is associated with 14 percent more funding for non-AI firms and 19 percent more for AI firms.

Still, the difference between these associations is imprecise. Recent fund commitments have positive but imprecise associations for both groups. We obtain the slopes for AI firms by adding the main effects and interactions, and we compute their standard errors using the covariance between the two.

After we account for targeted markets, founders, early employees, and potential investors together, the AI-to-non-AI funding ratio is lower than North America's in Africa, Europe and Central Asia, Latin America, East Asia and the Pacific, and South Asia, and we continue to reject that the regional premia are equal (Table 3, column 5). Africa's gap is the least robust of these: it is statistically significant only in this final specification ($p = 0.046$), and not when we cluster standard errors by firm (Section 6.1). In levels, the AI–non-AI difference is negative and statistically significant at the five percent level only in Europe and South Asia; as noted above, these levels reflect the expanded information controls as well as the added characteristics.

Because startups and investors choose one another, and because founders' backgrounds and their university connections to potential investors are observed for fewer than one in five firms or firm-years, these comparisons describe conditional associations among the characteristics we observe rather than the causal contribution of each set of characteristics. They do show that the observed markets, founders, and potential investors of AI firms account for little of the regional differences in the AI premium. Early teams account for part of Latin America's gap, but the gap between North America and Africa is not explained by the measured human capital of the people who start and staff AI firms, nor by the observed stage focus, typical round size, recent fund commitments, or university connections of the investors they could draw on.



(a) Africa

(b) East Asia and Pacific

(c) Europe and Central Asia

(d) Latin America and Caribbean

(e) Middle East

(f) South Asia

Figure 5: Regional AI financing differences after accounting for observed characteristics

Notes: We plot differences in AI financing premia relative to North America, in log points, as we add customer markets (Demand), founder characteristics (Founders), early-employee characteristics (Employees), and potential-investor characteristics (Investors) to the Baseline specification. All specifications use the same sample. Intervals are 95 percent confidence intervals clustered by country.

Table 3: Regional AI financing differences

	Annual financing (USD millions)				
	Baseline	Demand	Founders	Employees	Investors
	(1)	(2)	(3)	(4)	(5)
AI premium: North America	0.0369	-0.0738	-0.0742	-0.0756	0.0580
	(0.2445)	(0.2909)	(0.2882)	(0.3009)	(0.3092)
AI difference: Africa	-0.5096	-0.4548	-0.4507	-0.5494	-0.5755*
	(0.3174)	(0.3292)	(0.3308)	(0.2933)	(0.2887)
AI difference: East Asia and Pacific	-0.7073***	-0.6262***	-0.6243***	-0.5954***	-0.6325***
	(0.1601)	(0.1404)	(0.1410)	(0.1464)	(0.1298)
AI difference: Europe and Central Asia	-0.6716***	-0.6141***	-0.6114***	-0.5827***	-0.7263***
	(0.0918)	(0.0845)	(0.0836)	(0.0903)	(0.1116)
AI difference: Latin America and Caribbean	-1.5681***	-1.5443***	-1.5443***	-1.1031*	-1.1332*
	(0.4249)	(0.4399)	(0.4397)	(0.5003)	(0.5051)
AI difference: Middle East	0.1891	0.1574	0.1644	0.1096	0.1828
	(0.1165)	(0.1694)	(0.1707)	(0.1041)	(0.1088)
AI difference: South Asia	-0.9546***	-0.8978***	-0.8979***	-0.9515***	-1.2311***
	(0.0559)	(0.0439)	(0.0432)	(0.0412)	(0.0572)
Firms	114279	114279	114279	114279	114279
Country clusters	157	157	157	157	157
Regional premia equal: p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Regional differences changed: p-value		< 0.001	0.219	< 0.001	< 0.001
Observations	554,513	554,513	554,513	554,513	554,513
Firm age fixed effects	✓	✓	✓	✓	✓
Country × funding year fixed effects	✓	✓	✓	✓	✓
Country × founding year fixed effects	✓	✓	✓	✓	✓
Customer industry × funding year fixed effects		✓	✓	✓	✓

PPML estimates from the nested models in equation (5). Regional differences are relative to North America's AI premium. Parentheses contain country-clustered standard errors; joint tests assess equality of regional premia and changes from the preceding column. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

AI contrasts are evaluated at the model's centered reference profile and common information controls. Investor main effects and AI interactions use the same units.

6 Robustness and Discussion

6.1 Robustness

Two features of our measurement could shape the regional premia. We classify AI status from current business descriptions, and the AI supply chain we measure includes firms that supply computing or network infrastructure, whose financing differs from that of firms that build AI products. We examine each in turn, check whether AI firms' broader customer markets are visible near founding, and consider an alternative level of clustering. Appendix C reports the details of the first three checks, and Table B4 reports the firm-clustered estimates.

When AI activity is observed. We apply the current classification to all funding years (Section 2.2). A firm may begin to sell AI products after it raises capital, so the current classification could count funding that a firm raised before its AI activity began as funding of an AI firm. To address this concern, we identify firms' offerings from archived company websites and from dated accounts published by firms, investors, and regulators. We then reclassify AI status in two ways: from each firm's earliest qualifying description from the founding year onward, and from a description written in the founding year or either of the next two calendar years. We hold each classification fixed across funding years and re-estimate equations (3) and (4) (Appendix C.1). An early description can still postdate some of a firm's funding years, so these classifications reduce rather than eliminate this concern.

The historical classifications lower the North American premium but leave the main regional contrast in place (Tables C1 and C2). North American AI firms raise 2.51 times as much annual funding as comparable non-AI firms under the current classification, 2.22 times as much under the earliest description, and 2.03 times as much near founding. In Africa, AI firms raise 1.10 and 0.97 times as much as comparable non-AI firms under the two historical classifications, so we again detect no premium. The African AI-to-non-AI funding ratio is 65 percent below North America's under the current classification and 51 and 52 percent below it under the historical classifications, and both historical confidence intervals include equal ratios in the two regions. The gaps for East Asia and the Pacific, Europe and Central Asia, Latin America, and South Asia remain negative and statistically significant under both historical classifications, and the Middle East's premium remains statistically indistinguishable from North America's. Within regions, the historical classifications reduce the premium in Europe and Central Asia to about zero, and AI firms in South Asia raise about a quarter less than comparable non-AI firms.

The historical samples are smaller because they require a dated description, but they retain all but $0.79 million of recorded African funding under the earliest description and

93 percent of it near founding (Table C9). To separate the change in classification from the change in sample, we compare the two classifications on identical firm-years. On these observations, historical classifications reduce the North American premium by 0.085 log points using the earliest description and 0.120 log points near founding, and they narrow the Africa–North America gap by 0.30 and 0.36 log points; the paired confidence intervals for these changes in the gap include zero (Table C10).

Infrastructure providers. AI infrastructure providers, such as data-center operators and cloud hosts, supply the computing or network capacity on which other firms run workloads. They weigh heavily in African AI finance: they are 8 percent of African AI firms with observed financing but receive half of these firms' funding; in North America, they are 2 percent of AI firms and receive an eighth of their funding. We exclude these firms in every region, together with historical AI firms whose primary activity we could not determine, and re-estimate the regional premia under all three classifications (Appendix C.2).

Excluding infrastructure providers widens Africa's gap. The Africa–North America gap is −1.41, −1.48, and −1.61 log points under the current, earliest, and near-founding classifications, and each 95 percent confidence interval lies below zero (Tables C3–C5). Under the earliest classification, AI firms outside infrastructure raise 1.88 times as much annual funding as comparable non-AI firms in North America and 0.43 times as much in Africa (Figure C1). In this narrower group, moving from current to historical classifications on identical firm-years does not narrow the African gap: the estimated changes are −0.165 and −0.156 log points ($p = 0.497$ and $p = 0.641$). The point estimates therefore attribute the narrowing of the African gap under historical classifications, which is itself not statistically significant, to infrastructure providers. In the influence analysis, the two African firms whose added weight most narrows the historical gap are data-center operators, IXAfrica in Kenya and Africa Data Centres in South Africa. IXAfrica has the largest influence of any African firm, and excluding it alone yields a statistically significant African gap under both historical classifications (Appendix C.4).

Customer markets near founding. AI firms' broader customer markets are already visible near founding. When we use the same near-founding description to identify both AI status and customers, AI firms target 0.236 more broad sectors and 0.145 more detailed industries than comparable non-AI firms, and they are 5.1 percentage points more likely to target multiple sectors (Table C6). These differences exceed those based on current descriptions, although the two sets of estimates cover different firms. Near founding, AI firms target more sectors in every region and are more likely to have horizontal products in every

region except the Middle East, where the estimate is imprecise (Figure C2 and Table C7). They also target industries whose shared tasks are more suitable for AI (Table C8).

Clustering. Our main estimates cluster standard errors by country, so comparisons involving North America, which comprises two countries, and South Asia, which comprises four, rest on few clusters. When we cluster by firm instead, the gaps for East Asia and the Pacific, Europe and Central Asia, Latin America, and South Asia remain statistically significant in every specification of the explanatory sequence, and the Middle East's difference remains insignificant. Africa's gap, however, is not statistically significant in any specification with firm clustering, including the final one (Table B4).

Taken together, these checks indicate that the main regional contrast does not arise from when we observe firms' AI activity: the North American premium remains large, and we detect no premium in Africa, Latin America, or South Asia under any classification. Africa's gap relative to North America is the least robust of the regional gaps: its confidence intervals include zero under both historical classifications, in the first four specifications of the explanatory sequence, and in all five specifications when we cluster by firm. Infrastructure providers narrow, rather than create, this shortfall, and AI firms' broader markets are already visible near founding.

6.2 Discussion

AI firms in every region build the broad businesses that a general-purpose technology makes possible, yet investors favor AI firms over comparable non-AI firms in only some regions. Three features of our design and results shape how this contrast should be read.

First, the premium measures how much more AI businesses raise than other businesses in the same market, not the quantity of capital. We compare AI and non-AI firms within the same country and year, holding fixed the funding conditions they share. A region with a deep financial system can provide substantial funding to both groups while showing little difference between them, and a large premium can arise in a smaller startup market. Europe and Central Asia, with nearly as many startups in our sample as North America, shows a small premium, whereas the Middle East, with about a tenth as many, shows a premium similar to North America's. Because annual funding also reflects how much capital firms seek, the premium combines investors' assessment of AI businesses with those businesses' capital needs; the capital-intensive infrastructure providers discussed below illustrate the second channel.

Second, the characteristics we observe account for little of the regional gaps. Founders with doctorates, larger and more educated early teams, and potential investors with an

early-stage focus, larger rounds, and university connections to founders are all associated with more funding. Yet apart from the modest narrowing produced by targeted markets, only early teams account for part of a region's gap, and only in Latin America. Africa's gap is also sensitive to how we account for missing information: the expanded information controls of Section 5 alone narrow it by about half, to a gap that is no longer statistically significant, before any of these characteristics is added. The checks in Section 6.1 also give little support to two measurement explanations: that the regional pattern reflects when we observe firms' AI activity, or that infrastructure providers create Africa's gap. Our comparisons nonetheless describe conditional associations: startups and investors choose one another, several characteristics are observed for only a minority of firms, and characteristics we do not observe could differ across regions.

Third, the remaining gaps direct attention to complements that our data cannot measure. AI products run on data centers and computing capacity that are concentrated in a few countries (Sajadieh et al., 2026; Lehdonvirta et al., 2024), and access to infrastructure supplied by large technology firms can make it easier to establish an AI business while leaving substantial barriers to scaling it (Impink, 2026). In Africa, much of AI finance goes to building this infrastructure: firms that supply computing or network infrastructure receive half of the funding raised by AI firms, while the remaining AI firms raise less than comparable non-AI firms, 0.43 times as much under the earliest classification (Figure C1). Institutions specific to technology finance also matter: venture capital depends on exit markets (Black and Gilson, 1998), and the contracts that investors write and the valuations they pay depend on legal enforcement (Lerner and Schoar, 2005). For the regional AI premium, the relevant question is how valuable these complements are to AI firms relative to other businesses in the same economy.

Regional differences in AI financing matter even when AI tools are available everywhere. Firms can build businesses around AI tools developed elsewhere. They can adapt those tools to customers' needs, combine them with other products, and organize the work required to sell and support them. Such activities require teams and investment even when the underlying technology is available internationally, and firms whose tasks were more amenable to AI expanded their work activities and commercial staffing after ChatGPT's release. Differences in financing can therefore shape which local businesses pursue these opportunities as AI tools spread across borders. For policy, our results suggest that measures aimed only at the demand for AI, at founders' credentials, or at the observed characteristics of the investors active in a market are unlikely by themselves to close the regional gaps in AI finance. Investments in computing infrastructure and in the institutions that support technology finance are natural candidates whose effects remain to be measured.

7 Conclusion

National accounts will take years to reveal whether artificial intelligence narrows or widens income gaps across countries. Because venture capital and startup entry decisions are inherently forward-looking, the financing of the firms that build AI offers an early, high-stakes signal of where the supply side of the global AI economy is taking root. Examining 116,795 startups founded between 2015 and 2022 across 172 countries, we document a stark divergence between the real and financial sides of global AI entrepreneurship.

On the real side of the firm, AI startups everywhere display the defining hallmarks of a general-purpose technology. In every world region, AI startups target broader customer markets than non-AI startups founded in the same country and year, and they are 16 to 23 percentage points more likely to sell horizontal products that apply across industries. When AI firms serve multiple industries, they do not string together unrelated markets; they target sectors whose shared tasks are specifically suited to AI. Inside the firm, baseline task amenability to AI is similarly associated with organizational expansion: following the public release of ChatGPT, startups whose pre-existing tasks were more amenable to AI broadened the range of work activities performed by their employees and expanded their commercial staffing.

Yet the financing advantage that such scalable, multi-sector businesses should command is sharply localized. Holding local funding conditions fixed via country-by-funding-year and country-by-founding-year fixed effects, we find that AI startups raise 151 percent more annual capital than comparable non-AI startups in North America and 181 percent more in the Middle East, compared with 42 percent more in East Asia, 16 percent more in Europe, and no detectable premium in Africa, Latin America, or South Asia. This geographic divide is not an artifact of successful firms retroactively rebranding as AI startups; it persists when we classify firms using archived descriptions written near founding. Moreover, in Africa, half of all AI funding goes to providers of basic computing and network infrastructure. Excluding these data-center and cloud operators reveals that African startups building AI applications, models, and tools actually raise 57 percent less annual funding than comparable non-AI startups.

Firm, worker, and investor characteristics fail to explain this global divide. Controlling for global demand shifts across targeted customer industries, founders' prior entrepreneurship and graduate degrees, early nonfounder team size and education, and the stage focus, round scale, fund commitments, and university networks of local investors narrows the gap relative to North America in Latin America (where early-team human capital accounts for roughly 29 percent of the shortfall) but leaves the broader regional divide intact.

By ruling out differences in customer scope, founder credentials, and observable investor traits, our findings direct attention to the physical and institutional complements required to scale frontier technology. AI startups rely heavily on compute capacity and data infrastructure that remain concentrated in a few advanced economies, as well as financial and legal institutions (such as liquid exit markets and enforceable private equity contracts) that enable investors to back intangible-intensive ventures. Quantifying the causal returns to sovereign compute investments, cloud subsidies, and institutional reforms—and testing whether they narrow the regional AI financing gap—is a first-order priority for future research. Absent policies that build these supply-side complements, the financing of global startups warns that AI may rapidly reach users around the world without building firms around the world.

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A Measurement and coverage

This appendix describes how we construct the measures used in the main text. A.1 explains how we link firms across data sources and assign each firm an operating country. A.2 describes how we classify firms as AI or non-AI and measure their customer markets. A.3 and A.4 describe the founder, employee, and workforce-task measures. A.5 describes annual financing, and A.6 describes the potential-investor measures. **??** describes the sample restrictions.

A.1 Matching firms and identifying operating country

We link company records across datasets using standardized names, websites, aliases, locations, and employers. Confirmed duplicates are merged into a single firm, along with their financing histories. For company attributes, we use PitchBook where available, and Stears otherwise. To measure workforces, we link firms to Revelio employers through LinkedIn URLs and websites.

We define a firm's operating country as the country where it had the most employees in its founding year and the year after. That country must stay first even when every ambiguous location is assigned to the runner-up. Otherwise, we fall back on headquarters, then incorporation country, then a single country of operations confirmed by review. Regions follow the World Bank classification, except that North Africa is grouped with Africa.

When a founding year is missing, we recover it from company histories and matched employer profiles for the year the company began. Incorporation, acquisition, product-launch, and parent-company dates count only if they mark when the company itself began. Additionally, to measure investor resources, we match investors to Preqin using corroborating websites or LinkedIn identities, or a distinctive name that is unique within its country. Funds are linked to their managers through Preqin identifiers. For university connections, we match universities to OpenAlex by website and country.

A.2 Company classifications and customer markets

To classify firms, we apply a common questionnaire to company descriptions, keywords, sector labels, and homepage text using TypeSafe's Jev classifier (version `jev-1.13.0`). Yes/no classifications, such as AI status and whether a firm is horizontal (serving many industries rather than one), require a score above 0.5. Categorical ones take the most likely valid option. A firm is AI if it plays a qualifying role in the AI supply chain, offers a customer-facing AI product, or is confirmed as AI on review. Foundational firms qualify on their activities alone. Application and customer-facing firms must explicitly mention AI or machine learning; using

AI internally is not enough. A positive classification from any source makes a firm AI. A firm is non-AI only if its sources say so and no role or review says otherwise.

For product attributes, we use one source's classification throughout. When sources disagree about AI status, we use product information from a source that classifies the company as AI; otherwise, we use the first available classification. We classify the principal customer industry at the ISIC division level and aggregate to sections for the financing comparisons. Horizontal firms can have a principal industry. We use code `00` for either equal applicability across industries or insufficient information and distinguish these cases using the horizontal classification.

To measure customer breadth, we apply a questionnaire to full vendor descriptions: 99 questions about three-digit NAICS industries, 20 about broad sectors, and three about audience types. Each industry question names its code and title. We include an industry at a score of at least 0.8, chosen from predefined cutoffs in pilot content checks before examining economic outcomes. We count each broad sector once, whether identified directly or through a constituent detailed industry. A broad-sector classification alone does not establish a detailed industry. We ask about customers and explicitly intended users, including stated future targets. We count the firm's own industry, internal functions, suppliers, and partners only when they are also customers. Firms serving households and horizontal firms without specified customer industries can therefore have zero industries. We measure breadth for firms with text, including zero when no industry meets the threshold. For company aliases, we keep the counts, scores, and task measures from one source together. When the primary source lacks text, we require a matching description or agreement across candidate sources.

We compared two AI-assisted reviews of 140 stratified descriptions to assess agreement. In the scope comparisons, we account for data source and text length.

Shared customer tasks. We combine May 2021 BLS industry employment with O*NET version 27.2 mappings between tasks and work activities (U.S. Bureau of Labor Statistics, 2022; U.S. Department of Labor, Employment and Training Administration, 2023). We construct profiles for 81 of the 99 detailed customer industries. Within a detailed O*NET occupation, we give a core task twice the weight of another task and divide each task's weight equally across its associated detailed work activities. We average detailed occupation profiles within SOC occupations, weight occupations by industry employment, and normalize over activities with observed human AI ratings. Where the source combines industries, we use the combined profile once.

We use the human β ratings of Eloundou et al. (2024): direct LLM exposure plus one-half of exposure requiring complementary software. We average task ratings within activities

using the same normalized weights. Let p_{jt} be industry j's normalized weight on activity t and q_t its AI rating. For customer industries j and k, ordinary and AI-weighted overlap are

$$R_{jk} = \sum_t p_{jt} p_{kt}, \qquad A_{jk} = \sum_t p_{jt} q_t p_{kt}. \tag{A1}$$

For the covered unordered industry pairs $\mathcal{P}_i$ of startup i, shared-task AI suitability is

$$S_i^{AI} = \frac{\sum_{(j,k)\in\mathcal{P}_i} A_{jk}}{\sum_{(j,k)\in\mathcal{P}_i} R_{jk}}. \tag{A2}$$

We average R_{jk} over these pairs to measure ordinary overlap. Shared-task suitability requires at least two covered industries and positive ordinary overlap. When some customer industries lack profiles, we use the covered pairs. At the alternative 0.5 score cutoff, both customer classifications and the set of measurable firms change. We use U.S. production patterns to describe the tasks shared by customer industries.

A.3 Founders and nonfounder employees

We measure founders' characteristics using matched histories through December 31 of the founding year. Early employees are people with valid active employment spells on December 31 of the following year. We count each person once per startup and use the latest active position for occupation. We identify founders through reviewed matches to named founders and explicit founder roles at the focal employer. We remove them before calculating any employee characteristic or coverage. Employees who founded other companies remain in the employee sample. Like Choi et al. (2025), we distinguish founders from early nonfounder employees.

Careers and education. We identify previous founding from an explicit founder role at another employer begun by December 31 of the founding year. For employees, we use prior jobs begun strictly before their first usable joining date at the focal startup. Prior startup experience requires a matched employer with a known founding year and age zero through ten when that job began.

We classify education from Revelio's Bachelor, Master, MBA, Doctor, Associate, and High School categories. We use a qualification only if its completion date is known and no later than the person's reference date, and any reported start date does not follow completion. Missing completion dates and unrecognized categories remain unknown unless another completed qualification establishes a positive trait.

For employees, a completed Bachelor, Master, MBA, or Doctor qualification establishes bachelor's-or-higher education. Associate and High School qualifications alone establish a negative only when all contributing records have known categories and completion dates. This education share adapts conventional attainment measures to the available profile data; Dahl and Klepper (2015) measured education duration for individual hires.

Aggregation and coverage. For each characteristic, we assign one if any matched founder has it. We assign zero if at least one founder is matched and all matched founders are known not to have it. Otherwise, the characteristic is missing. We report the number of matched founders and the fraction with usable information for each trait. We also calculate the fraction of founders listed by each provider whom we match to individual profiles, counting entries within each provider.

For employee background h, we calculate

$$\text{Share}_{ih} = \frac{\text{employees known to have } h}{\text{employees with usable information on } h}, \tag{A3}$$

$$\text{Coverage}_{ih} = \frac{\text{employees with usable information on } h}{\text{nonfounder employees}}. \tag{A4}$$

We calculate shares when their denominators are positive. Firms with an observed team consisting only of founders have zero nonfounder headcount and undefined employee shares. A firm without an observed early team has missing headcount. Missing histories do not establish the absence of previous startup work or higher education.

We match 52,203 founder–firm pairs across 47,425 firms. From the 766,069 person–firm pairs in the early teams, we remove 46,711 identified founder–firm pairs, leaving 719,358 nonfounder employee–firm pairs. We observe no early team for 32,055 firms and only founders for 3,816 firms. The employee sample includes 36,534 pairs for which founder status is unresolved, or 5.1% of employee–firm pairs. We report these counts by region and AI status in Tables A1 and A2.

Prior startup experience is known for 89,538 nonfounder employee–firm pairs, of which 88,947 are positive. Its firm-level share is available for 33,083 firms: 32,734 have a share of one, 108 have zero, and 241 lie between zero and one. Average underlying employee coverage across firms with nonfounder employees is 11.9%. The financing comparisons retain the common annual sample using the expanded information controls of Section 5. Among the 114,279 firms in the financing comparisons, previous-founder status is observed for 17.8 percent, MBA status for 12.9 percent, and doctorate status for 12.3 percent. Nonfounder headcount is observed for 72.6 percent, prior startup employment share for 28.3 percent, and bachelor's-or-higher share for 60.8 percent. These are firm-level availability rates; each

observed share also has a separate person-coverage measure. We report firm-level availability of the founder and employee characteristics in Tables A3 and A4.

A.4 Firm tasks and amenability to AI adoption

We count each person once per startup in the last month of each quarter, including the start and end months of valid spells. We use the latest active position for occupation. Employment is zero for matched firms without an active job with usable dates. We identify jobs with missing or invalid employment dates and construct task profiles from mapped occupations.

Task breadth is the number of distinct O*NET intermediate work activities associated with the firm's occupations. Commercial staffing equals one when at least one employee has a mapped commercial occupation. For baseline task amenability, we map the December 2021 team to detailed activities and use 59 ISIC industry profiles based on 2014 BLS employment. Let w_{it}^0 be firm i's normalized baseline weight on covered activity t and $\bar{p}_t$ the equally weighted mean of industry task shares. With the human AI ratings q_t defined above, firm task amenability to AI adoption is

$$E_i = \sum_t w_{it}^0 q_t \bar{p}_t. \tag{A5}$$

Ordinary affinity is $\sum_t w_{it}^0 \bar{p}_t$, and the firm's own task suitability is $\sum_t w_{it}^0 q_t$. We standardize these measures in the December 2021 sample. The other baseline measures are log workforce size, task coverage, the number of countries represented in the workforce, and missing-country status. We use the whole December 2021 team, including observed founders.

We examine firms founded in 2015–2020 with a measurable December 2021 workforce. For each outcome, we require an observation in 2022Q3 and at least one other quarter, including zero outcomes. We analyze all 20 quarters from 2021Q1 through 2025Q4. For task breadth, we have 63,020 firms and 1,258,697 observations; for commercial staffing, we have 62,894 firms and 1,256,660 observations. Both comparisons span 164 countries. For the dynamic summary, we average the 2023–2025 coefficients. The static comparison begins its post period in 2022Q4.

A.5 Annual financing amounts

We combine duplicate financing reports across providers and company aliases, then sum funding within each year. We include reported or announced equity, debt, grants, and other financing in nominal U.S. dollars, excluding valuations and imputed investor contributions.

Table A1: Founder matching and early employee coverage

Region	Firms	Total	Matched founder	Missing employee data	Founder only	Unresolved candidate
North America	AI	14,771	6,666	3,259	302	4,133
	Non-AI	25,580	9,446	7,565	1,283	4,454
Africa	AI	1,128	464	223	20	253
	Non-AI	4,997	1,449	1,874	144	862
East Asia and Pacific	AI	7,338	2,149	3,349	210	1,150
	Non-AI	9,499	3,003	4,127	385	1,402
Europe and Central Asia	AI	12,626	6,508	2,121	267	3,284
	Non-AI	23,838	10,158	5,792	826	4,518
Latin America and Caribbean	AI	1,429	721	218	19	403
	Non-AI	2,890	1,259	539	70	702
Middle East	AI	1,844	1,019	248	22	724
	Non-AI	2,463	1,025	624	71	526
South Asia	AI	3,176	1,545	487	46	848
	Non-AI	5,216	2,013	1,629	151	826

Notes: We count firms by region and AI status. Matched founders have personal histories. Employee coverage refers to the end of the year after founding; employee characteristics exclude identified founders. Unresolved candidates are employees whose founder status is uncertain.

Table A2: Matching founders to personal histories

Region	Firms	Firms with founder lists	Founder entries	Matched entries	Overall matched (%)	Mean firm matched (%)
North America	AI	10,183	10,277	5,412	52.7	52.7
	Non-AI	14,596	14,634	7,515	51.4	51.4
Africa	AI	565	744	431	57.9	57.9
	Non-AI	2,017	2,414	1,198	49.6	50.0
East Asia and Pacific	AI	4,415	4,436	1,371	30.9	30.8
	Non-AI	5,326	5,329	2,041	38.3	38.3
Europe and Central Asia	AI	8,869	8,942	5,313	59.4	59.5
	Non-AI	14,059	14,104	8,023	56.9	56.9
Latin America and Caribbean	AI	999	1,005	564	56.1	56.2
	Non-AI	1,706	1,709	895	52.4	52.4
Middle East	AI	1,199	1,214	800	65.9	65.9
	Non-AI	1,347	1,355	793	58.5	58.6
South Asia	AI	2,239	2,253	1,273	56.5	56.7
	Non-AI	3,718	3,725	1,730	46.4	46.4

Notes: We count founder entries in company lists and matches to personal histories; founders listed by both providers contribute two entries. Overall coverage is matched entries divided by all entries; mean firm coverage is the unweighted average of firms' matched shares.

Table A3: Availability of selected founder characteristics in the financing sample

Region	Firm type	Firms	Prior founder experience	Founder MBA	Founder doctorate
North America	AI	14,422	21.5	15.4	14.9
	Non-AI	25,327	16.1	13.1	12.8
Africa	AI	1,071	16.1	11.7	10.4
	Non-AI	4,694	9.7	9.0	7.9
East Asia and Pacific	AI	7,146	12.1	9.3	9.5
	Non-AI	9,346	11.8	9.6	9.4
Europe and Central Asia	AI	12,296	23.8	15.0	15.4
	Non-AI	23,503	18.3	11.3	11.0
Latin America and Caribbean	AI	1,368	21.9	12.6	7.7
	Non-AI	2,813	18.9	10.8	6.6
Middle East	AI	1,776	24.9	24.9	21.7
	Non-AI	2,360	17.9	17.8	15.6
South Asia	AI	3,053	24.5	17.8	14.3
	Non-AI	5,104	16.6	14.3	12.0

Notes: We report the percentage of firms in the common financing sample with an observed founder characteristic. We count each firm once. Observed zeros count as known; missing values do not.

Table A4: Availability of selected employee characteristics in the financing sample

Region	Firm type	Firms	Recorded early employees	Employees with prior startup work	Employees with bachelor degree or higher
North America	AI	14,422	78.0	44.0	70.0
	Non-AI	25,327	70.4	24.3	56.3
Africa	AI	1,071	80.8	33.7	69.5
	Non-AI	4,694	63.0	24.5	51.9
East Asia and Pacific	AI	7,146	54.4	18.8	41.4
	Non-AI	9,346	56.6	16.1	42.9
Europe and Central Asia	AI	12,296	83.3	38.0	74.5
	Non-AI	23,503	75.7	24.4	62.2
Latin America and Caribbean	AI	1,368	84.9	35.8	69.7
	Non-AI	2,813	81.4	25.8	62.7
Middle East	AI	1,776	86.6	52.0	79.9
	Non-AI	2,360	74.9	29.0	65.9
South Asia	AI	3,053	84.9	41.7	79.6
	Non-AI	5,104	68.6	20.7	60.7

Notes: We report the percentage of firms in the common financing sample with an observed early nonfounder employee characteristic. We count each firm once. Observed zeros count as known; missing values do not.

For financing reported in installments, we use the documented amounts and timing of each installment.

When a round's date is missing, we use the next dated round in the same provider's round sequence. If no later round is dated, we use the provider's latest dated round for that company, followed by the latest financing date in its company profile. We also apply this timing rule to rounds with undisclosed amounts.

We treat annual financing as missing when an amount is undisclosed or when we cannot resolve overlapping reports, currency conversion, or the division of an amount across years. Undated rounds, company funding totals without a year, and uncertain founding dates can affect several years; problems confined to one year leave other years' amounts unchanged. Annual financing is zero when there is no positive funding in that year and no financing with an unknown amount or timing that could affect it.

A.6 Potential investors, resources, and university connections

Potential-investor pool. For startup i in year t, we include explicitly classified VC organizations with at least one recorded investment in a sampled company in the same operating country and primary PitchBook industry between January 1 of $t-3$ and December 31 of $t-1$. The same investee must match both categories. We include initial and follow-on financing events and use the company's own industry, not its customer industries. Conflicting or unavailable own-industry classifications remain unknown. Investor headquarters need not be in the startup's country. Membership can reflect an earlier investment in the focal startup, but does not require one.

We use only recorded investments in the study's 2015–2022 founding cohorts. Country and industry are fixed company attributes from the data collection. Dates must fall entirely within the three-year period; a known calendar year is sufficient, while wholly undated events do not qualify. These records describe recent activity among sampled companies, not complete investor portfolios. For each firm-year, we use the same potential pool for all four investor characteristics, including in zero-funding years.

Stage focus and typical round size. We remove all of the focal startup's rounds from an investor's history before forming either characteristic. Each distinct financing event counts once per investor. For early-stage share, we divide seed, angel, and early-stage VC participations by classified early and later-stage participations. Later stages include later-stage VC and growth equity; corresponding restart categories follow the same assignment. Generic equity and unclassified equity crowdfunding do not establish a stage. We classify stages using instruments and participant roles. Conflicting instruments, whole-round non-equity financing,

and mixed or convertible financing without a verified equity component do not establish an equity stage. We average the defined stage shares equally across pool investors.

For each investor, we calculate the median disclosed total amount of supported financing rounds in other sampled companies during the same three years. We express amounts in USD millions, take the natural log of one plus each investor's median, and average equally across investors with observed values. This measures the size of rounds in which investors participated, including eligible non-equity financing. An individual investor's contribution to a round is not observed.

Recent fund commitments. We use the investor–manager matches described above and eligible VC-fund closes from Preqin. For each distinct fund, we select the latest close before January 1 of the funding year, giving the final close priority if it shares a date with an interim close. Closing amounts are commitment levels, so interim and final closes are not added. We retain closes from the previous three calendar years and sum commitments in USD millions for each investor. We observe an investor's commitments only when it has at least one eligible recent closing and all retained fund amounts are known. We average these amounts equally across covered pool investors and take log one plus the mean. This adapts the use of committed fund capital in Kaplan and Schoar (2005) to the potential pool; it does not measure undrawn or uninvested capital. No recorded recent close, an unmatched manager, or a missing amount produces an unknown value rather than zero.

University connections. We use matched founders' qualifications completed by December 31 of the founding year. For potential investors, we identify all employees whose dated employment began before January 1 of the funding year and remained active at that date. We apply no occupation or seniority restriction. We use exact institution identifiers and completed Associate, Bachelor, Master, MBA, or Doctor qualifications with valid dates. An investor employee's qualification must be completed before the funding year.

For each founder with an observed institution, we divide the number of pool investors employing another person with a qualification from at least one of that founder's institutions by the number with at least one employee whose institution is observed. Multiple employees, qualifications, or shared institutions do not count an investor twice for a founder. A founder cannot form a connection to themself. We then average the shares equally across founders whose institutions are observed. We adapt the founder–VC partner connections studied by Garfinkel et al. (2026) to annual university links with investor employees, giving equal weight to investors within each founder's share.

Coverage and common reference values. For stage focus, typical round size, and recent commitments, we record the fraction of the potential pool with a defined measure. We separately measure the fraction of candidate equity participations with a classified stage and of funding-eligible participations with a supported disclosed amount, averaging these coverage fractions across investors with defined denominators after focal-company exclusion. For university connections, we measure the shares of matched founders and pool investors with usable school information. An empty pool or absent required history produces a missing characteristic; it does not imply a zero share or zero resources. Stage focus is observed for 72.1 percent of the 554,513 firm-years, typical round size for 71.9 percent, recent fund commitments for 61.3 percent, and university connections for 17.5 percent (Table A5). Among firm-years with a nonempty potential pool, the average fraction of investors with usable stage information is 98.2 percent and with a supported round size is 97.0 percent. Fund commitments cover only 20.4 percent of pool investors on average, and completed employee schooling covers 45.4 percent. These differences limit how fully each measure describes the potential pool, even when a firm-year has an observed aggregate.

We center each characteristic at its observed mean in the common annual estimation sample and use those values across regions and specifications. We replace missing centered values with zero and include missing-value indicators and coverage controls, including AI interactions with investor information indicators. Main investor slopes and AI interactions use the same units. We report the coefficients on shares per ten-percentage-point increase. The total slope for AI firms is the sum of the main and interaction estimates; its standard error uses their covariance. The information controls are shared across the five models, preserving observations with partial or missing measurements.

Table A5: Availability of prospective investor characteristics in the financing sample

Region	Firm type	Firm-years	Early-stage orientation	Typical startup round size	Recent fund commitments	Founder–investor university links
North America	AI	66,187	60.0	60.0	59.2	17.9
	Non-AI	128,160	93.7	93.7	91.1	19.9
Africa	AI	4,814	48.8	45.1	30.7	13.4
	Non-AI	22,661	32.9	31.9	19.4	7.2
East Asia and Pacific	AI	32,631	42.5	42.4	38.3	10.7
	Non-AI	44,589	77.6	77.2	64.2	12.9
Europe and Central Asia	AI	57,751	61.2	61.1	50.6	21.0
	Non-AI	118,447	78.0	77.7	54.1	17.8
Latin America and Caribbean	AI	6,465	59.5	59.3	50.0	15.0
	Non-AI	13,908	67.3	67.0	49.2	11.9
Middle East	AI	8,122	56.6	56.6	48.9	23.4
	Non-AI	11,657	61.2	60.8	40.1	16.8
South Asia	AI	14,524	58.1	58.0	51.9	21.8
	Non-AI	24,597	84.8	84.8	70.9	21.6

Notes: We report the percentage of firm-years in the common financing sample with an observed investor characteristic. Observed zeros count as known; missing values do not. We use the same pre-year definition before and after first funding.

B Estimation and supporting results

B.1 Financing samples and inference

We estimate the AI financing premium using PPML. We observe annual financing for 675,923 firm-years, including 108,652 with positive funding. In the broad comparison, we exclude 2,732 zeros in fixed-effect groups with no positive funding and 44 additional zeros separated by the fixed effects and information controls. We estimate the model on the remaining 672,906 observations, including all 108,652 positive outcomes. We omit redundant controls only where they are exact linear combinations of the other controls and fixed effects.

Among firms at age two or older, we observe financing for 557,601 firm-years, including 82,807 with positive funding. We exclude 2,854 zeros in fixed-effect groups with no positive funding and another 140 separated zeros. We use the same 554,513 observations in all five explanatory models, including all 82,807 positive outcomes. We handle separation as in Correia et al. (2026).

We cluster financing standard errors by country. Confidence intervals use the normal reference distribution, and joint Wald tests use a chi-squared reference distribution. We also report firm-clustered standard errors.

To compare coefficients across specifications, let s_{gm} be the sum of profiled scores for country g in model m, and let B_m be the inverse profiled Hessian. With G countries, we calculate

$$\widehat{V}_{mn} = \frac{G}{G-1} B_m \left(\sum_{g=1}^{G} s_{gm} s_{gn}' \right) B_n'. \tag{B1}$$

For each model, $\widehat{V}_{mm}$ is the country-clustered covariance matrix with correction $G/(G-1)$ and no additional parameter-count correction. For adjacent models, the covariance of a coefficient difference is $V_{nn} + V_{mm} - V_{mn} - V_{nm}$, restricted to the relevant regional interactions. We use this covariance for individual confidence intervals and the joint test of all six changes.

B.2 Characteristics associated with financing

We use the nested models to estimate how annual funding varies with customer, founder, employee, and investor characteristics. Every specification includes the expanded information controls of Section 5; Appendices A.3 and A.6 define the coverage measures.

Table B1: AI financing estimates

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.6280**	0.9207***
	(0.2109)	(0.0671)
AI difference: Africa		-1.0430**
		(0.3327)
AI difference: East Asia and Pacific		-0.5711***
		(0.0941)
AI difference: Europe and Central Asia		-0.7739***
		(0.0741)
AI difference: Latin America and Caribbean		-1.4434***
		(0.3794)
AI difference: Middle East		0.1112
		(0.0688)
AI difference: South Asia		-0.9991***
		(0.0367)
Firms	114621	114621
Country clusters	163	163
Observations	672,906	672,906
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

PPML estimates of equations (3) and (4). Column 1 reports the AI financing premium across all regions; column 2 reports North America's premium and regional differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B2: Financing samples and regional AI differences

	Annual financing (USD millions)	
	Broad	Age two or older
	(1)	(2)
AI premium: North America	0.9207***	0.9311***
	(0.0671)	(0.0690)
AI difference: Africa	-1.0430**	-1.0293**
	(0.3327)	(0.3231)
AI difference: East Asia and Pacific	-0.5711***	-0.5802***
	(0.0941)	(0.1003)
AI difference: Europe and Central Asia	-0.7739***	-0.7674***
	(0.0741)	(0.0846)
AI difference: Latin America and Caribbean	-1.4434***	-1.5045***
	(0.3794)	(0.4080)
AI difference: Middle East	0.1112	0.1072
	(0.0688)	(0.0854)
AI difference: South Asia	-0.9991***	-1.0348***
	(0.0367)	(0.0394)
Firms	114621	114279
Country clusters	163	157
Observations	672,906	554,513
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

PPML estimates of equation (4) for the broad financing sample and firms aged two or older. Regional differences are relative to North America's AI premium. Both columns use the information controls of the broad financing model. The five-column explanatory sequence additionally controls for availability of the newly introduced characteristics in every column. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B3: Changes in regional AI financing premia relative to North America

	Added characteristics			
Region	Demand	Founders	Employees	Investors
Africa	0.0548	0.0041	-0.0987	-0.0261
	(0.0403)	(0.0042)	(0.1049)	(0.0499)
East Asia and Pacific	0.0811*	0.0018	0.0290	-0.0372
	(0.0372)	(0.0020)	(0.0546)	(0.0599)
Europe and Central Asia	0.0575**	0.0027	0.0287	-0.1436***
	(0.0192)	(0.0025)	(0.0256)	(0.0419)
Latin America and Caribbean	0.0239	-0.0001	0.4412***	-0.0301
	(0.0307)	(0.0022)	(0.0960)	(0.0415)
Middle East	-0.0317	0.0070	-0.0548	0.0732*
	(0.0670)	(0.0055)	(0.0881)	(0.0335)
South Asia	0.0568*	-0.0001	-0.0536*	-0.2797***
	(0.0232)	(0.0020)	(0.0256)	(0.0394)
Joint change: p-value	< 0.001	0.219	< 0.001	< 0.001

Notes: Changes are relative to North America after adding the indicated characteristics. Parentheses contain standard errors from the joint country-clustered covariance in equation (B1). The final row tests whether all six changes are zero. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B4: Regional AI financing differences with firm clustering

	Annual financing (USD millions)				
	Baseline	Demand	Founders	Employees	Investors
	(1)	(2)	(3)	(4)	(5)
AI premium: North America	0.0369	-0.0738	-0.0742	-0.0756	0.0580
	(0.1598)	(0.1644)	(0.1632)	(0.1584)	(0.1689)
AI difference: Africa	-0.5096	-0.4548	-0.4507	-0.5494	-0.5755
	(0.3204)	(0.3272)	(0.3292)	(0.3862)	(0.3916)
AI difference: East Asia and Pacific	-0.7073***	-0.6262***	-0.6243***	-0.5954**	-0.6325***
	(0.1986)	(0.1871)	(0.1873)	(0.1852)	(0.1882)
AI difference: Europe and Central Asia	-0.6716***	-0.6141***	-0.6114***	-0.5827**	-0.7263***
	(0.1760)	(0.1653)	(0.1655)	(0.1793)	(0.1908)
AI difference: Latin America and Caribbean	-1.5681***	-1.5443***	-1.5443***	-1.1031**	-1.1332**
	(0.3891)	(0.3922)	(0.3928)	(0.4077)	(0.4107)
AI difference: Middle East	0.1891	0.1574	0.1644	0.1096	0.1828
	(0.2064)	(0.1929)	(0.1941)	(0.1765)	(0.1875)
AI difference: South Asia	-0.9546**	-0.8978**	-0.8979**	-0.9515**	-1.2311***
	(0.3142)	(0.3125)	(0.3126)	(0.3188)	(0.3357)
Firms	114279	114279	114279	114279	114279
Country clusters	157	157	157	157	157
Regional premia equal: p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Regional differences changed: p-value		< 0.001	0.219	< 0.001	< 0.001
Observations	554,513	554,513	554,513	554,513	554,513
Firm age fixed effects	✓	✓	✓	✓	✓
Country × funding year fixed effects	✓	✓	✓	✓	✓
Country × founding year fixed effects	✓	✓	✓	✓	✓
Customer industry × funding year fixed effects		✓	✓	✓	✓

PPML estimates from the nested models in equation (5). Regional differences are relative to North America's AI premium. Parentheses contain firm-clustered standard errors; the joint tests use country clustering and assess equality of premia and changes from the preceding column. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

AI contrasts are evaluated at the model's centered reference profile and common information controls. Investor main effects and AI interactions use the same units.

Table B5: Customer markets and annual funding

	Annual financing (USD millions)			
	Demand	Founders	Employees	Investors
	(1)	(2)	(3)	(4)
Horizontal applicability	0.0749	0.0758	0.0451	0.0524
	(0.0453)	(0.0464)	(0.0367)	(0.0387)
Customer-industry breadth	0.0837	0.0833	0.1103	0.1300
	(0.1894)	(0.1907)	(0.1616)	(0.1652)
Firms	114279	114279	114279	114279
Country clusters	157	157	157	157
Observations	554,513	554,513	554,513	554,513
Firm age fixed effects	✓	✓	✓	✓
Country × funding year fixed effects	✓	✓	✓	✓
Country × founding year fixed effects	✓	✓	✓	✓
Customer industry × funding year fixed effects	✓	✓	✓	✓

PPML estimates from the nested models in equation (5). Columns successively add founder, employee, and investor characteristics. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B6: Founder backgrounds and annual funding

	Founders	Employees	Investors
Prior founder experience (0 to 1)	0.1472	0.0073	-0.0072
	(0.1134)	(0.1268)	(0.1307)
Founder MBA (0 to 1)	-0.0545	-0.1944	-0.2351
	(0.1431)	(0.1783)	(0.2017)
Founder doctorate (0 to 1)	0.2775***	0.3142***	0.2642***
	(0.0539)	(0.0562)	(0.0534)
Firms	114,279	114,279	114,279
Country clusters	157	157	157
Observations	554,513	554,513	554,513

PPML estimates from the nested annual models in equation (5). Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B7: Early nonfounder employees and annual funding

	Employees	Investors
Recorded early employees (ln(1 + count))	1.1907***	1.1788***
	(0.0602)	(0.0641)
Employees with prior startup work (10 percentage points)	0.0484	0.0474
	(0.0719)	(0.0685)
Employees with bachelor degree or higher (10 percentage points)	0.0764***	0.0759***
	(0.0144)	(0.0150)
Firms	114,279	114,279
Country clusters	157	157
Observations	554,513	554,513

PPML estimates from the nested annual models in equation (5). Country-clustered standard errors are in parentheses. Employee shares use 10-percentage-point increments where labeled. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B8: Investor characteristics and the AI financing premium

	Investors
AI × Early-stage orientation (10 percentage points)	-0.0757
	(0.0389)
AI × Typical startup round size (mean ln(1 + USD millions))	-0.5471***
	(0.1408)
AI × Recent fund commitments (ln(1 + mean USD millions))	-0.0528
	(0.1012)
AI × Founder–investor university links (10 percentage points)	0.0438
	(0.0417)
Firms	114,279
Country clusters	157
Observations	554,513

PPML estimates of annual financing in USD millions from the Investors specification in equation (5). We define potential-investor characteristics before each funding year for all annual observations, including zero-financing years. The sample and information controls match the nested financing sequence. Interactions are AI-minus-non-AI slope differences. Shares use 10-percentage-point increments; logarithmic increments follow the row labels. Main effects and interactions use the same units. Appendix A.6 describes construction. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B9: Investor characteristics and annual funding

	Investors
Early-stage orientation (10 percentage points)	0.2105***
	(0.0335)
Typical startup round size (mean ln(1 + USD millions))	1.1095***
	(0.1221)
Recent fund commitments (ln(1 + mean USD millions))	0.1175
	(0.1172)
Founder–investor university links (10 percentage points)	0.1267*
	(0.0630)
Firms	114,279
Country clusters	157
Observations	554,513

PPML estimates of annual financing in USD millions from the Investors specification in equation (5). We define potential-investor characteristics before each funding year for all annual observations, including zero-financing years. The sample and information controls match the nested financing sequence. Main effects are associations for non-AI firms. Shares use 10-percentage-point increments; logarithmic increments follow the row labels. Main effects and interactions use the same units. Appendix A.6 describes construction. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B10: Investor characteristics and annual funding among AI firms

	Investors
AI total: Early-stage orientation (10 percentage points)	0.1348**
	(0.0505)
AI total: Typical startup round size (mean ln(1 + USD millions))	0.5623**
	(0.1838)
AI total: Recent fund commitments (ln(1 + mean USD millions))	0.0647
	(0.0485)
AI total: Founder–investor university links (10 percentage points)	0.1705**
	(0.0630)
Firms	114,279
Country clusters	157
Observations	554,513

PPML estimates of annual financing in USD millions from the Investors specification in equation (5). We define potential-investor characteristics before each funding year for all annual observations, including zero-financing years. The sample and information controls match the nested financing sequence. AI total slopes add the main and interaction coefficients; their standard errors include their covariance. Shares use 10-percentage-point increments; logarithmic increments follow the row labels. Main effects and interactions use the same units. Appendix A.6 describes construction. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

B.3 Customer scope and organizational changes

We estimate regional AI–non-AI differences in customer scope and the AI suitability of shared customer tasks using equation (1). We also estimate whether changes in task breadth and commercial staffing after ChatGPT's release vary with firms' initial task amenability to AI adoption.

Table B11: Customer scope across regions

	Customer sectors (1)	Multiple sectors (2)	Customer industries (3)	Horizontal products (4)
North America	0.098***	0.015***	0.057***	0.209***
	(0.005)	(0.0002)	(0.004)	(0.010)
Africa	0.133***	0.039***	0.080***	0.232***
	(0.016)	(0.004)	(0.011)	(0.032)
East Asia and Pacific	0.120***	0.024***	0.048***	0.160***
	(0.010)	(0.004)	(0.009)	(0.015)
Europe and Central Asia	0.095***	0.016***	0.052***	0.163***
	(0.006)	(0.003)	(0.006)	(0.007)
Latin America and Caribbean	0.059***	0.007	0.018	0.188***
	(0.009)	(0.004)	(0.012)	(0.013)
Middle East	0.118**	0.018	0.061***	0.156***
	(0.038)	(0.010)	(0.017)	(0.022)
South Asia	0.119***	0.029***	0.064***	0.230***
	(0.003)	(0.002)	(0.0010)	(0.0010)
Country clusters	172	172	172	172
Observations	116,787	116,787	116,787	116,786
Country-by-founding-year fixed effects	✓	✓	✓	✓
Data source fixed effects	✓	✓	✓	✓
Text length controls	✓	✓	✓	✓

Notes: OLS estimates of AI–non-AI differences by region from equation (1). All models include quadratic controls for text length. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

To show that AI firms tend to target industries whose shared work is well suited to AI, consider the three pairs of companies below.[1]

- **Financial software**
  - *Resistant AI* is an AI firm serves credit intermediation and related activities (NAICS 522) and insurance carriers and related activities (NAICS 524). Their shared tasks include: Check figures, postings, and documents for correct entry, mathematical accuracy, and proper codes (ONET Task ID: 2486); Check to ensure that appropriate changes were made to resolve customers' problems (ONET Task ID: 2580); Keep records of customer interactions or transactions, recording details

[1] ONET task IDs are from the O*NET version 27.2.

Table B12: AI suitability of shared customer-industry tasks

	0.8 threshold (1)	0.5 threshold (2)
AI firm	0.08049***	0.03527***
	(0.00609)	(0.00180)
Ordinary shared-task overlap	-15.82764***	-14.09346***
	(3.95944)	(0.81792)
Country clusters	83	147
Observations	1,708	32,300
Country-by-founding-year fixed effects	✓	✓
Data source fixed effects	✓	✓
Text length controls	✓	✓

Notes: OLS estimates of equation (1), including ordinary task overlap. Customer-industry assignments and samples use each column's score threshold. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of inquiries, complaints, or comments, as well as actions taken (ONET Task ID: 2578); Discuss financial options with clients and keep them informed about transactions (ONET Task ID: 23200); Complete contract forms, prepare change of address records, or issue service discontinuance orders, using computers (ONET Task ID: 2584). Four of the five are AI-suited; only the first is not.

– *ProjectPAY*, on the other hand, is a non-AI firm that serves construction of buildings (NAICS 236) and specialty trade contractors (NAICS 238). Their shared tasks include: Assign work to employees, based on material or worker requirements of specific jobs (ONET Task ID: 11432); Read plans, instructions, or specifications to determine work activities (ONET Task ID: 11456); Erect scaffolding or ladders for assembling structures above ground level (ONET Task ID: 23440); Coordinate work activities with other construction project activities (ONET Task ID: 11428); Install sewer, water, or storm drain pipes, using pipe-laying machinery or laser guidance equipment (ONET Task ID: 11469). Only the fourth is AI-suited.

- **Healthcare technology**

  – *Clarrio.ai* (AI firm) serves insurance carriers and related activities (NAICS 524) and hospitals (NAICS 622). Their shared tasks include: Complete contract forms, prepare change of address records, or issue service discontinuance orders, using computers (ONET Task ID: 2584); Check to ensure that appropriate changes were

made to resolve customers' problems (ONET Task ID: 2580); Keep records of customer interactions or transactions, recording details of inquiries, complaints, or comments, as well as actions taken (ONET Task ID: 2578); Consult and coordinate with healthcare team members to assess, plan, implement, or evaluate patient care plans (ONET Task ID: 1843); Refer unresolved customer grievances to designated departments for further investigation (ONET Task ID: 2582). All five of these are AI-suited.

– *City Health Tech*, on the other hand, a non-AI firm serves educational services (NAICS 611) and food services and drinking places (NAICS 722). Their shared tasks include: Serve prepared foods, such as muffins, biscotti, or bagels (ONET Task ID: 17589); Prepare daily food items, and cook simple foods and beverages, such as sandwiches, salads, soups, pizza, or coffee, using proper safety precautions and sanitary measures (ONET Task ID: 23106); Monitor and order supplies or food items, and restock as necessary to maintain inventory (ONET Task ID: 23108); Perform cleaning duties, such as sweeping, mopping, and washing dishes, to keep equipment and facilities sanitary (ONET Task ID: 23102); Stock customer service stations with paper products or beverage preparation items (17590). None of the five are AI-suited.

Table B13: Firm task amenability and organizational changes

	Task breadth (1)	Commercial staffing (2)
Firm task amenability × 2021Q1	-0.416	6.16×10^{-5}
	(0.328)	(0.006)
Firm task amenability × 2021Q2	-0.400	0.004
	(0.280)	(0.004)
Firm task amenability × 2021Q3	-0.169	0.006
	(0.289)	(0.004)
Firm task amenability × 2021Q4	-0.276	0.003
	(0.233)	(0.003)
Firm task amenability × 2022Q1	-0.173	-0.0008
	(0.156)	(0.004)
Firm task amenability × 2022Q2	-0.114	-0.0003
	(0.108)	(0.002)
Firm task amenability × 2022Q4	-0.028	-0.003
	(0.102)	(0.003)
Firm task amenability × 2023Q1	0.267	0.002
	(0.158)	(0.005)
Firm task amenability × 2023Q2	0.484^{*}	0.006
	(0.192)	(0.005)
Firm task amenability × 2023Q3	0.704^{***}	0.010^{**}
	(0.194)	(0.003)
Firm task amenability × 2023Q4	0.850^{***}	0.010^{*}
	(0.246)	(0.004)
Firm task amenability × 2024Q1	1.02^{***}	0.015^{***}
	(0.209)	(0.004)
Firm task amenability × 2024Q2	1.18^{***}	0.016^{**}
	(0.261)	(0.005)
Firm task amenability × 2024Q3	1.27^{***}	0.021^{***}
	(0.266)	(0.005)
Firm task amenability × 2024Q4	1.47^{***}	0.022^{***}
	(0.278)	(0.005)
Firm task amenability × 2025Q1	1.38^{***}	0.021^{***}
	(0.301)	(0.005)
Firm task amenability × 2025Q2	1.41^{***}	0.023^{***}
	(0.282)	(0.005)
Firm task amenability × 2025Q3	1.51^{***}	0.024^{***}
	(0.270)	(0.005)
Firm task amenability × 2025Q4	1.54^{***}	0.026^{***}
	(0.271)	(0.006)
Other baseline controls by quarter	✓	✓
Observations	1,258,697	1,256,660
Firm fixed effects	✓	✓
Country-by-quarter fixed effects	✓	✓
Founding-cohort-by-quarter fixed effects	✓	✓

Notes: OLS estimates of equation (2) for 2021Q1–2025Q4, relative to 2022Q3. Task amenability to AI adoption is measured in standard deviations. Country-clustered standard errors are in parentheses. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table B14: Firm task amenability and organizational changes after 2022Q3

	Task breadth (1)	Commercial staffing (2)
Firm task amenability × Post	1.22***	0.013**
	(0.300)	(0.004)
Other baseline controls by quarter	✓	✓
Observations	1,258,697	1,256,660
Firm fixed effects	✓	✓
Country-by-quarter fixed effects	✓	✓
Founding-cohort-by-quarter fixed effects	✓	✓

Notes: OLS estimates comparing 2021Q1–2022Q3 with 2022Q4–2025Q4, using the controls in equation (2). Task amenability to AI adoption is measured in standard deviations. Country-clustered standard errors are in parentheses. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

C Robustness

This appendix reports the robustness checks summarized in Section 6.1. Appendix C.1 classifies AI status from earlier business descriptions, Appendix C.2 excludes AI infrastructure providers, Appendix C.3 measures customer markets near founding, and Appendix C.4 examines African sample coverage and the influence of individual firms.

C.1 AI status in earlier business descriptions

We identify firms' offerings from archived company websites and dated accounts published by firms, investors, and regulators. We match each source to the firm or a verified predecessor. We exclude parked domains, pages advertising domains for sale, and descriptions that give no information about the business. We count firms that develop or sell AI products, services, data tools, or computing infrastructure as AI firms. A firm can enter or leave that category as its business changes. For the earliest-source measure, we use the first qualifying description from the founding year onward. The near-founding measure uses the founding year or either of the following two calendar years. We hold each classification fixed across funding years. An early description can still postdate an individual financing observation.

QuickCheck described its use of machine learning to make credit decisions in January 2017. We classify it as an AI firm. In October 2017, Hollard described Naked, one of its investments, as a digital insurer. We classify Naked as non-AI at that date. Its founders described an AI-enabled product at launch in April 2018.[2]

We follow the 2015–2022 founding cohorts in funding years 2019–2025. We include zero-funding years and treat years with unresolved financing amounts as missing. We attribute each financing transaction to its named recipient. In 2023, IFC lent $100 million to Safaricom Ethiopia and invested $157.4 million in its Dutch holding company. We count the loan in the Ethiopian firm's funding.[3]

We estimate equations (3) and (4) by PPML with the fixed effects and information controls Q_{it} of Section 4, and we report regional premia at zero values of the missing-investor-information indicators. Table B1 reports the estimates using current descriptions. Tables C1 and C2 report the estimates using the earliest description and descriptions near founding.

[2] QuickCheck, January 2017, Hollard, October 2017, and Naked launch interview, April 2018.
[3] IFC, June 8, 2023.

Table C1: AI financing premia using the earliest description

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.5410**	0.7979***
	(0.1818)	(0.0498)
AI difference: Africa		-0.7050
		(0.4239)
AI difference: East Asia and Pacific		-0.5002***
		(0.0671)
AI difference: Europe and Central Asia		-0.7713***
		(0.0919)
AI difference: Latin America and Caribbean		-1.0154***
		(0.2135)
AI difference: Middle East		-0.1886
		(0.1823)
AI difference: South Asia		-1.0988***
		(0.0344)
Firms	95935	95935
Country clusters	162	162
Observations	588,028	588,028
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

We estimate annual financing by PPML. Column 1 gives the AI funding premium across all regions. Column 2 gives the North American premium and each other region's difference from it. We classify AI firms from their earliest verified description on or after founding. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table C2: AI financing premia using descriptions near founding

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.4688**	0.7059***
	(0.1631)	(0.0429)
AI difference: Africa		-0.7396
		(0.5229)
AI difference: East Asia and Pacific		-0.3705***
		(0.0606)
AI difference: Europe and Central Asia		-0.7031***
		(0.0922)
AI difference: Latin America and Caribbean		-1.5932***
		(0.2997)
AI difference: Middle East		-0.1876
		(0.4365)
AI difference: South Asia		-0.9951***
		(0.0362)
Firms	68461	68461
Country clusters	153	153
Observations	416,912	416,912
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

We estimate annual financing by PPML. Column 1 gives the AI funding premium across all regions. Column 2 gives the North American premium and each other region's difference from it. We classify AI firms from a verified description in the founding year or either of the next two calendar years. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

C.2 Financing premia outside AI infrastructure

AI infrastructure providers supply the computing and network capacity on which other firms run workloads. We use the primary activity in each description to identify cloud hosting, data centers and colocation, rented compute clusters, edge networks, and managed connectivity. The classification assigns chip design, model development, and data tools to separate activities. Under the current classification, 848 of the 42,312 AI firms worldwide and 93 of the 1,128 African AI firms supply infrastructure. We exclude these firms in every region. For each historical comparison, we also exclude firms whose primary AI activity was infrastructure in the description used for that comparison. We remove each excluded firm's entire financing history.

For historical AI firms, we use the business role recorded for the selected description when available. For the remaining 17,623 descriptions, we used Jev to classify the primary activity using the same business-role definitions. Before the financing regression's fixed-effect restrictions, earlier descriptions identify 270 additional providers in the earliest-source sample and 218 in the near-founding sample. We also set aside AI firms for which we could not determine the earlier activity. Under the earliest-source measure, 280 such firms raised $7.92 billion worldwide. Near founding, 197 raised $6.89 billion. In Africa, the same 5 firms account for $2.50 million under either definition.

Among African firms with observed financing, the 91 current providers raised $1.06 billion. They account for 8.3 percent of African AI firms and 50.9 percent of their funding. In North America, infrastructure providers account for 2.3 percent of AI firms and 12.2 percent of their funding.

After excluding infrastructure providers, the estimated Africa–North America gap is -1.407, -1.477, and -1.606 log points using current, earliest, and near-founding descriptions, respectively (Tables C3–C5). Under the earliest classification, AI firms raised 1.88 times as much annual funding as comparable non-AI firms in North America and 0.43 times as much in Africa (Figure C1). On identical firm-years, changing from current to historical AI status changes the regional gap by -0.165 log points using the earliest description ($p = 0.497$) and -0.156 near founding ($p = 0.641$).

Table C3: AI financing premia excluding infrastructure providers, current AI

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.5198**	0.7836***
	(0.1796)	(0.0542)
AI difference: Africa		-1.4069***
		(0.2951)
AI difference: East Asia and Pacific		-0.4656***
		(0.0873)
AI difference: Europe and Central Asia		-0.7016***
		(0.0686)
AI difference: Latin America and Caribbean		-1.3348***
		(0.3874)
AI difference: Middle East		0.1954***
		(0.0590)
AI difference: South Asia		-0.8981***
		(0.0363)
Firms	113794	113794
Country clusters	162	162
Observations	668,159	668,159
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

We estimate annual financing by PPML. Column 1 gives the AI funding premium across all regions. Column 2 gives the North American premium and each other region's difference from it. We classify AI firms from their current descriptions. We exclude firms whose primary current business is workload infrastructure. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table C4: AI financing premia excluding infrastructure providers, earliest description

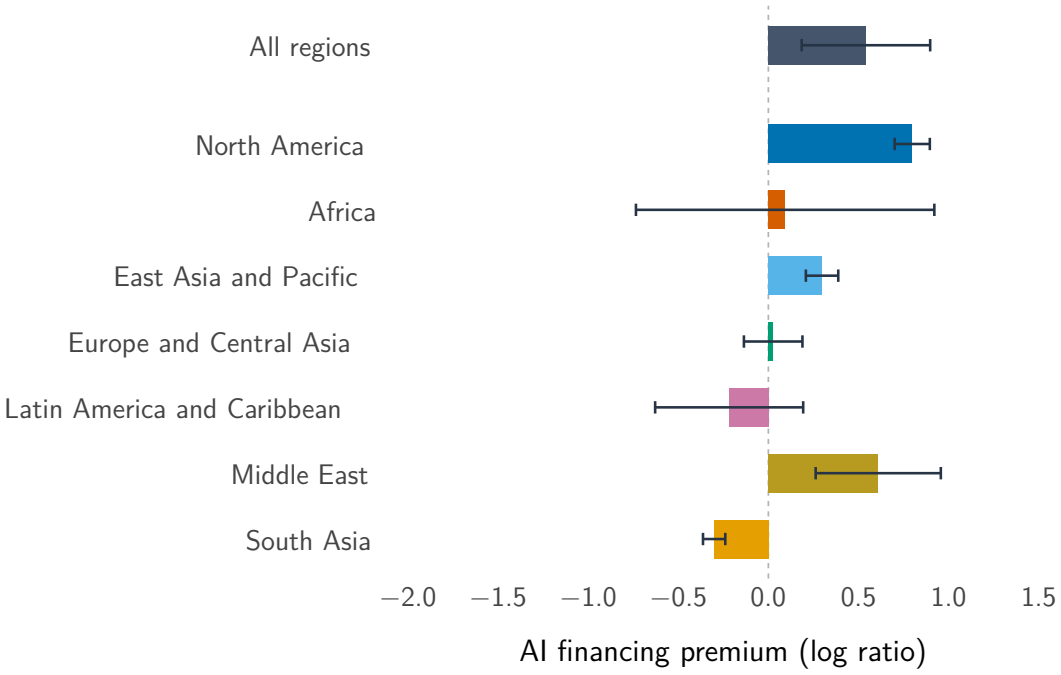
	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.4011**	0.6305***
	(0.1538)	(0.0452)
AI difference: Africa		-1.4775***
		(0.3246)
AI difference: East Asia and Pacific		-0.3824***
		(0.0815)
AI difference: Europe and Central Asia		-0.6716***
		(0.0706)
AI difference: Latin America and Caribbean		-0.8523***
		(0.2177)
AI difference: Middle East		-0.1234
		(0.0720)
AI difference: South Asia		-0.9792***
		(0.0405)
Firms	94677	94677
Country clusters	161	161
Observations	580,431	580,431
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

We estimate annual financing by PPML. Column 1 gives the AI funding premium across all regions. Column 2 gives the North American premium and each other region's difference from it. We classify AI firms from their earliest verified description on or after founding. We exclude firms classified as workload infrastructure in their current or selected historical descriptions. We also omit historical AI firms whose role we cannot determine. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

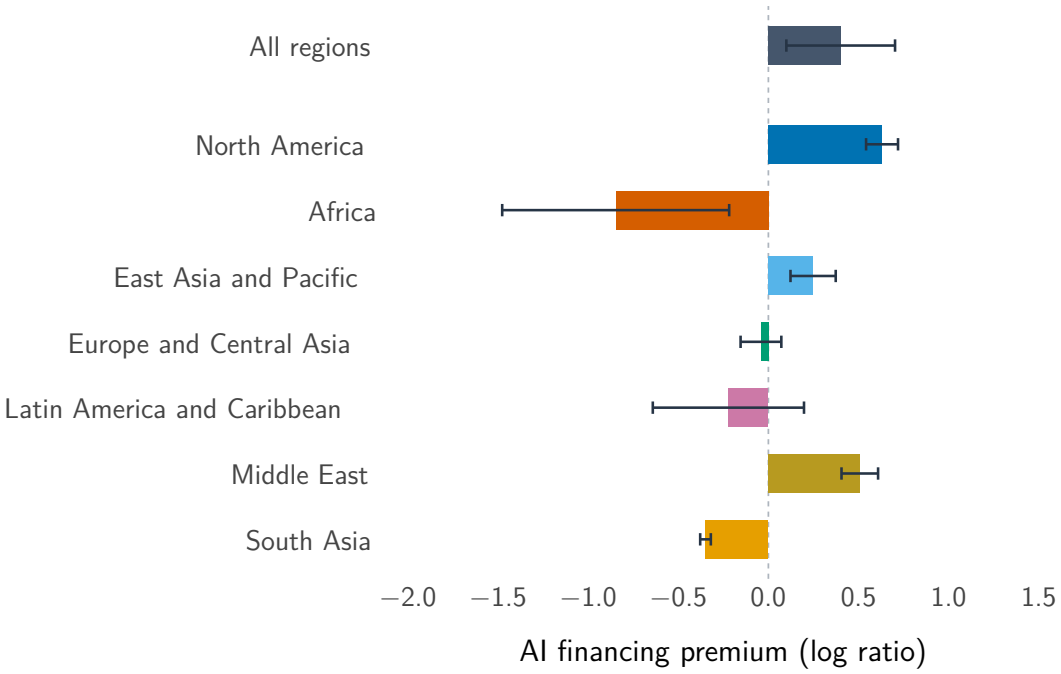
Table C5: AI financing premia excluding infrastructure providers, near founding

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm (North America in column 2)	0.2384*	0.4044***
	(0.0987)	(0.0307)
AI difference: Africa		-1.6061***
		(0.4586)
AI difference: East Asia and Pacific		-0.1402
		(0.0786)
AI difference: Europe and Central Asia		-0.4450***
		(0.0888)
AI difference: Latin America and Caribbean		-1.3136***
		(0.3257)
AI difference: Middle East		-0.1563
		(0.2056)
AI difference: South Asia		-0.7387***
		(0.0405)
Firms	67536	67536
Country clusters	153	153
Observations	411,377	411,377
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

We estimate annual financing by PPML. Column 1 gives the AI funding premium across all regions. Column 2 gives the North American premium and each other region's difference from it. We classify AI firms from a verified description in the founding year or either of the next two calendar years. We exclude firms classified as workload infrastructure in their current or selected historical descriptions. We also omit historical AI firms whose role we cannot determine. Parentheses contain country-clustered standard errors. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.



(a) All eligible firms



(b) Excluding AI infrastructure providers

Figure C1: AI financing premia by region using the earliest description

Notes: We report the log funding ratio for AI firms relative to non-AI firms. Lines give 95 percent confidence intervals clustered by country.

C.3 Customer markets near founding

Using descriptions from the early years of company's founding, we measure customer scope for 69,660 firms. AI firms targeted 0.236 more broad customer sectors and 0.145 more three-digit customer industries than comparable non-AI firms. They were 5.1 percentage points more likely to target multiple sectors. Using current descriptions for 116,787 firms, the corresponding estimates are 0.102 sectors, 0.054 industries, and 1.8 percentage points. The historical and current estimates cover different sets of firms (Table C6).

We estimate equation (1), comparing AI and non-AI firms founded in the same country and year and controlling for the data source $d(i)$ and the length L_i of the description. The outcome S_i is the number of customer sectors, an indicator for multiple sectors, the number of detailed customer industries, or an indicator for horizontal applicability. We also estimate a common AI coefficient in the pooled model and a separate coefficient for each region. Historical AI status, text length, and customer measures come from the same early description. Additionally, for the shared-task regressions, we retain a firm when each of its two descriptions yields a pair of customer industries with task information at the specified threshold. The qualifying pair can differ across descriptions.

Table C6: Customer scope and AI near founding

	Customer sectors (1)	Multiple sectors (2)	Customer industries (3)
AI firm	0.236***	0.051***	0.145***
	(0.020)	(0.005)	(0.011)
Country clusters	162	162	162
Observations	69,660	69,660	69,660
Country-by-founding-year fixed effects	✓	✓	✓
Data source fixed effects	✓	✓	✓
Text length controls	✓	✓	✓

Notes: We estimate overall AI–non-AI differences by OLS using equation (1). Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table C7: Customer scope and AI near founding by region

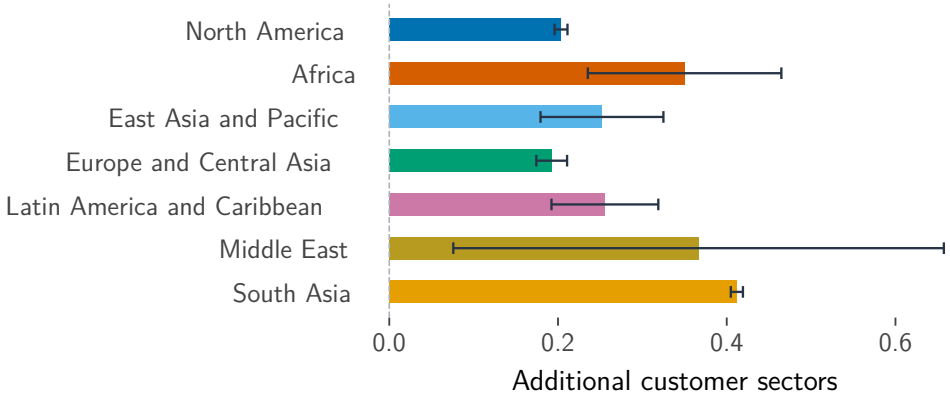
	Customer sectors (1)	Multiple sectors (2)	Customer industries (3)	Horizontal products (4)
North America	0.204***	0.046***	0.121***	0.218***
	(0.004)	(0.0017)	(0.004)	(0.015)
Africa	0.350***	0.092***	0.228***	0.262***
	(0.058)	(0.016)	(0.036)	(0.025)
East Asia and Pacific	0.252***	0.050***	0.167***	0.201***
	(0.037)	(0.010)	(0.030)	(0.012)
Europe and Central Asia	0.193***	0.037***	0.125***	0.151***
	(0.009)	(0.005)	(0.011)	(0.011)
Latin America and Caribbean	0.256***	0.055***	0.182***	0.173***
	(0.032)	(0.008)	(0.026)	(0.026)
Middle East	0.367*	0.092*	0.217**	0.086
	(0.147)	(0.036)	(0.074)	(0.046)
South Asia	0.412***	0.095***	0.211***	0.245***
	(0.004)	(0.001)	(0.0024)	(0.0020)
Country clusters	162	162	162	162
Observations	69,660	69,660	69,660	69,660
Country-by-founding-year fixed effects	✓	✓	✓	✓
Data source fixed effects	✓	✓	✓	✓
Text length controls	✓	✓	✓	✓

Notes: OLS estimates of AI–non-AI differences by region from equation (1). All models include quadratic controls for text length. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

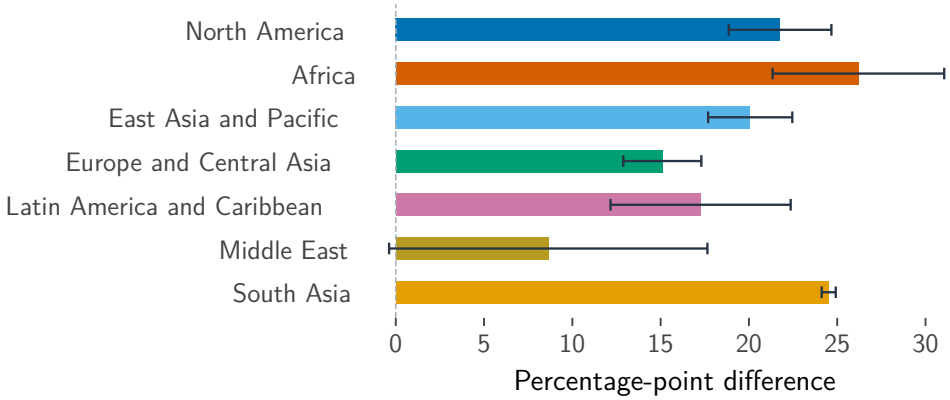
Table C8: AI suitability of shared customer-industry tasks near founding

	0.8 threshold (1)	0.5 threshold (2)
AI firm	0.07146*	0.03349***
	(0.02992)	(0.00295)
Ordinary shared-task overlap	-8.46887	-8.42187***
	(10.11691)	(1.30074)
Country clusters	52	121
Observations	228	10,058
Country-by-founding-year fixed effects	✓	✓
Data source fixed effects	✓	✓
Text length controls	✓	✓

Notes: OLS estimates of equation (1), including ordinary task overlap. Customer-industry assignments and samples use each column's score threshold. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.



(a) Customer breadth



(b) Horizontal applicability

Figure C2: AI firms' customer markets across regions near founding

Notes: We estimate AI–non-AI differences using equation (1). Customer sectors range from zero to 20. We measure horizontal applicability in percentage points. Lines give 95 percent confidence intervals clustered by country.

C.4 African sample coverage and firm influence

Of the 5,948 African firms eligible for the financing regression, 5,663 have a dated description, and 3,917 have one near founding. The earliest-source sample covers all but $0.79 million of the $12.30 billion in recorded African funding. Restricting descriptions to the first three calendar years covers 93 percent of that funding. Both samples retain firm-years with zero funding (Table C9).

Table C9: African firms with dated evidence of AI status

	Eligible African panel	Earliest source	Near founding
Firms	5,948	5,663	3,917
Firm-years	35,174	33,554	22,789
Zero-funding firm-years	32,094	30,506	20,509
Recorded funding (US$ millions)	12,298.62	12,297.83	11,410.19

Notes: We count African firms and firm-years with observed annual financing before the regression's fixed-effect support restrictions. Each firm with a qualifying description contributes all its eligible years, including its zero-funding years.

Table C10: Change in the regional funding gap on identical observations

	Earliest source	Near founding
Historical minus current gap	0.303	0.360
Paired standard error	0.200	0.251
95% confidence interval	[−0.09, 0.70]	[−0.13, 0.85]
p, equality across classifications	0.130	0.151
Firm-years	588,028	416,912

Notes: We subtract the Africa–North America gap using current AI status from the gap using historical AI status on the same firm-years. A positive change narrows the estimated shortfall in Africa. We use the covariance between estimates and cluster by country.

We measure how the Africa–North America gap changes when we give a firm slightly more weight in the regression. Using the earliest source, more weight on IXAfrica Data Centre and Africa Data Centres narrows the gap. More weight on Chevron Nigeria–NNPC venture and Envusa Energy widens it (Table C11). In the earliest-source comparison, Nigeria, Kenya, and South Africa account for 43, 33, and 17 percent of the estimated variance of the regional gap, respectively.

IXAfrica supplies data-center capacity in Kenya and qualifies as an AI firm under both historical measures. Its five firm-years include $250 million in recorded financing. PitchBook values its 2025 debt financing at $200 million. IXAfrica and Rand Merchant Bank confirm

Table C11: African firms with the greatest influence on the historical funding gap

			Influence on the regional gap	
Firm	Country	Historical AI	Earliest source	Near founding
IXAfrica Data Centre	Kenya	AI	+0.211	+0.262
Chevron Nigeria–NNPC venture	Nigeria	Non-AI	−0.110	−0.146
Envusa Energy	South Africa	Non-AI	−0.083	−0.114
Africa Data Centres	South Africa	AI	+0.080	+0.103
OPay	Nigeria	Non-AI	−0.076	−0.087
CodeLn	Nigeria	AI	−0.052	−0.089

Notes: We report firms among the five largest absolute values in either column. Entries are derivatives of the estimated log funding gap with respect to a firm's weight, evaluated at its observed weight of one. Each derivative includes all of that firm's eligible years.

the closing in their joint announcement.[4] We repeat both regressions excluding IXAfrica because it had the largest absolute influence in both historical comparisons before the source review. We apply the same sample and estimation rules (Table C12).

Table C12: Regional funding gaps with and without IXAfrica

	Earliest source	Near founding
All firms	−0.705 (0.424)	−0.740 (0.523)
95% confidence interval	[−1.536, 0.126]	[−1.764, 0.285]
Excluding IXAfrica	−0.940 (0.319)	−1.038 (0.393)
95% confidence interval	[−1.565, −0.315]	[−1.808, −0.268]

Notes: Entries give the Africa minus North America gap in log funding premia. Parentheses contain country-clustered standard errors.

[4] IXAfrica and Rand Merchant Bank, September 2025.