Frontier Technology in Frontier Markets? Financing Global AI Entrepreneurship*

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Abstract

Does the global diffusion of artificial intelligence (AI) extend to the creation and financing of the firms that innovate with it? Using a novel dataset of 116,795 startups founded between 2015 and 2022 across 172 countries, we link company and financing records to the employment and education histories of their founders, early employees, and potential venture capital investors. We document a stark divergence between the real and financial sides of global AI entrepreneurship. On the real side, AI appears to generate economies of scope consistent with a general purpose technology. Across all world regions, AI startups serve broader customer markets and following ChatGPT's release, firms performing more AI-amenable tasks expanded the breadth of their work activities and became more likely to employ commercial staff. However, the financing advantage that such scalable businesses command is localized: in North America and the Middle East, AI startups raise more than twice the annual funding of comparable non-AI startups, with smaller premia of 29 and 47 percent in Europe and East Asia respectively, and no discernible premium in Africa, Latin America, or South Asia. Accounting for customer markets, founders' backgrounds, and potential investors explains little of the regional financing differences, although early teams account for part of Latin America's gap. In Africa, half of AI funding goes to computing and network infrastructure providers; AI startups outside infrastructure raise 60 percent *less* annual funding than comparable non-AI startups. These patterns provide an early warning that artificial intelligence 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).

The spread of venture capital beyond advanced economies offers a more encouraging precedent. Lerner et al. (2026) found that China's rise as a center of venture-backed innovation stimulated entrepreneurship in other developing economies, particularly where Chinese business models suited local conditions. Large AI producers, however, remain concentrated in a small number of economies led by the United States and China (Rishabh and Shreeti, 2026). Venture funding for AI is concentrated in advanced economies: in 2025, firms in the United States alone received three-quarters of global AI venture investment (OECD, 2026).

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 potential 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 Intelligence to ensure deep coverage of African ventures, including startups that never raised external capital or subsequently closed. We link these firms to employment and educational histories from Revelio Labs covering 52,200 founder–firm pairs and 719,337 early nonfounder employee–firm pairs, and to investor and fund-commitment records from Preqin. Using a structured questionnaire and a natural language model, we classify 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; Agrawal et al., 2024). Using a quarterly panel of roughly 63,000 AI and non-AI

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 work-activity breadth evolved in parallel across startups with higher and lower baseline task amenability 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 103 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 174 percent and 185 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 47 percent; in Europe and Central Asia, it is just 29 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 53 percent lower in Europe, 65 percent lower in South Asia, 67 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 554,524 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 9 percent of the original Baseline gap in Europe, 12 percent in East Asia, and about 5 percent each in South Asia and Latin America), with no significant change in Africa.

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 with a PhD founder raise 41 percent more capital, founder credentials explain little of the regional financing gaps. 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 23 percent of its original Baseline value. Yet early-team human capital does not narrow the gap for Africa or South Asia.

Third, we test an 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—does not significantly 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 -1.48 log points under current classifications and -1.58 log points under the earliest-description classification: under the latter, African AI product startups raise 60 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). In a model with globally traded AI services, Björkegren, Lagakos and VanVuren (2026) showed that developing economies can fall behind because they lack complementary skills or because demand from richer countries keeps AI services expensive. 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), and firm entry in exposed sectors (Bena et al., 2026). Rishabh and Shreeti (2026) mapped large AI producers across the world and found more of them in economies with deeper venture capital markets. 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 163 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). Using online job postings, Goldfarb, Taska and Teodoridis (2023) found that machine learning and related data science technologies are used across industries and in research, consistent with their potential as general-purpose technologies. AI lowers the cost of prediction, changing the tasks firms automate and the decisions workers can undertake (Agrawal, Gans and Goldfarb, 2019). The gains also depend on how firms coordinate those decisions (Agrawal, Gans and Goldfarb, 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). Workers in Denmark took on new tasks as firms adopted AI chatbots, while earnings and recorded hours changed little (Humlum and Vestergaard, 2026). 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 became more likely to employ commercial staff 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). Lerner et al. (2026) showed that China's emergence as a venture capital hub stimulated entrepreneurship in other emerging economies, largely through local investors backing firms that adapted Chinese business models. Montanaro et al. (2024) found that AI ventures raised smaller venture capital rounds than other Industry 4.0 ventures, comparing AI with technologies such as cloud computing, robotics, and the Internet of Things. At the regional level, Hennings and Schiereck (2026) compared aggregate venture capital flows in the United States and Europe over 2000–2025 and found a larger increase in AI's share of funding in the United States. We compare AI firms with a broader set of non-AI startups within the same country and year, asking where AI commands a financing premium and why that premium remains geographically concentrated even as AI firms build broader businesses across regions.

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). Training foundation models involves large fixed costs, giving model developers substantial economies of scale (Korinek and Vipra, 2025). At the same time, venture contracting relies on liquid exit markets and legal enforcement (Black and Gilson, 1998; Lerner and Schoar, 2005). By showing that demand, human capital, and observable investor traits do not close the regional gaps—and by showing that African AI finance goes predominantly to computing and network infrastructure rather than application builders—our paper highlights physical compute and institutional ecosystems as critical margins for global AI policy.

Outline. Section 2 describes our sources, sample, measures, and the composition of the firms we study. In Section 3, we compare AI and non-AI startups' customer markets, then examine how startups with more and less AI-amenable tasks reorganized work after ChatGPT's release. We turn to the regional financing premium in Section 4 and ask in Section 5 how much customer markets, founders, early employees, and potential investors account for the differences. Section 6 examines AI infrastructure financing in Africa and its implications for local entrepreneurship, and Section 7 concludes.

2 Data and measurement

We build a global dataset linking startups' products and customer markets to their financing, founders, early employees, and potential investors. Appendix A provides additional construction details.

2.1 Data sources

Startups and funding. Our primary data source is PitchBook, one of the major global databases of high-growth startups and venture capital investment (Lerner et al., 2026). Because global venture databases have thinner coverage of African startups, we supplement it with data from Stears Intelligence, which focuses on firms headquartered or operating in Africa (Colonnelli et al., 2026). Both sources provide business descriptions, funding rounds and amounts, investor information, and company characteristics, including locations, industries, and website addresses.

Company websites. To observe how startups describe their businesses at different points in their development, we collect text from their websites and recover earlier webpages through the Internet Archive Wayback Machine. Historical press releases, investor announcements,

and regulatory filings provide additional accounts of their products, including near founding (Appendix C.1).

Employment and education. We use employment and education histories from Revelio Labs to study startups' organizational characteristics and the backgrounds of their founders, employees, and potential investors. Revelio compiles these histories from online resumes on platforms such as LinkedIn, recording employers, job titles, employment dates, and schools attended. We obtain records for both startups and institutional investors, along with firm–occupation-level job postings.

Investor funds. For institutional venture capital investors, we supplement the deal histories with Preqin's information on fund commitments, general partners, and limited partners. Preqin covers both venture capital and private equity firms and allows us to link investors participating in startup financing to the funds they manage.

Tasks and AI exposure. We use O*NET version 27.2 to link occupations to tasks and to intermediate and detailed work activities, allowing us to describe the work done within startups and across their customer industries (U.S. Department of Labor, Employment and Training Administration, 2023). We combine these mappings with the human task-level AI-exposure ratings of Eloundou et al. (2024) and industry occupational employment from the U.S. Bureau of Labor Statistics Occupational Employment and Wage Statistics (U.S. Bureau of Labor Statistics, 2022).

2.2 Sample construction

Our sample includes startups founded between 2015 and 2022 that appear in PitchBook or Stears, whether or not they raised external capital or subsequently closed. We do the matching using company names, web domains, locations, and LinkedIn profiles. Startups found in both sources enter once, with a combined financing history. We match startups and investors to Revelio employer profiles using company domains and LinkedIn URLs. We separately match investors to Preqin fund managers and funds (Appendix A.1).

We assign operating country from workers' locations in the founding year and the following calendar year because firms may incorporate in Delaware or another jurisdiction to access investor networks while operating elsewhere. We use company records to assign operating

country when no country has a clear plurality (Appendix A.1). We group operating countries into seven regions using the World Bank classification.[1]

The compiled data cover 116,795 startups with an operating country and an AI classification, spanning 172 countries. PitchBook covers 116,286 of these firms and Stears covers 1,058; 549 appear in both. We retain firms without a match to individual employment or education histories.

We follow annual financing from 2019 through 2025 (Appendix B). For the analysis of founders, early employees, and potential investors, we restrict the sample to firms that are two years or older in order to capture early teams. To study organizational changes around ChatGPT's release, we follow the 2015–2020 founding cohorts quarterly from 2021Q1 through 2025Q4 (Appendix A.4).

2.3 Variable construction

AI firms. Adapting the supply-chain classification of Rishabh and Shreeti (2026), we classify a startup 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. Internal use of AI alone does not make a firm an AI producer.[2]

We use TypeSafe's generative natural language model, `Jev 1.13.0`, to categorize firms as AI or non-AI, using text data from their business descriptions and available homepages. Given a questionnaire about the firm's products and customers, the model returns a response and a confidence score between 0 and 1 for each item. Appendix A.2 gives the classification rules, including how we combine multiple accounts of the same firm.

Target markets. To measure firm scope, we need to characterize the sectors that startups serve as customers. As Bernstein et al. (2026) pointed out, databases such as PitchBook often classify startups by the technology used in their solutions. Two firms may therefore both be classified as fintechs even though one offers credit to farmers and the other develops payment solutions for retailers. We distinguish these customer markets using business descriptions, which Hoberg and Phillips (2025) showed can be used to construct economically useful measures of firm scope.

[1] We combine North Africa and sub-Saharan Africa into a single Africa region and assign Pakistan and Malta to the Middle East. North America comprises Canada and the United States; China belongs to East Asia and the Pacific and India to South Asia. For brevity, we refer to Europe and Central Asia as Europe, East Asia and the Pacific as East Asia, and Latin America and the Caribbean as Latin America.

[2] Kim and Koning (2026) distinguished AI embedded in firms' products from AI used in their internal processes.

We build on this idea by asking Jev which customer industries and sectors each startup targets. The questionnaire covers 99 three-digit NAICS customer industries and 20 broad customer sectors. For each startup, we also ask Jev for its principal customer market at the ISIC-section level and whether its product applies horizontally across industries. We count an industry as a startup's customer market when its score is at least 0.8, and classify the product as horizontal when its score is above 0.5. We compare these classifications with two independent human reviews of 300 startups (Appendix A.2).

Even when customers produce different goods, they may share tasks that a single AI product can perform. We compare the work activities of customer industries for startups serving at least two industries covered by BLS and O*NET. Our measure, $S_i^{AI} \in [0, 1]$, is the ratio of AI-exposure-weighted overlap to unweighted overlap across all pairs of customer industries (Appendix A.2). Higher values correspond to shared work that is more suited to AI across the startup's customer industries.

Organizational tasks and AI suitability. We link employees' occupations in the workforce histories to O*NET activities and use these activities as a proxy for tasks performed within AI and non-AI startups. We follow two quarterly outcomes: *task breadth*, the number of distinct work activities represented in the workforce, and *commercial staffing*, whether the startup employs at least one worker in sales, marketing, or a related commercial occupation.

We measure initial *task amenability to AI adoption* from the December 2021 workforce, including founders, nearly a year before ChatGPT's release. This is the AI-weighted overlap between the tasks performed by that workforce and the average industry's task profile across 59 ISIC industries. It is high when the startup's initial work activities are both suited to AI and common across industries (Appendix A.4).

Annual financing. We measure the capital startups raise by summing equity, debt, grants, and other financing within each calendar year, in millions of nominal U.S. dollars. We record zero funding in years without a financing event, including the years between founding and the first round. If a financing event occurs but its amount is undisclosed or cannot be established, that firm-year remains missing. This gives us 675,657 firm-years before estimation exclusions. Appendix A.5 explains the treatment of transaction dates, installments, and recipients.

Founders and early nonfounder employees. We measure founder backgrounds through December 31 of the startup's founding year. Adapting the founder human capital measures of Hsu (2007), we construct indicators for whether any founder had previously founded another company, completed an MBA, or completed a doctorate.

Early employees also contribute to startup outcomes (Choi et al., 2025), so we measure the early nonfounder team on December 31 of the following calendar year. We include employees active at the startup on that date, excluding founders of the focal startup but retaining people who founded other firms. For the early team, we define size as the log of one plus nonfounder headcount, experience as the share previously employed at another startup, and education as the share with a completed bachelor's degree or higher. A prior employer counts as a startup if it was ten years old or younger when the employee joined (Appendix A.3).

Potential investors. We define potential investors as those VC organizations that participated in initial or follow-on investments in sampled startups in the focal startup's operating country and primary PitchBook industry during the three preceding calendar years, $t-3$ through $t-1$. The pool includes investors headquartered abroad and is formed for every startup and funding year, whether or not the startup raises capital.

Stage focus is the average investor's share of stage-classified equity rounds that are seed, angel, or early-stage VC (Barrot, 2017), while *typical round size* describes the median disclosed amount raised in the rounds each investor joined. For both measures, we use deals from the preceding three years in sampled startups other than the focal startup. We measure the capital investors have raised using Preqin records of commitments to VC funds that closed over the same period (Kaplan and Schoar, 2005). Appendix A.6 explains the aggregation and log transformations.

Founders may also reach investors through university ties. Following Garfinkel et al. (2026), we measure each founder's *university connections* as the share of potential investors with employee school information that employ another graduate of the same university at the start of the funding year. We then compute the average connection share across founders with university data for each startup (Appendix A.6).

2.4 Sample composition

North America and Europe contribute similar numbers of startups but cover very different numbers of countries: 40,351 firms in two countries in North America, compared with 36,464 in 52 countries in Europe and Central Asia. The African sample is smaller, with 6,125 startups, but extends across 47 countries (Table 1). Of the 116,795 startups in the full sample, 42,312, or 36.2 percent, are AI firms. Their share ranges from 18.4 percent in Africa to 43.6 percent in East Asia and the Pacific; the Middle East has a similarly high share, 42.8 percent, despite its much smaller sample of 4,307 firms.

The matched sample contains 52,200 founder–firm pairs across 47,425 companies and 719,337 early nonfounder employee–firm pairs.

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. AI shares are the percentage of sampled startups in each region classified as AI firms.

3 AI and Economies of Scope

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 investigate the reach of AI producers by studying their customer industries, focusing in particular on work to which the same technology can apply. Next, we move beyond customer markets and investigate the organization of work inside startups, including firms that use AI without selling it. This comparison includes both AI and non-AI firms.

3.1 Customer markets

We compare the customer markets of AI and non-AI firms founded in the same country and year. We measure how many broad sectors they target out of 20, whether they target multiple sectors, how many detailed three-digit NAICS industries they target out of 99, and whether their products apply horizontally across industries. We include database fixed effects to account for whether a firm appears in PitchBook, Stears, or both. We also control for a quadratic in log one plus the number of words in the business text, since longer descriptions can name more customers. 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 indicates 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, and L_i is log one plus the number of words in its business text. The regional AI–non-AI difference is β_r. We estimate the equation by ordinary least

squares, clustering standard errors by country, and also estimate a pooled specification with a common AI–non-AI difference across all seven regions.

AI firms target customers in more sectors than non-AI firms in every region (Figure 1). Across regions, the difference is 0.102 broad sectors; AI firms also target more detailed industries and are more likely to target multiple sectors (Table 2). Their products more often apply across industries: 48.8 percent of AI firms offer horizontal products, compared with 30.2 percent of non-AI firms in the full company sample. When we compare firms within countries and founding cohorts, the difference ranges from 16 to 23 percentage points across regions.

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	✓	✓	✓
Database 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. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Industries that produce different goods can share work to which the same AI capability applies. For example, *Resistant AI* sells fraud-detection software to credit intermediaries and insurance carriers. Both industries log customer inquiries and complete contract forms on computers. Consistent with this, four of their five primary shared tasks are suited to AI. *ProjectPAY*, by contrast, is a non-AI billing vendor whose customers are building contractors and specialty trade contractors. These industries also share work, but much of it involves physical construction and site supervision: erecting scaffolding, laying pipe, and coordinating work on site. Only one of their five primary shared tasks—coordinating project schedules—is AI-exposed (Appendix B).

We estimate equation (1) with shared customer-task AI suitability, S_i^{AI}, as the outcome to ask whether this pattern extends across multi-industry startups. The specification controls for average unweighted overlap across each startup's customer-industry pairs: customers can share a great deal of work without that work being suited to AI. For the 1,708 firms with BLS–O*NET task profiles at the baseline industry-assignment cutoff of 0.8, we find that the

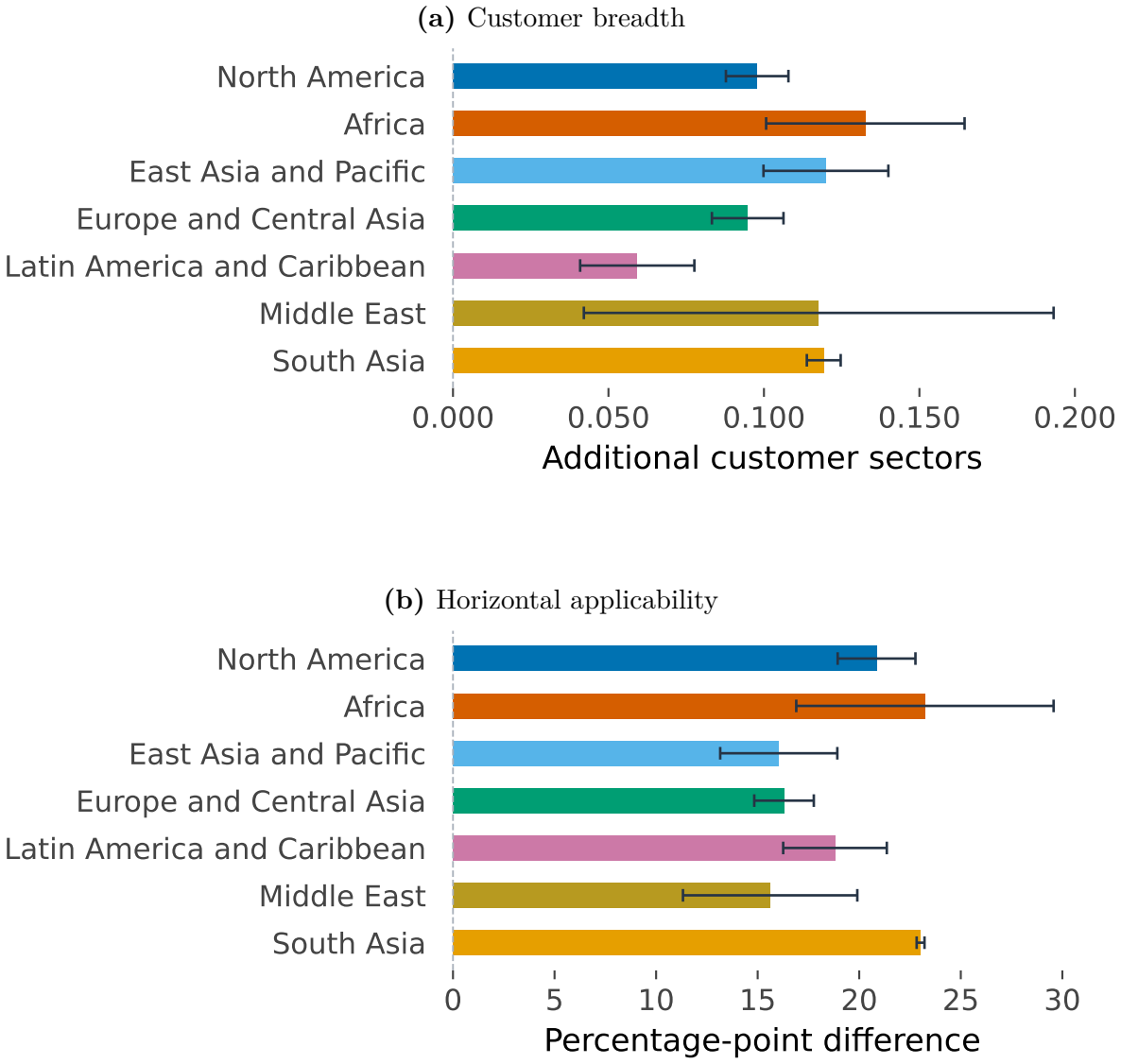


Figure 1: AI firms' customer markets across regions

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

shared tasks of AI firms' customers score 0.080 higher on the zero-to-one AI-suitability index (Appendix Table B12).[3]

Startups can enter new customer markets as they grow. To examine whether the differences were already present near founding, we classify both AI status and customers from descriptions written in the founding year or either of the next two calendar years. Among the 69,660 startups with these descriptions, AI firms target 0.236 more broad sectors (Appendix C.3 and Table C6). AI firms target more sectors in every region, and their early customer industries share tasks more suitable for AI (Appendix Table C8). They are also more likely to offer horizontal products in every region except the Middle East, where the estimate is imprecise (Appendix Figure C1).

3.2 Organizational changes

The public release of ChatGPT in November 2022 (2022Q4) made generative AI widely available. We compare changes in work activities and commercial staffing before and after the release across firms with higher or lower task amenability in their December 2021 workforce. When tasks are suited to AI and common across industries, firms have opportunities to apply the technology to a wider range of work. We follow both AI and non-AI startups founded in 2015–2020 quarterly in Revelio from 2021Q1 through 2025Q4. We standardize initial task amenability to unit variance and denote it Z_i. For quarterly organizational outcome W_{iq}, we estimate

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

Here q_0 is 2022Q3, the reference quarter before the release. Firm fixed effects absorb persistent differences across firms (α_i). The operating-country-by-quarter and founding-cohort-by-quarter effects account for common changes within countries and cohorts ($\lambda_{c(i),q}$ and $\eta_{b(i),q}$). The December 2021 controls in B_i are unweighted cross-industry task affinity, mean AI exposure of the firm's own tasks, log headcount, the share of workforce task mass covered by the task and AI-exposure mappings, the number of employee countries, and an indicator for missing country data. We interact each control with quarter indicators, allowing its coefficient to vary across quarters. Thus, δ_s compares the evolution of firms whose AI-suited work was shared across more or fewer industries, holding ordinary task affinity and own-task AI exposure fixed. We use the quarters before 2022Q3 to examine whether these

[3]Using an assignment cutoff of 0.5 gives a measure for 32,300 firms and a difference of 0.035.

differences had already begun to emerge before the release. We cluster standard errors by country; Appendix A.4 gives the task construction.

Before ChatGPT's release, the task-breadth coefficients from 2021Q1 through 2022Q2 are close to zero and statistically insignificant (Figure 2). After the release, however, firms with more amenable tasks expanded the range of work they performed. 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, rising to 1.54 by 2025Q4. The growing difference points to the creation of new work alongside the automation of existing tasks as generative AI became available (Acemoglu and Restrepo, 2019).

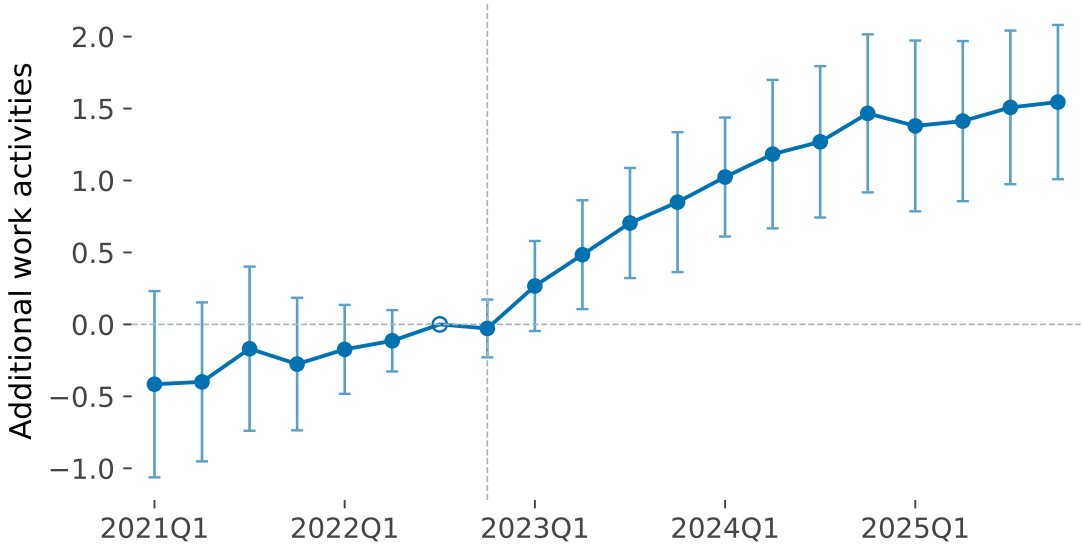


Figure 2: Task amenability to AI adoption and work activities

Notes: We plot the coefficients δ_s from equation (2): the difference in the number of distinct 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 pre-release coefficients are zero is 0.367.

At *Health Cost IQ*, an American health-plan analytics firm, employees initially worked on customer documentation and resolving inquiries, tasks both suited to AI and common across industries. With this workforce, the firm ranked at the 93rd percentile of initial task amenability and went from 56 work activities in 2022 to 88 by the end of 2025. *Vitomy*, a German health-coaching app developer, started with software-design and testing tasks shared by few other industries; at the 19th percentile of task amenability, it remained at 51 work

activities throughout. Appendix B describes the initial tasks at both firms and the activities Health Cost IQ added.

Firms with more amenable tasks also became more likely to employ commercial staff. Among 62,894 firms, a one-standard-deviation difference in initial task amenability is associated with a 1.62-percentage-point increase in this probability on average in 2023–2025 (Figure 3).[4] Unlike the work-activity comparison, commercial staffing also shows a prerelease difference: the coefficients before 2022Q3 are jointly significant at the 10 percent level.

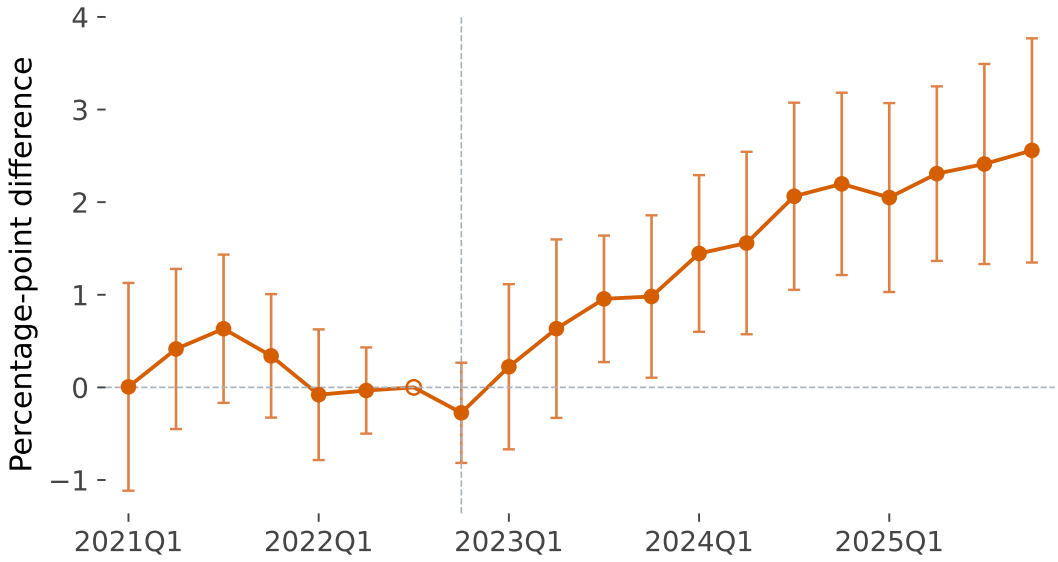


Figure 3: Task amenability to AI adoption and commercial staffing

Notes: We plot 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 pre-release coefficients are zero is 0.093.

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.

[4]The before–after comparison using 2022Q4–2025Q4 as the post period yields 1.22 additional work activities and a 1.29-percentage-point increase in commercial staffing. Appendix Tables B13 and B14 report the dynamic and static comparisons.

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

AI firms could raise more funding because they operate in markets where startups of all kinds attract more capital. To distinguish an AI financing advantage within these markets, we compare AI and non-AI firms facing the same local funding conditions. 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. First, country-by-funding-year fixed effects control for local funding conditions ($\alpha_{c(i),t}$). Second, country-by-founding-year fixed effects control for differences across entry cohorts ($\eta_{c(i),b(i)}$). Finally, categorical firm-age fixed effects control for financing over the firm life cycle ($\tau_{a(i,t)}$). The information controls in Q_{it} account for founder and early-employee coverage, missing product and workforce characteristics, and the length of the business description. Within this comparison, β is the log AI-to-non-AI funding ratio, and the corresponding premium is $\exp(\beta) - 1$.

We estimate equation (3) by Poisson pseudo-maximum likelihood (PPML), which retains zero-funding years and estimates proportional differences in expected funding (Santos Silva and Tenreyro, 2006; Correia et al., 2026). The sample includes 672,928 firm-years from 114,622 firms in 163 countries, and we cluster standard errors by country. Appendix B reports the sample accounting and alternative inference.

On average, AI firms receive 103 percent more annual funding than non-AI firms in the same country, founding cohort, and funding year (Appendix Table B1, column 1). To examine whether this premium extends across regions as broadly as their customer markets do, we allow each region's AI premium to differ from North America's:

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

Within region r, the AI-to-non-AI funding ratio is $\exp(\beta_{NA} + \kappa_r)$. The difference in log premia, κ_r, compares that ratio with North America's. Country-by-year effects absorb region main effects, so this is a comparison of AI firms' relative financing advantages across regions.

The financing advantage is concentrated in North America and the Middle East, where AI firms receive 174 and 185 percent more annual funding than non-AI firms (Figure 4). Europe and East Asia have smaller premia, at 29 and 47 percent. In Africa, Latin America, and South Asia, we find no premium: the AI–non-AI differences are negative and statistically insignificant.

Relative to North America, the AI-to-non-AI funding ratio is 67 percent lower in Africa, 76 percent lower in Latin America, and 65 percent lower in South Asia. Europe and East Asia also have lower ratios, and all five differences are statistically significant. Only the Middle Eastern ratio is statistically indistinguishable from North America's (Appendix Table B1, column 2).

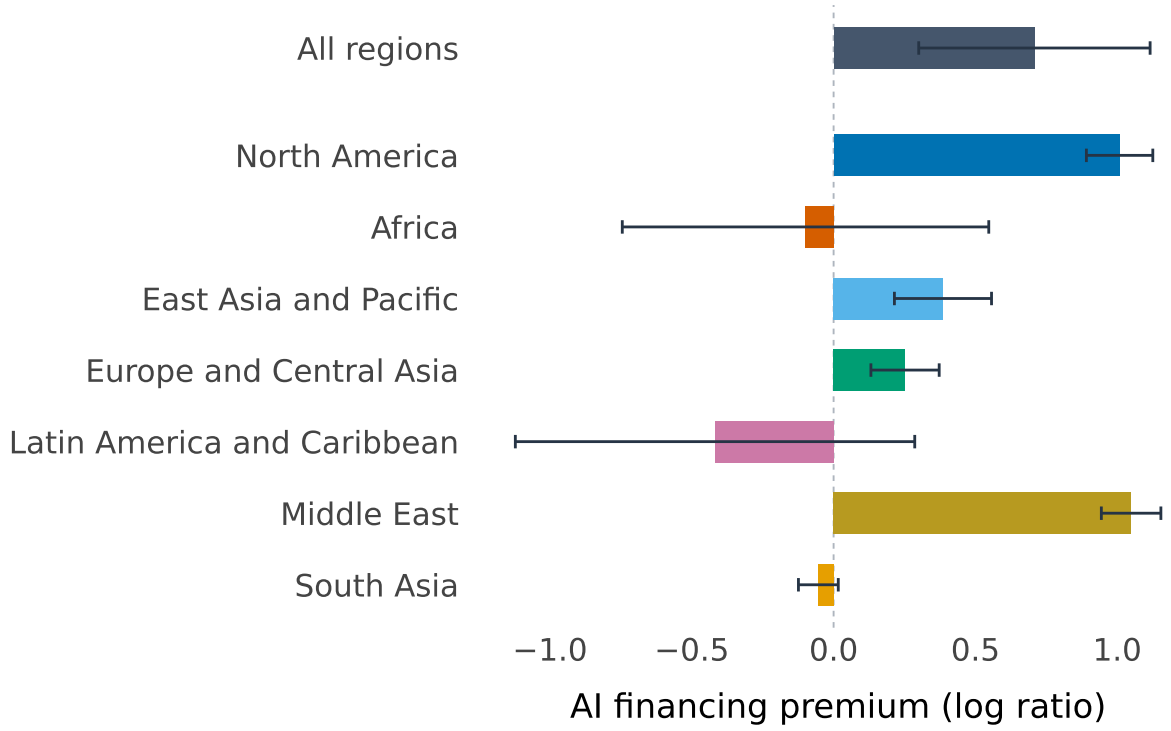


Figure 4: The AI financing premium across regions

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 of 672,928 firm-years. Intervals are 95 percent confidence intervals clustered by country.

Europe has nearly as many startups as North America—36,464 versus 40,351—yet its AI premium is 29 percent. The Middle East has only 4,307 startups, but an AI premium of 185

percent. AI firms need not enjoy a large financing advantage simply because they operate in a large startup market.

A startup's current description can include AI products introduced after its early funding. We therefore use archived websites and press, investor, and regulatory announcements to construct two historical AI classifications and repeat the baseline analysis. For the earliest-description classification, we use the first description from the founding year onward. For the near-founding classification, we use a description from the founding year or either of the next two calendar years. Both historical classifications remain fixed for each firm across funding years (Appendix C.1).

Nigerian lender *QuickCheck* described its machine-learning credit model in January 2017. It therefore enters both historical classifications as AI. Hollard described South African insurer *Naked* as a digital insurance platform in October 2017; the firm launched its AI quoting system in April 2018.

North American AI firms retain a large financing advantage under the historical classifications, receiving 2.33 times as much annual funding as non-AI firms under the earliest description and 2.17 times as much near founding (Appendix Tables C1 and C2). We again find no African premium. As in the baseline, the AI financing premium remains significantly lower than North America's in East Asia, Europe, Latin America, and South Asia, while the Middle Eastern premium remains indistinguishable from North America's. Within regions, Europe's premium falls to about 10 percent and is imprecise. South Asian AI firms receive 21 to 25 percent less funding than non-AI firms, and Latin American AI firms receive 56 percent less under the near-founding classification.

Earlier descriptions are available for fewer firms. We repeat the comparison after restricting attention to identical firm-years, separating changes in AI status from changes in the sample. Africa's gap relative to North America narrows, although the changes are imprecise (Appendix C.1). In Section 6, we examine how the financing of the data-center operators behind this shift shapes the African comparison.

AI firms in Africa, Latin America, and South Asia target broader customer markets, yet we find no positive financing premium under any of the three classifications.

5 Explaining regional differences

Why do AI firms command a premium in some regions but not in others? Broadly applicable products may face different customer demand across regions. The firms developing them may also differ in their founders, early employees, or access to investors. We examine these explanations in turn by adding the corresponding characteristics to equation (4). Each

specification uses the same 554,524 firm-years from 114,279 startups in 157 countries. We begin at firm age two so that early nonfounder employees can be measured at the end of the year after founding.[5]

Every specification uses the same information controls, including indicators for missing founder, employee, and potential-investor information. We interact AI status with the missing-investor indicators and calculate premia with those indicators set to zero. Thus, the premia refer to firm-years with potential-investor information, while firm-years with missing information remain in the estimation sample.[6]

We label the successive additions Demand, Founders, Employees, and Investors. Denoting customer-market characteristics by D_i, founders' backgrounds by F_i, early-team capabilities by E_i, and potential investors' resources and connections by I_{it}, the full specification for expected annual funding, μ_{it}, is

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

Here $j(i)$ is the principal customer industry. The information controls in Q_{it} and the common reference values for investor characteristics in $\overline{I}$ remain fixed across specifications. In this specification, we also include investor characteristics on their own and interacted with AI status, thereby allowing for different funding associations for AI and non-AI firms. Centering these characteristics at the common reference values makes the regional premia comparable across specifications.

Table 3 and Figure 5 show how each region's gap relative to North America changes as we add characteristics. The change in κ_r between adjacent specifications measures the contribution of the added characteristics; we express each change as a share of that region's original Baseline gap, using the same denominator throughout. Appendix Table B3 reports the changes, with standard errors computed from the models' joint country-clustered covariance (Appendix B).

[5]Appendix Table B2 reports how restricting the sample changes the regional financing estimates from Section 4.

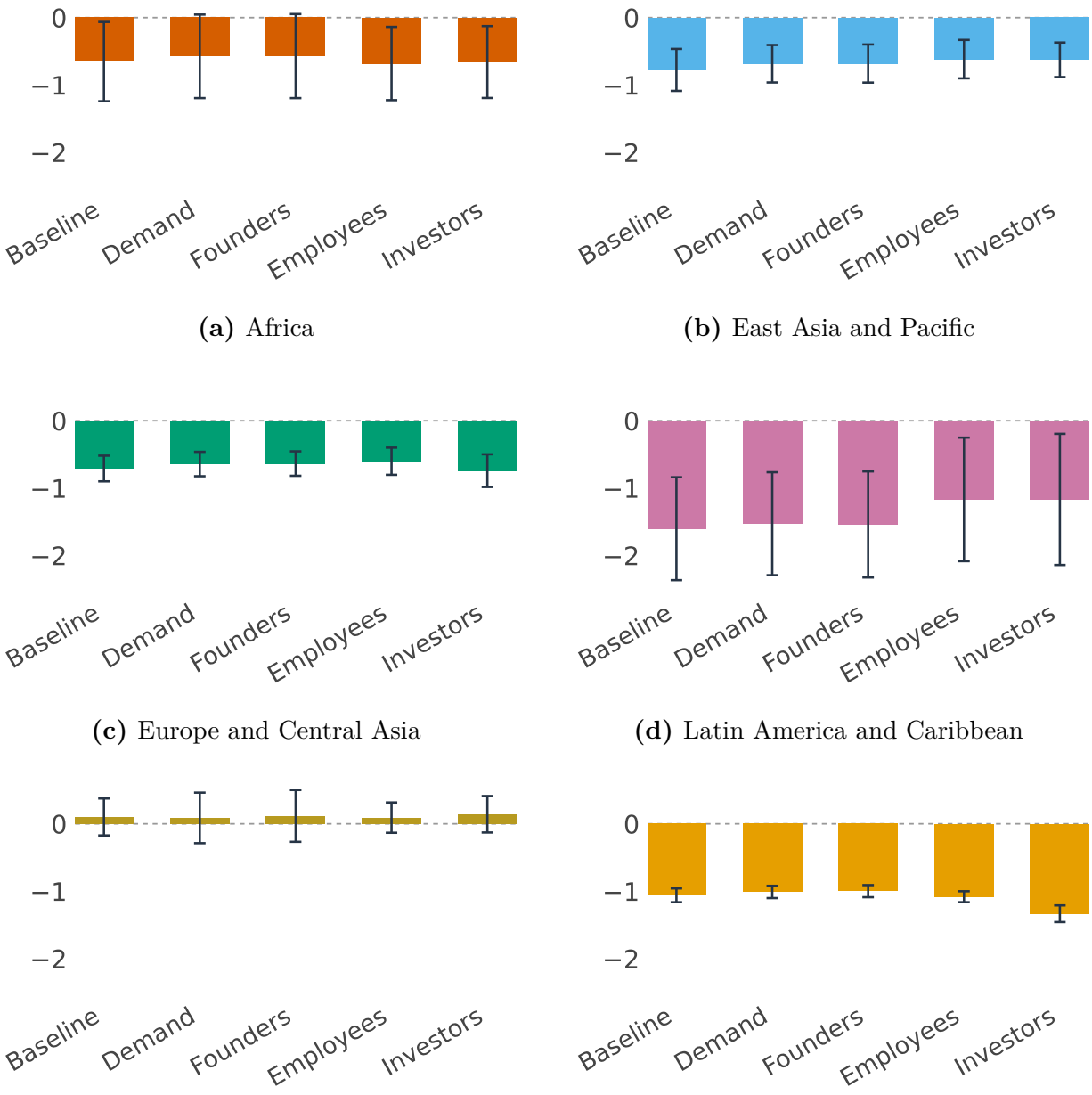
[6]Potential investors' stage focus and typical round size are each available for 60.0 percent of North American AI firm-years and 93.7 percent of non-AI firm-years. In Africa, stage focus is available for 48.7 percent of AI and 32.9 percent of non-AI firm-years; round size is available for 45.1 and 31.9 percent, respectively (Appendix Table A5).

Table 3: Regional AI financing differences

	Annual financing (USD millions)				
	Baseline	Demand	Founders	Employees	Investors
	(1)	(2)	(3)	(4)	(5)
AI firm	-0.1219	-0.2189	-0.2187	-0.2957	-0.2516
	(0.4931)	(0.4810)	(0.4802)	(0.5034)	(0.5780)
Reference: North America					
AI × Africa	-0.6531*	-0.5749	-0.5713	-0.6812*	-0.6592*
	(0.3002)	(0.3162)	(0.3181)	(0.2776)	(0.2723)
AI × East Asia and Pacific	-0.7763***	-0.6849***	-0.6818***	-0.6163***	-0.6262***
	(0.1588)	(0.1417)	(0.1442)	(0.1455)	(0.1307)
AI × Europe and Central Asia	-0.7095***	-0.6427***	-0.6357***	-0.6010***	-0.7413***
	(0.0973)	(0.0925)	(0.0926)	(0.1030)	(0.1238)
AI × Latin America and Caribbean	-1.6027***	-1.5287***	-1.5397***	-1.1678*	-1.1680*
	(0.3896)	(0.3898)	(0.4016)	(0.4679)	(0.4968)
AI × Middle East	0.1018	0.0879	0.1175	0.0917	0.1419
	(0.1400)	(0.1913)	(0.1959)	(0.1147)	(0.1382)
AI × South Asia	-1.0611***	-1.0111***	-0.9993***	-1.0819***	-1.3342***
	(0.0523)	(0.0465)	(0.0459)	(0.0414)	(0.0631)
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	0.005	< 0.001	< 0.001
Observations	554,524	554,524	554,524	554,524	554,524
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 use North America's AI premium as the reference. We report standard errors clustered by country in parentheses. Joint tests assess whether regional premia are equal and whether they change from the preceding column. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

We use the model's centered reference profile and common information controls to evaluate AI contrasts. Investor main effects and AI interactions are expressed in the same units.



(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 (κ_r), 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 five specifications use the same 554,524 firm-years. Intervals are 95 percent confidence intervals clustered by country.

5.1 Targeted markets

If AI firms in some regions target markets with weaker demand, accounting for those markets should narrow their financing gaps. Country-year fixed effects control for conditions common to startups in the same local economy. The Demand specification includes customer-industry-by-funding-year fixed effects that account for worldwide funding conditions in the industries startups serve. We also include horizontal applicability and customer breadth to distinguish products that can reach beyond their principal market.

With the Demand controls, Europe's gap narrows by 9 percent of its original Baseline level, East Asia's by 12 percent, and Latin America's and South Asia's by about 5 percent each. The changes in Africa and the Middle East are imprecise (Appendix Table B3). Within customer industries and years, neither targeting more industries nor offering a horizontal product is associated with significantly more funding (Appendix Table B5).

5.2 Founders

Investors place great weight on founding teams (Hsu, 2007; Bernstein et al., 2017; Gompers et al., 2020). We estimate a version of the financing specification in which we also include indicators for whether founders previously started a firm, hold an MBA, or hold a doctorate. In the final specification, startups with a founder who previously started another firm receive 54 percent more annual funding, while those with a doctorate-holding founder receive 41 percent more. The MBA association is negative and imprecise (Appendix Table B6).

The founder characteristics account for only 1 percent of South Asia's original Baseline gap and little of the shortfalls elsewhere. In the Middle East, the positive difference widens by 29 percent of its baseline level. The changes are jointly statistically significant, but founders' backgrounds account for little of the regional pattern.[7]

5.3 Early employees

Early teams account for the largest reduction in Latin America's financing gap. When we add early nonfounder employees' team size, prior startup experience, and education, the gap narrows by 23 percent of its original Baseline value relative to North America, a statistically significant reduction and the largest attributable to any set of characteristics in the sequence (Figure 5d). South Asia's gap moves in the other direction, widening by 8 percent of its

[7]We observe these traits for 12 to 18 percent of the firms (Appendix A.3) and include indicators for missing founder information in every specification. Appendix Table B3 reports the regional changes and their joint test.

Baseline value. Changes in the remaining regions, including Africa, are imprecise (Appendix Table B3).

Firms with larger early teams receive more funding, with expected funding increasing slightly more than proportionally with one plus team size (Appendix Table B7). Employee education also predicts funding: a ten-percentage-point increase in the share with a bachelor's degree or higher is associated with 11 percent more capital. The association with prior startup employment is positive but imprecise.

5.4 Potential investors

Venture capital, and the experience and networks of those who provide it, are concentrated in a few places (Chen et al., 2010; Lerner and Nanda, 2020; Colonnelli et al., 2026). Startups with similar markets and teams can consequently have different access to investors able to evaluate and finance AI businesses. We next investigate whether differences in access to investors account for the regional financing gaps, adding potential-investor characteristics to the specification. Adding these characteristics instead widens Europe's and South Asia's gaps by 20 and 24 percent of their original baseline values, while changes elsewhere are imprecise (Table 3, column 5, and Appendix Table B3).

Both AI and non-AI firms receive more funding when their potential investors focus on early-stage companies, participate in larger rounds, and share university connections with their founders (Appendix Tables B8, B9, and B10). The associations with stage focus and typical round size are stronger for non-AI firms. For stage focus, a ten-percentage-point increase corresponds to 23 percent more funding for non-AI firms and 13 percent more for AI firms. University connections have the opposite ordering, with a larger estimated association for AI firms, but the difference is imprecise. Recent fund commitments have positive, imprecise associations in both groups.

Accounting for all four sets of characteristics leaves the AI-to-non-AI funding ratio below North America's in Africa, East Asia, Europe, Latin America, and South Asia; we continue to reject equal regional premia (Table 3, column 5). Africa's remaining gap is about as large as in the baseline. It is statistically significant with country clustering but not with firm clustering, whereas the other four regional gaps remain significant throughout the sequence under either choice (Appendix Table B4).

The characteristics associated with a startup's funding explain little of the regional differences in the AI premium. Customer markets, founders' backgrounds, and potential investors leave most gaps little changed or wider. Latin America provides the largest exception through its early teams: all four sets of characteristics together account for 27 percent of the

region's original Baseline gap; adding early employees' characteristics accounts for 23 percent of that original gap. For Africa, we turn next to the businesses that receive the region's AI funding.

6 AI infrastructure and entrepreneurship

6.1 AI infrastructure providers in Africa

Half of African AI funding goes to firms that supply computing and network infrastructure. There are 93 such firms among the region's 1,128 AI startups—data-center operators, colocation providers, cloud hosts, and managed connectivity networks. The 91 with observed financing raised $1.06 billion, accounting for 50.9 percent of AI funding. Infrastructure occupies a much smaller share of the North American AI sector: 2.3 percent of startups and 12.2 percent of funding (Appendix C.2).

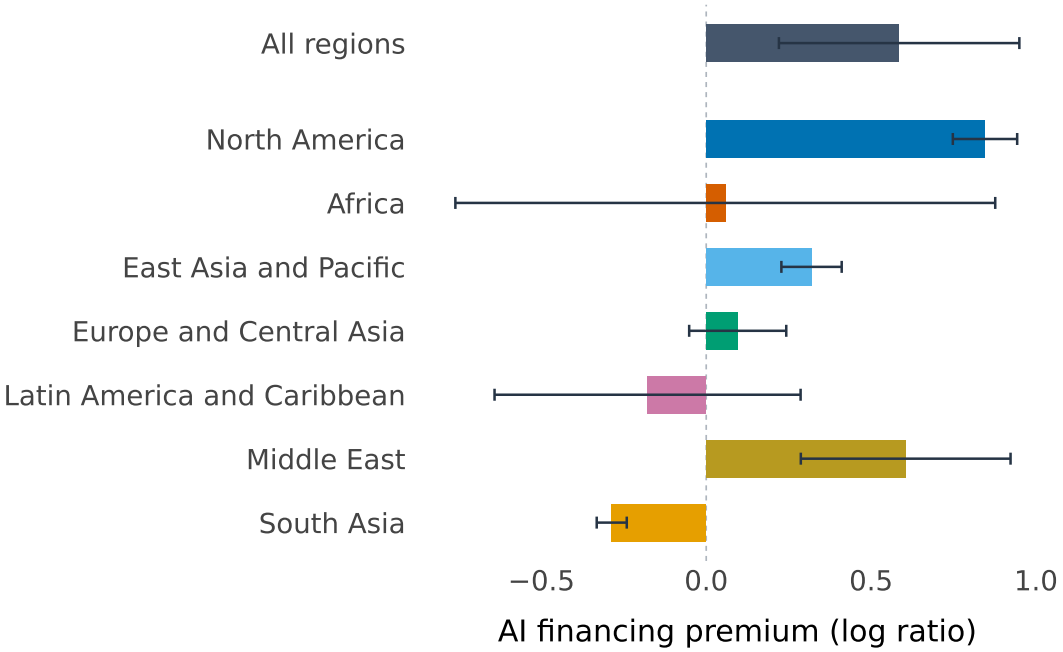
We repeat our regional financing analysis after restricting attention to firms outside infrastructure in every region, using equation (4) and the current, earliest, and near-founding AI classifications to examine financing for startups developing AI applications, models, and tools. The historical comparisons also exclude AI firms whose primary activity cannot be determined from their descriptions (Appendix C.2).

Under the earliest-description classification, African AI startups outside infrastructure raise 60 percent less annual funding than non-AI startups, while North American AI startups raise 1.96 times as much as non-AI startups in their region (Figure 6). The gap relative to North America is large and statistically significant under all three classifications (Appendix Tables C3–C5).

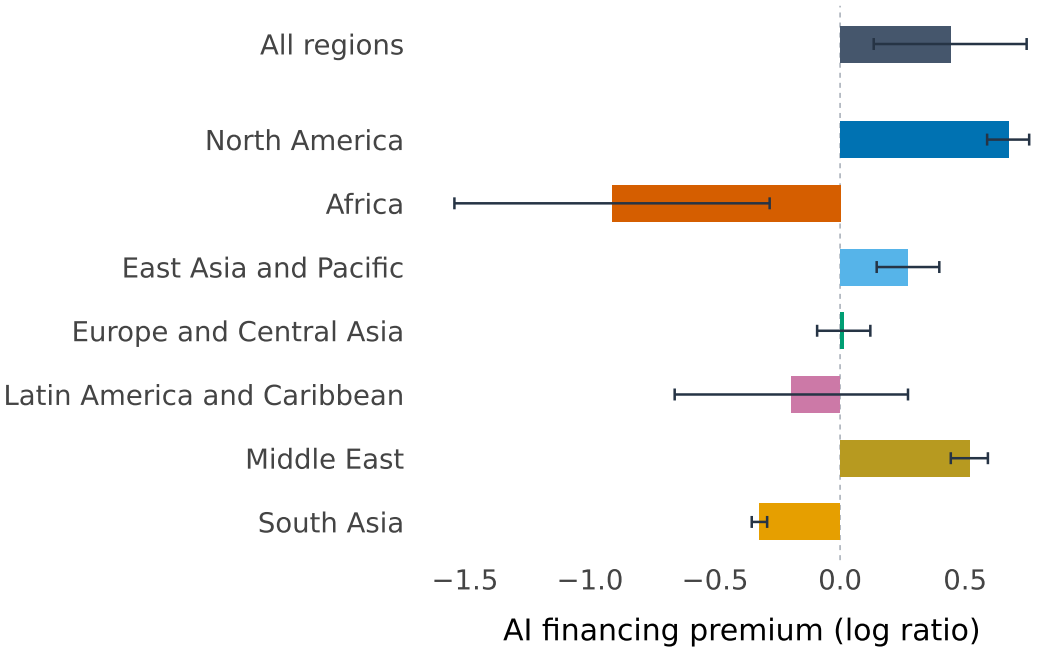
Excluding infrastructure also changes the comparison between current and historical classifications. In Section 4, using earlier descriptions narrowed the Africa–North America gap on identical firm-years; outside infrastructure, the gap instead becomes slightly wider, although these changes are imprecise (Appendix C.2).

The narrowing when infrastructure is included comes from two data-center operators, *IXAfrica Data Centre* in Kenya and *Africa Data Centres* in South Africa. Over its five years in the panel, IXAfrica raised $250 million, of which $200 million came from a debt facility closed with Rand Merchant Bank in September 2025.[8] When we exclude IXAfrica alone, the Africa–North America gap is statistically significant under both historical classifications. The cost of building data centers helps explain why these financing amounts are large. They reflect the businesses being built as well as investors' willingness to supply capital.

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



(a) All eligible firms



(b) Excluding AI infrastructure providers

Figure 6: AI financing premia by region using the earliest description

Notes: We report the log funding ratio for AI firms relative to non-AI firms estimated from equation (4) using each startup's earliest description. Lines give 95 percent confidence intervals clustered by country.

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 above 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 40 percent before any of these characteristics is added, but the gap remains statistically significant. The checks in Appendix C 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, 0.40 times as much under the earliest classification (Figure 6). 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 became more likely to employ commercial staff.

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 174 percent more annual capital than comparable non-AI startups in North America and 185 percent more in the Middle East, compared with 47 percent more in East Asia, 29 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. Under the earliest-description classification, excluding these infrastructure providers reveals that African startups building AI applications, models, and tools actually raise 60 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 potential investors narrows the gap relative to North America in Latin America (where early-team human capital accounts for roughly 23 percent of the original Baseline shortfall) but leaves the broader regional divide intact.

By showing that differences in customer scope, founder credentials, and observable investor traits do not close the regional gaps, 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

A.1 Matching firms and assigning operating country

We first combine the PitchBook and Stears company records. We do the matching using standardized company names, web domains, known aliases, headquarters locations, and LinkedIn company profiles. For companies found in both sources, we pool their financing rounds in one record and use PitchBook for company attributes. We then match these firms to Revelio Labs employer profiles using company domains and LinkedIn URLs.

We match investor organizations to Preqin using website domains, LinkedIn profiles, or names that are unique within the investor's country. We do the matching for university connections using the school identifiers recorded in founders' and investor employees' Revelio education histories.

When the founding year is missing for a given startup, we establish when it began operating by using archived company histories and matched employer profiles. We use the date of an incorporation, acquisition, product launch, or parent-company event only when it also marks the venture's launch.

Our first approach is to use workers' locations in the founding year and the following calendar year to assign operating country. The country with the most workers must have a strict plurality even after all workers with missing or ambiguous locations are assigned to the second-largest country.

When this condition is not met, we use headquarters location, country of incorporation, and manual review of single-country operations, in that order. We group countries into World Bank regions, combining North Africa and sub-Saharan Africa as Africa and assigning Pakistan and Malta to the Middle East.

A.2 Company classifications and customer markets

We use TypeSafe's Jev model (version `jev-1.13.0`) to predict whether a startup produces AI and which customers it serves. The model answers a questionnaire using company descriptions, keywords, sector tags, and homepage text. Appendix D reproduces the questions used in the paper. In our analysis, we define a response to be positive if its score is above 0.5 for a binary question, including AI production and horizontal applicability across industries. For questions with multiple categories, we select the highest-probability category.

We define AI firms as startups that supply models, data tools, infrastructure, or compute within the foundational supply chain, or offer a customer-facing product whose description refers to AI or machine learning. We also include firms confirmed as AI producers through

manual review. A startup is classified as non-AI when all its descriptions score below 0.5 and none shows a supply-chain role.

We classify a startup as AI if any confirmed source record does so. When source records conflict, we take product and customer-market attributes from the AI-positive record; otherwise, we use the primary database record.

We assign each startup's principal customer industry to an ISIC division, then aggregate divisions to ISIC sections for the financing regressions. Code `00` covers both products that apply equally across sectors and descriptions without sector-specific detail; the horizontal indicator distinguishes the former from the latter.

The customer questionnaire includes 99 questions about three-digit NAICS industries, using their official codes and titles, and 20 about broad sectors. We define an industry to be a customer market if its Jev score is at least 0.8, the cutoff selected in pilot audits before outcome analysis. A broad sector counts when either its own question or one of its three-digit industries reaches this cutoff.

We define customers as both current buyers and those the startup states it intends to serve. The startup's own industry, suppliers, and distribution partners count only if they also buy its product. Consumer-facing ventures and horizontal tools without named client sectors can therefore have zero targeted industries despite having a business description.

For customer counts and task scores, we use an alias record only when the primary record lacks text and the alias description matches across PitchBook and Stears. We check the classifications of 300 startup descriptions by hand, using two independent human reviews.

Shared customer tasks. To build task profiles for 81 three-digit NAICS industries, we link May 2021 BLS Occupational Employment and Wage Statistics to O*NET version 27.2 task-to-work-activity mappings (U.S. Bureau of Labor Statistics, 2022; U.S. Department of Labor, Employment and Training Administration, 2023). When BLS combines adjacent industries, we use one profile for the group.

We follow Eloundou et al. (2024) in giving core tasks twice the weight of supplemental tasks within each detailed O*NET occupation. Each task's weight is divided equally among its detailed work activities. We calculate the average of the detailed-occupation profiles within six-digit SOC codes and weight the resulting profiles by industry occupational employment. The final industry profiles are normalized over activities with human AI-exposure scores.

Let p_{jt} denote industry j's normalized employment weight on activity t. For its AI exposure, q_t, we use the human β ratings of Eloundou et al. (2024), adding direct LLM exposure to 0.5 times exposure requiring complementary software and averaging within each detailed work activity using the same occupational weights. We then calculate, for two

industries j and k, unweighted task overlap, R_{jk}, and AI-weighted overlap, A_{jk}, as

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

For a startup serving at least two covered industries, let $\mathcal{P}_i$ contain all unordered pairs of those industries. When their total unweighted overlap is positive, $\sum_{(j,k)\in\mathcal{P}_i} R_{jk} > 0$, we calculate the AI suitability of shared tasks as

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

which measures AI-weighted overlap relative to the amount of work the industries share. We also calculate unweighted customer-task overlap as the pair average $|\mathcal{P}_i|^{-1} \sum_{(j,k)\in\mathcal{P}_i} R_{jk}$, using both the 0.8 and 0.5 industry-assignment thresholds.

A.3 Founders and nonfounder employees

We measure founder credentials from matched Revelio profiles through December 31 of the founding year. Our early-team sample includes employees whose Revelio job start and end dates show them active on December 31 of the year after founding, following Choi et al. (2025). We exclude focal-startup founders named in PitchBook, Stears, or Revelio job titles, but retain employees who founded other firms. Each person enters once per startup, under their latest active occupation at the reference date.

Careers and education. In our analysis, we define a person to be a prior founder if they held a founder title at another employer on or before December 31 of the startup's founding year. An early employee has prior startup experience if they began a job at another matched company, then aged ten years or younger, strictly before first joining the focal startup.

We measure schooling using Revelio's degree histories, adapting individual measures such as those in Dahl and Klepper (2015). Qualifications fall into six categories: High School, Associate, Bachelor, Master, MBA, and Doctor. A degree must be completed by the reference date and cannot be completed before its reported start date. For early employees, we define bachelor's-or-higher attainment as a completed Bachelor, Master, MBA, or Doctor degree. We record non-attainment only when all qualifications are Associate or High School and every degree record has a known category and completion date.

Aggregation and coverage. We set the founder indicator equal to one if any matched founder has the characteristic. It equals zero if at least one founder is matched and all

matched founders are known not to have it; otherwise it is missing. The controls include the number of matched founders, the share with information on the characteristic, and the share of database-listed founders linked to Revelio.

For early employees, we distinguish the share with a characteristic from the coverage of that characteristic. For characteristic h, we calculate

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

$$\text{Coverage}_{ih} = \frac{\text{employees with observed data on } h}{\text{nonfounder employees}}, \tag{A4}$$

where Share_{ih} requires a positive denominator. If the matched workforce in the year after founding consists only of founders, nonfounder headcount is zero and the employee share is missing. If no workforce is matched, nonfounder headcount is also missing.

The compiled data cover 52,200 founder–firm pairs across 47,425 companies in the full sample. In the workforce active on December 31 of the year after founding, 46,708 of 766,045 person–firm records belong to founders. After excluding founders, we have 719,337 early nonfounder employee–firm pairs, of which 36,531, or 5.1 percent, have unknown founder status.

We find no matched early workforce for 32,055 firms and a workforce consisting only of founders for 3,816 firms. In Tables A1 and A2, we report these counts by region and AI status.

For some startups with matched workforces, the information used in the financing analysis is missing. Among the 114,279 firms in the explanatory sample of Section 5, prior founding is observed for 17.8 percent, founder MBA attainment for 12.9 percent, and founder doctorate attainment for 12.3 percent. Early-team headcount is observed for 72.6 percent of these firms, as compared to 28.4 percent for startup experience and 60.8 percent for bachelor's-or-higher education.

Startup experience is observed for 32,406 firms, including 104 with a zero employee share. On average, the share of employees with information on startup experience is 11.9 percent across firms with at least one matched nonfounder employee. Tables A3 and A4 give the coverage of these characteristics.

A.4 Firm tasks and amenability to AI adoption

The quarterly workforce panel runs from 2021Q1 through 2025Q4 and uses job records active in the final month of each quarter. We count each employee once per startup, using their latest active occupation. If a matched startup has no active job in that month, its employment

Table A1: Founder matching and early employee coverage

Region	Firms	Total	Matched founder	Missing employee data	Founder only	Unknown founder status
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 named founders. Unknown founder status counts startups with early 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: Coverage of 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 data on each founder characteristic. We count each firm once. These percentages include zeros and exclude missing values.

Table A4: Coverage of employee characteristics in the financing sample

Region	Firm type	Firms	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 data on each early nonfounder employee characteristic. We count each firm once. These percentages include zeros and exclude missing values.

is zero. We link these occupations to O*NET intermediate work activities. Throughout our analysis, we define task breadth as the number of distinct O*NET intermediate work activities and define commercial staffing as having at least one employee in a mapped sales, marketing, or related commercial occupation.

For initial task amenability, we use occupations in the December 2021 workforce, including matched founders. We map these occupations to detailed O*NET activities and combine them with profiles for 59 ISIC industries built from 2014 BLS occupational employment. Let w_{it}^0 denote startup i's normalized December 2021 weight on covered activity t, $\bar{p}_t$ the unweighted mean task share across those industries, and q_t the human AI rating from Eloundou et al. (2024). Baseline task amenability is

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

so activities receive more weight when they are both suited to AI and common across industries. We also measure ordinary cross-industry task affinity, $\sum_t w_{it}^0 \bar{p}_t$, and own-task AI suitability, $\sum_t w_{it}^0 q_t$. In the December 2021 sample, we standardize each measure to unit variance. We include baseline controls for log employment, occupational task coverage, the number of employee countries, and missing country data.

Our sample includes only firms with a December 2021 task profile and workforce observations in 2022Q3 and at least one other quarter. The compiled data cover 63,020 firms and 1,258,697 firm-quarters for task breadth, and 62,894 firms and 1,256,660 firm-quarters for commercial staffing, spanning the 2015–2020 founding cohorts in 164 countries. While we average the dynamic coefficients δ_s over 2023Q1–2025Q4, we set the post-period indicator equal to one for 2022Q4–2025Q4 in the static difference-in-differences comparison.

A.5 Annual financing amounts

For 2019 through 2025, we use deals from PitchBook and Stears to sum equity, debt, grants, and other financing in each calendar year. We count each round once, in nominal USD millions, and exclude post-money valuations and imputed allocations to individual investors. For installments, we assign each transaction to its named operating recipient using the tranche date and amount. For example, in June 2023 the International Finance Corporation provided a $100 million loan to Safaricom Ethiopia, while its $157.4 million equity investment went to the Dutch holding company. Only the $100 million loan is ascribed to the Ethiopian operating company's annual funding.[9]

[9] IFC, June 8, 2023.

If a deal has no date, we assign it to the year of the next round in the database's sequence for that startup. If there is no later round, we use the latest round or profile financing date for that startup. This rule applies whether or not the amount is disclosed.

We treat a firm-year as missing if a round assigned to that year has an undisclosed amount, a currency conversion that cannot be established, conflicting reports across PitchBook and Stears, or an unallocated multi-year total. We retain the startup's unaffected years in the panel. If a year has neither positive funding nor a financing event with one of these problems, we record zero funding.

A.6 Potential investors, resources, and university connections

Potential-investor pool. We define potential investors for startup i in year t as those that participated in an initial or follow-on round during $t-3$ through $t-1$ for a sampled 2015–2022 cohort startup with the same operating country as i and the same primary PitchBook industry as i. We use the startup's own industry, not its customers' industries; if the industry code is missing or conflicting, the pool is undefined. For funded and unfunded firm-years alike, we fix membership before January 1 of year t and include foreign-headquartered investors. We construct all four investor measures from this pool.

Stage focus and typical round size. To measure investors' stage focus and typical round size, we use deals from the three prior calendar years, excluding the focal startup's rounds and counting every other round once per investor. We define early-stage rounds as those classified as seed, angel, or early-stage VC, and define later-stage rounds as later-stage VC, growth equity, or their restart equivalents. Early-stage focus is the share of an investor's stage-classified equity rounds in the early-stage category. We exclude generic equity, unclassified crowdfunding, whole-round debt and grants, and convertible instruments without stage labels from the denominator. We average these shares across all pool investors with at least one stage-classified deal, giving each investor equal weight.

The data do not readily identify individual syndicate shares, so we characterize investors' deals using total round size. For each investor, we take the median disclosed round amount in USD millions across equity and non-equity deals in other sampled startups during $t-3$ through $t-1$. Typical round size is the equally weighted mean of $\log(1 + \text{median disclosed round size in USD millions})$ across pool investors with these data.

Recent fund commitments. Adapting Kaplan and Schoar (2005), we match investors to Preqin fund managers and select the latest close for each distinct VC fund during $t-3$ through $t-1$, before January 1 of year t. In case of a final and an interim close on the same date, we

use the final close. We do not add cumulative interim and final amounts for the same fund. For investors whose retained closes all have known amounts, we sum commitments in USD millions. The pool measure is $\log(1+\text{mean committed capital across covered pool investors})$. An investor's commitments are missing if no manager is matched, no fund closes in the three-year period, or amounts are incomplete.

University connections. We follow the alumni-network approach of Garfinkel et al. (2026) to measure university connections between founders and potential investors. We do the matching using exact Revelio school identifiers for Associate, Bachelor, Master, MBA, and Doctor degrees. Founder degrees must be completed by December 31 of the startup's founding year; investor employees' degrees must be completed before funding year t. Investor employees must also hold an active job at a pool VC firm on January 1 of that year.

For each founder with university data, the connection share is the fraction of pool investors with employee school information that employ another graduate of the founder's university. Each investor counts once for that founder, and self-matches are excluded. We then compute the equally weighted average of these shares across all founders with university data.

Coverage and reference values. The compiled data cover 554,524 firm-years in the explanatory sample of Section 5. Stage focus is observed for 72.1 percent, typical round size for 72.0 percent, recent Preqin commitments for 61.3 percent, and university connections for 17.5 percent (Table A5).

On average across the 401,152 firm-years with a nonempty pool, 98.2 percent of investors have stage-focus data, as compared to 97.0 percent for round size, 20.4 percent for Preqin commitments, and 45.4 percent for employee university records.

We compare regional premia at common investor characteristics by subtracting a fixed reference value from each measure, using the same values in all five specifications of equation (5). We set missing to zero and include missingness indicators and their interactions with AI status.

The investor-information controls include the shares of pool investors with data, stage and amount information on their past rounds, and founders' and investor employees' school records. We also include each investor-information control interacted with AI status, thereby allowing for separate relationships with financing for AI and non-AI firms.

Table A5: Coverage of 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	4,823	48.7	45.1	30.6	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	57,753	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 data on each investor characteristic. These percentages include zeros and exclude missing values. We use the same pre-year definition before and after first funding.

B Estimation and supporting results

B.1 Financing samples and inference

Our full 2019–2025 panel contains 675,657 firm-years, including 108,625 with positive funding. In estimating equations (3) and (4) by PPML, we exclude 2,729 zero-funding observations separated by the fixed effects and information controls (Correia et al., 2026). After these exclusions, 672,928 firm-years remain in the estimation sample, including all 108,625 positive-funding observations. We omit a control for collinearity only if it is an exact linear combination of the remaining covariates and fixed effects.

We first restrict the sample to startups aged two and older for the five specifications of equation (5). The resulting sample contains 557,390 firm-years, including 82,781 with positive funding. We exclude 2,860 observations in all-zero fixed-effect cells and six additional separated zeros. As a result, the same 554,524 firm-years enter all five specifications, including every one of the 82,781 positive outcomes.

We cluster the main standard errors by operating country and report firm-clustered standard errors in Table B4. Confidence intervals use normal critical values, and joint Wald tests use chi-squared reference distributions.

Estimates from the same firms and countries are correlated, so we account for this correlation when testing changes in regional gaps across successive models. For models estimated on the same G country clusters, let s_{gm} denote the summed profiled score vector for

country g in model m and B_m the inverse profiled Hessian. The cross-model country-clustered covariance is

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

When $m = n$, this gives the within-model covariance $\widehat{V}_{mm}$. For changes in the six regional interaction coefficients between adjacent columns of Table 3, the difference covariance is $V_{nn} + V_{mm} - V_{mn} - V_{nm}$. Table B3 reports these changes and their joint tests.

In Table B1, the pooled log premium of 0.708 corresponds to 103 percent more annual funding for AI firms. The North American log premium is 1.008, or an AI-to-non-AI funding ratio of 2.74, compared with a log premium of 1.049 in the Middle East. Gaps relative to North America are −1.107 log points in Africa, −1.426 in Latin America, −1.062 in South Asia, −0.756 in Europe, and −0.623 in East Asia. The European and East Asian ratios are therefore 53 and 46 percent lower than North America's; the Middle Eastern ratio is 4 percent higher, with an insignificant difference.

Table B3 compares each region's gap with the preceding specification; percentage contributions use the original Baseline gap throughout. Demand controls narrow the European, East Asian, South Asian, and Latin American gaps by 0.067, 0.091, 0.050, and 0.074 log points, respectively, while changes of +0.078 in Africa and −0.014 in the Middle East are imprecise. Employee controls widen South Asia's gap by 0.083 log points, and investor controls increase the Middle East's positive difference by an imprecise 0.050 log points. Each addition jointly changes the regional gaps, including Founders, whose changes are small in magnitude.

After all characteristics enter, the gaps relative to North America are −0.66 log points in Africa, −0.63 in East Asia, −0.74 in Europe, −1.17 in Latin America, and −1.33 in South Asia. Table B4 reports the sequence with firm clustering; the African inference comparison is discussed in Section 5.

Table B1: AI financing estimates

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.7081***	1.0084***
	(0.2081)	(0.0598)
Reference: North America		
AI × Africa		-1.1074***
		(0.3338)
AI × East Asia and Pacific		-0.6228***
		(0.0975)
AI × Europe and Central Asia		-0.7565***
		(0.0735)
AI × Latin America and Caribbean		-1.4264***
		(0.3637)
AI × Middle East		0.0406
		(0.0718)
AI × South Asia		-1.0621***
		(0.0376)
Firms	114622	114622
Country clusters	163	163
Observations	672,928	672,928
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 pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are 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 firm	1.0084***	1.0174***
	(0.0598)	(0.0614)
Reference: North America		
AI × Africa	-1.1074***	-1.0880***
	(0.3338)	(0.3267)
AI × East Asia and Pacific	-0.6228***	-0.6303***
	(0.0975)	(0.1028)
AI × Europe and Central Asia	-0.7565***	-0.7506***
	(0.0735)	(0.0836)
AI × Latin America and Caribbean	-1.4264***	-1.4911***
	(0.3637)	(0.3957)
AI × Middle East	0.0406	0.0467
	(0.0718)	(0.0828)
AI × South Asia	-1.0621***	-1.0964***
	(0.0376)	(0.0397)
Firms	114622	114279
Country clusters	163	157
Observations	672,928	554,524
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	0.0783	0.0036	-0.1099	0.0221
	(0.0456)	(0.0080)	(0.1307)	(0.0721)
East Asia and Pacific	0.0914**	0.0030	0.0655	-0.0099
	(0.0333)	(0.0042)	(0.0518)	(0.0745)
Europe and Central Asia	0.0667***	0.0070	0.0347	-0.1402**
	(0.0202)	(0.0037)	(0.0319)	(0.0430)
Latin America and Caribbean	0.0740***	-0.0110	0.3719***	-0.0002
	(0.0202)	(0.0157)	(0.0908)	(0.0634)
Middle East	-0.0139	0.0296*	-0.0258	0.0502
	(0.0597)	(0.0125)	(0.0977)	(0.0402)
South Asia	0.0500*	0.0118**	-0.0826***	-0.2523***
	(0.0220)	(0.0045)	(0.0213)	(0.0386)
Joint change: p-value	< 0.001	0.005	< 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 firm	-0.1219	-0.2189	-0.2187	-0.2957	-0.2516
	(0.3529)	(0.3246)	(0.3287)	(0.3535)	(0.3749)
Reference: North America					
AI × Africa	-0.6531*	-0.5749	-0.5713	-0.6812	-0.6592
	(0.3048)	(0.3159)	(0.3159)	(0.3874)	(0.3926)
AI × East Asia and Pacific	-0.7763***	-0.6849***	-0.6818***	-0.6163***	-0.6262***
	(0.1985)	(0.1868)	(0.1871)	(0.1861)	(0.1896)
AI × Europe and Central Asia	-0.7095***	-0.6427***	-0.6357***	-0.6010**	-0.7413***
	(0.1788)	(0.1695)	(0.1695)	(0.1877)	(0.1998)
AI × Latin America and Caribbean	-1.6027***	-1.5287***	-1.5397***	-1.1678**	-1.1680**
	(0.3885)	(0.3820)	(0.3871)	(0.3991)	(0.4107)
AI × Middle East	0.1018	0.0879	0.1175	0.0917	0.1419
	(0.2148)	(0.2016)	(0.1980)	(0.1791)	(0.1872)
AI × South Asia	-1.0611***	-1.0111**	-0.9993**	-1.0819***	-1.3342***
	(0.3185)	(0.3172)	(0.3163)	(0.3283)	(0.3438)
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	0.005	< 0.001	< 0.001
Observations	554,524	554,524	554,524	554,524	554,524
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. Standard errors in parentheses are clustered by firm. For joint tests of equal premia and changes from the preceding column, we cluster by country. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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.

B.2 Characteristics associated with financing

Tables B5–B10 report the funding associations for the customer, founder, early-employee, and potential-investor characteristics added in equation (5). Section 5 describes the common information controls, and Appendices A.3 and A.6 define the characteristics and their coverage.

Previous founding experience and doctorate attainment are associated with 54 and 41 percent more annual funding in the final specification, with coefficients of 0.429 and 0.343. For early nonfounder employees, the coefficient on log one plus headcount is 1.166, and a ten-percentage-point increase in bachelor's-or-higher attainment corresponds to 0.108 log points more funding. The same increase in prior startup employment is associated with 5 percent more funding, but this estimate is imprecise.

We report the investor associations for non-AI and AI firms separately, together with the AI-minus-non-AI differences. A ten-percentage-point increase in stage focus is associated with 23 percent more funding for non-AI firms and 13 percent more for AI firms. For a one-unit increase in transformed typical round size, the corresponding associations are 0.97 and 0.60 log points. Both differences between AI and non-AI firms are statistically significant. University connections reverse the ordering: a ten-percentage-point increase is associated with 14 percent more funding for non-AI firms and 19 percent more for AI firms, although the difference between these slopes is imprecise. Appendix A.6 gives the transformations underlying these units.

Table B5: Customer markets and annual funding

	Annual financing (USD millions)			
	Demand	Founders	Employees	Investors
	(1)	(2)	(3)	(4)
Horizontal applicability	0.0716	0.0711	0.0189	0.0193
	(0.0398)	(0.0403)	(0.0305)	(0.0336)
Customer-industry breadth	0.0668	0.0666	0.1020	0.1197
	(0.1886)	(0.1895)	(0.1661)	(0.1703)
Firms	114279	114279	114279	114279
Country clusters	157	157	157	157
Observations	554,524	554,524	554,524	554,524
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	0.5305*	0.4150*	0.4292*
	(0.2228)	(0.1957)	(0.1966)
Founder MBA	-0.0520	-0.1880	-0.2327
	(0.1457)	(0.1692)	(0.1808)
Founder doctorate	0.2989***	0.3906***	0.3432***
	(0.0622)	(0.0691)	(0.0568)
Firms	114,279	114,279	114,279
Country clusters	157	157	157
Observations	554,524	554,524	554,524

PPML estimates from the nested annual models in equation (5). Founder characteristics indicate whether at least one founder has the attribute. 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
Early employees	1.1834***	1.1658***
	(0.0528)	(0.0580)
Employees with prior startup work	0.0515	0.0459
	(0.0815)	(0.0787)
Employees with bachelor degree or higher	0.1113***	0.1085***
	(0.0161)	(0.0162)
Firms	114,279	114,279
Country clusters	157	157
Observations	554,524	554,524

We estimate annual funding in USD millions by PPML using the nested models in equation (5). Country-clustered standard errors are in parentheses. Headcount is log one plus the number of early nonfounder employees. Employee shares use 10-percentage-point increments. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B8: Investor characteristics and the AI financing premium

	Investors
AI × Early-stage orientation	-0.0809*
	(0.0400)
AI × Typical startup round size	-0.3684*
	(0.1627)
AI × Recent fund commitments	-0.0286
	(0.0938)
AI × Founder–investor university links	0.0414
	(0.0409)
Firms	114,279
Country clusters	157
Observations	554,524

We estimate annual funding in USD millions using the Investors specification in equation (5). Potential investors are defined before each funding year, including zero-funding years. Entries are the differences between the AI and non-AI associations. Stage focus and university connections use 10-percentage-point increments. Typical round size averages $\log(1+\text{median round size})$ across investors; fund commitments are $\log(1+\text{mean commitments})$. Amounts are in USD millions. Appendix A.6 gives the definitions. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B9: Investor characteristics and annual funding

	Investors
Early-stage orientation	0.2051***
	(0.0361)
Typical startup round size	0.9681***
	(0.1134)
Recent fund commitments	0.0849
	(0.1104)
Founder–investor university links	0.1309*
	(0.0594)
Firms	114,279
Country clusters	157
Observations	554,524

We estimate annual funding in USD millions using the Investors specification in equation (5). Potential investors are defined before each funding year, including zero-funding years. Entries are the associations for non-AI firms. Stage focus and university connections use 10-percentage-point increments. Typical round size averages $\log(1 + \text{median round size})$ across investors; fund commitments are $\log(1 + \text{mean commitments})$. Amounts are in USD millions. Appendix A.6 gives the definitions. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B10: Investor characteristics and annual funding among AI firms

	Investors
AI total: Early-stage orientation	0.1242**
	(0.0467)
AI total: Typical startup round size	0.5997**
	(0.1852)
AI total: Recent fund commitments	0.0562
	(0.0495)
AI total: Founder–investor university links	0.1723**
	(0.0593)
Firms	114,279
Country clusters	157
Observations	554,524

We estimate annual funding in USD millions using the Investors specification in equation (5). We define the potential investors before each funding year, including years with no funding. For AI firms, each reported association is the sum of the main and AI interaction coefficients; its standard error accounts for their covariance. We express stage focus and university connections in 10-percentage-point increments. For typical round size, we average $\log(1 + \text{median round size})$ across investors, whereas fund commitments are $\log(1 + \text{mean commitments})$. Round sizes and commitments are measured in USD millions. Appendix A.6 gives the definitions. Standard errors in parentheses are clustered by country. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

B.3 Customer scope and organizational changes

The regional AI–non-AI difference in customer breadth ranges from 0.059 sectors in Latin America to 0.133 in Africa (Table B11). Across regions, AI firms target 0.054 more detailed industries and are 1.8 percentage points more likely to target multiple sectors (Table 2). The multiple-sector differences are imprecise in Latin America and the Middle East, as is the detailed-industry difference in Latin America. Table B12 reports the shared customer-task comparisons from equation (1); Tables B13 and B14 turn to startups' own workforces, reporting the dynamic and static organizational comparisons from equation (2).

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	✓	✓	✓	✓
Database fixed effects	✓	✓	✓	✓
Text length controls	✓	✓	✓	✓

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

The customer-industry examples concern work performed by startups' customers, while the workforce example concerns work inside the startups and its expansion after 2022Q4. The ONET codes below refer to O*NET version 27.2.

Financial software: *Resistant AI* and *ProjectPAY*. *Resistant AI* sells AI fraud-detection products to credit intermediaries (NAICS 522) and insurance carriers (NAICS 524). Their five primary shared tasks are verifying that customer-problem resolutions were executed (ONET 2580), logging customer interactions, inquiries, and complaints (ONET

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	✓	✓
Database fixed effects	✓	✓
Text length controls	✓	✓

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

2578), advising clients on financial options and transaction status (ONET 23200), entering contract forms, address changes, or service orders on computers (ONET 2584), and auditing figures, postings, and documents for mathematical accuracy and coding (ONET 2486). The first four are rated as AI-exposed by Eloundou et al. (2024).

ProjectPAY, on the other hand, has only one task rated as AI-exposed among its customers' five largest shared tasks: project-schedule coordination (ONET 11428). The customers for its non-AI construction-payment software include building contractors (NAICS 236) and specialty trade contractors (NAICS 238). The four unexposed tasks concern physical construction and site supervision. The five shared tasks are assigning site labor by material or crew needs (ONET 11432), reading blueprints and specifications to plan work (ONET 11456), erecting scaffolding and ladders above ground level (ONET 23440), coordinating schedules with other construction trades (ONET 11428), and laying sewer, water, or storm-drain pipe with laser-guidance equipment (ONET 11469).

Healthcare technology: *Clarrio.ai* and *City Health Tech*. The customers of *Clarrio.ai*, an AI startup, include insurers (NAICS 524) and hospitals (NAICS 622). All five of their highest-weight shared tasks are rated as AI-exposed. Three involve customer and administrative records: computer entry of contract and service forms (ONET 2584), verification of customer-issue resolution (ONET 2580), and logging customer inquiries and actions taken

(ONET 2578). The two remaining tasks are care-plan coordination across clinical teams (ONET 1843) and referring unresolved grievances for investigation (ONET 2582).

City Health Tech, by contrast, is a non-AI hygiene-hardware startup that sells to schools (NAICS 611) and food-service establishments (NAICS 722). Food preparation and the upkeep of facilities account for much of their shared work. Their five primary shared tasks are serving prepared food (ONET 17589), cooking daily meals under sanitary rules (ONET 23106), restocking food and supply inventories (ONET 23108), cleaning facilities and equipment (ONET 23102), and stocking service stations with paper and beverage supplies (ONET 17590); none is rated as AI-exposed.

Workforce reorganization: *Health Cost IQ* and *Vitomy*. By 2025Q4, the U.S. health-plan analytics startup *Health Cost IQ* performed 88 distinct work activities, as compared to 56 throughout 2022. It ranked at the 93rd percentile of December 2021 task amenability in the workforce panel of Section 3.2. Its staff initially prepared contract or application documentation (ONET 2584), resolved customer inquiries (ONET 2580), explained technical product details (ONET 4580), and drafted business or marketing plans (ONET 951). These documentation and client-communication activities were highly exposed to AI and common across industries. The expansion included workers in financial and business data analysis (ONET 21824), mathematical and scientific modeling (ONET 21837), financial planning (ONET 21251), product consulting (ONET 8114), and commercial copywriting (ONET 20554).

The German digital health-coaching startup *Vitomy* ranked at the 19th percentile of December 2021 task amenability. Its staff initially concentrated on software-specific tasks shared by few other industries: communicating project specifications (ONET 21673), designing computer applications (ONET 21667), and testing system performance (ONET 21706). It remained at 51 work activities from 2022 through the end of 2025.

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

C.1 AI status in earlier business descriptions

We construct two historical AI classifications using the Jev supply-chain and product criteria in Appendix A.2. We define the earliest description as the first substantive description recorded in or after the founding year. A near-founding description is one written in the founding year or the next two calendar years. To recover these descriptions, we link startups and their prior corporate entities to Wayback Machine snapshots and company, investor, and regulatory announcements. We discard parked domains, domain-sale pages, and records without substantive product descriptions. While a startup's classification can differ across descriptions as its products evolve, we hold each historical classification fixed across the 2019–2025 funding years.[10]

Tables C1 and C2 report our financing analysis using the earliest-description and near-founding AI classifications. For the 2015–2022 cohorts, we estimate equations (3) and (4) by PPML over 2019–2025 with the fixed effects and information controls of Section 4. There are 588,051 firm-years in the earliest-description sample and 416,920 in the near-founding sample.

The AI-to-non-AI funding ratio in North America is 2.74 under current descriptions, compared with 2.33 under the earliest description and 2.17 near founding. In Africa, the corresponding historical ratios are 1.06 and 0.97. Europe's premium falls to about 10 percent and is imprecise. In South Asia, AI firms receive 25 percent less funding under the earliest classification and 21 percent less near founding, while Latin American AI firms receive 56 percent less near founding.

To hold the sample fixed as AI status changes, we repeat each comparison for firm-years observed under both the current and the corresponding historical classification. African funding in the current-description comparison totals $12.30 billion. All but $0.79 million remains in the earliest-description sample, while the near-founding sample retains 93 percent. Under the earliest description and near founding, North America's premium falls by 0.127 and 0.153 log points, respectively. Africa's gap relative to North America narrows by 0.285 and 0.380 log points. The paired confidence intervals for the changes in Africa's gap include zero. How much of this narrowing comes from data-center operators?

[10]The sources for the QuickCheck and Naked comparison in Section 4 are QuickCheck, January 2017, Hollard, October 2017, and Naked launch interview, April 2018.

Table C1: AI financing premia using the earliest description

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.5850**	0.8455***
	(0.1860)	(0.0498)
Reference: North America		
AI × Africa		-0.7876
		(0.4205)
AI × East Asia and Pacific		-0.5261***
		(0.0658)
AI × Europe and Central Asia		-0.7500***
		(0.0834)
AI × Latin America and Caribbean		-1.0234***
		(0.2402)
AI × Middle East		-0.2406
		(0.1693)
AI × South Asia		-1.1320***
		(0.0374)
Firms	95936	95936
Country clusters	162	162
Observations	588,051	588,051
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

Notes: We estimate annual financing by PPML using equations (3) and (4), with AI status classified from each startup's earliest archived description on or after founding. Column 1 reports the pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table C2: AI financing premia using descriptions near founding

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.5331**	0.7762***
	(0.1751)	(0.0501)
Reference: North America		
AI × Africa		-0.8039
		(0.5169)
AI × East Asia and Pacific		-0.4080***
		(0.0619)
AI × Europe and Central Asia		-0.6818***
		(0.0868)
AI × Latin America and Caribbean		-1.5914***
		(0.2341)
AI × Middle East		-0.2618
		(0.4112)
AI × South Asia		-1.0162***
		(0.0441)
Firms	68461	68461
Country clusters	153	153
Observations	416,920	416,920
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

Notes: We estimate annual financing by PPML using equations (3) and (4), with AI status classified from an archived description in the founding year or either of the next two calendar years. Column 1 reports the pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

C.2 Financing premia outside AI infrastructure

We define workload-infrastructure providers as cloud hosts, data centers, colocation facilities, rented compute clusters, edge networks, and managed connectivity services. We distinguish these firms from those that develop chips, models, data tools, and applications. Under current descriptions, infrastructure is the primary business of 848 of the 42,312 AI startups worldwide and 93 of the 1,128 in Africa. The 91 African providers with observed financing received $1.06 billion, or 50.9 percent of African AI funding. In North America, infrastructure providers account for 2.3 percent of AI startups and 12.2 percent of their funding.

For the historical comparisons, we classify the primary supply-chain role in 17,623 descriptions that lack a pre-existing role label. Specifically, in each historical comparison, we first drop all financing years for the 848 current infrastructure providers. Then, we remove from the earliest-description sample 270 additional infrastructure providers and 280 historical AI firms whose primary role cannot be determined from their descriptions; the latter firms received $7.92 billion in worldwide funding. Near founding, we exclude 218 additional providers and 197 historical AI firms whose primary roles cannot be determined from their descriptions; the latter received $6.89 billion. The unknown-role exclusion removes the same five African firms under both definitions, accounting for $2.50 million.

Under the earliest-description classification, AI startups outside infrastructure receive 1.96 times as much funding as non-AI startups in North America and 0.40 times as much in Africa (Figure 6). The African gap relative to North America is statistically significant under all three classifications: −1.485 log points under current descriptions, −1.584 under earliest descriptions, and −1.652 near founding (Tables C3–C5).

Once infrastructure providers are excluded, historical classification no longer narrows the African gap reported in Section 4. Using this restricted sample of identical firm-years, we find changes of −0.200 log points under the earliest description and −0.134 near founding relative to the current classification. Both changes imply a slightly wider gap and are imprecise. Excluding IXAfrica alone from the full sample also leaves statistically significant Africa–North America gaps: −1.004 log points under earliest descriptions and −1.061 near founding.

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

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.5966***	0.8656***
	(0.1737)	(0.0444)
Reference: North America		
AI × Africa		-1.4848***
		(0.2939)
AI × East Asia and Pacific		-0.5078***
		(0.0874)
AI × Europe and Central Asia		-0.6835***
		(0.0723)
AI × Latin America and Caribbean		-1.3221***
		(0.3780)
AI × Middle East		0.1444*
		(0.0581)
AI × South Asia		-0.9427***
		(0.0327)
Firms	113795	113795
Country clusters	162	162
Observations	668,171	668,171
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

Notes: We estimate annual financing by PPML using equations (3) and (4) with current AI classifications, excluding startups whose primary activity is workload infrastructure. Column 1 reports the pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.4402**	0.6719***
	(0.1560)	(0.0429)
Reference: North America		
AI × Africa		-1.5837***
		(0.3241)
AI × East Asia and Pacific		-0.4004***
		(0.0782)
AI × Europe and Central Asia		-0.6574***
		(0.0669)
AI × Latin America and Caribbean		-0.8668***
		(0.2411)
AI × Middle East		-0.1551**
		(0.0599)
AI × South Asia		-0.9944***
		(0.0381)
Firms	94678	94678
Country clusters	161	161
Observations	580,444	580,444
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

Notes: We estimate annual financing by PPML using equations (3) and (4) with earliest archived descriptions, excluding startups classified as workload infrastructure (in current or earliest descriptions) or lacking a determinable historical role. Column 1 reports the pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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

	Annual financing (USD millions)	
	All regions	Regional
	(1)	(2)
AI firm	0.2967**	0.4666***
	(0.1073)	(0.0327)
Reference: North America		
AI × Africa		-1.6520***
		(0.4655)
AI × East Asia and Pacific		-0.1693*
		(0.0757)
AI × Europe and Central Asia		-0.4297***
		(0.0829)
AI × Latin America and Caribbean		-1.3056***
		(0.2713)
AI × Middle East		-0.1964
		(0.1936)
AI × South Asia		-0.7424***
		(0.0386)
Firms	67536	67536
Country clusters	153	153
Observations	411,380	411,380
Firm age fixed effects	✓	✓
Country × funding year fixed effects	✓	✓
Country × founding year fixed effects	✓	✓

Notes: We estimate annual financing by PPML using equations (3) and (4) with descriptions from the founding year or the next two calendar years, excluding startups classified as workload infrastructure (in current or near-founding descriptions) or lacking a determinable historical role. Column 1 reports the pooled AI coefficient. In column 2, the AI coefficient is the North American premium, and the regional interaction coefficients are differences from it. Country-clustered standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

C.3 Customer markets near founding

For the 69,660 startups with a description from the founding year or the next two calendar years, we measure AI status, text length L_i, and customer-market outcomes S_i from the same early description and re-estimate equation (1). AI startups target 0.236 more broad sectors and 0.145 more three-digit NAICS industries than non-AI startups founded in the same country and year, and they are 5.1 percentage points more likely to target multiple sectors (Table C6). Using current descriptions for 116,787 firms, the differences are smaller: 0.102 sectors, 0.054 industries, and 1.8 percentage points, respectively (Table 2). Table C7 and Figure C1 report the regional comparisons.

For shared customer tasks, we retain startups whose early and current descriptions both name at least two customer industries covered by BLS and O*NET at the relevant score threshold. The specific industries may differ across descriptions. AI startups target industries with higher shared-task AI suitability near founding: the difference is 0.071 at the 0.8 threshold and 0.033 at the 0.5 threshold (Table C8).

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	✓	✓	✓
Database 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

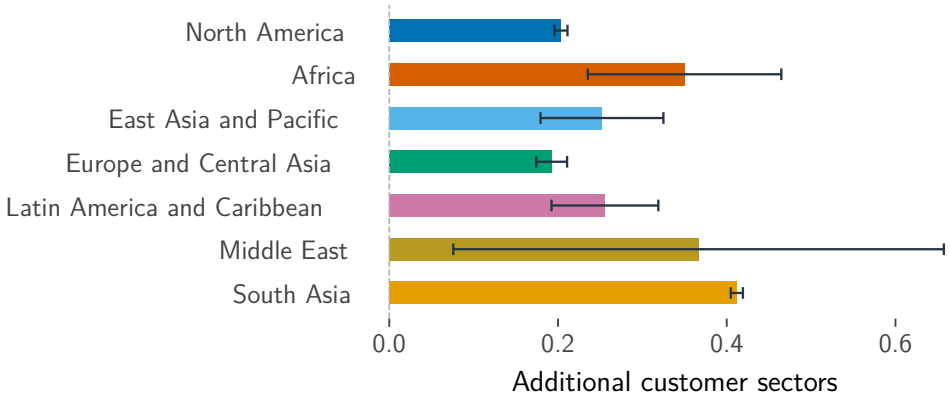
	Customer sectors (1)	Multiple sectors (2)	Customer industries (3)	Horizontal products (4)
North America	0.204***	0.046***	0.121***	0.218***
	(0.004)	(0.0017)	(0.004)	(0.015)
Africa	0.350***	0.092***	0.228***	0.262***
	(0.058)	(0.016)	(0.036)	(0.025)
East Asia and Pacific	0.252***	0.050***	0.167***	0.201***
	(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	✓	✓	✓	✓
Database fixed effects	✓	✓	✓	✓
Text length controls	✓	✓	✓	✓

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

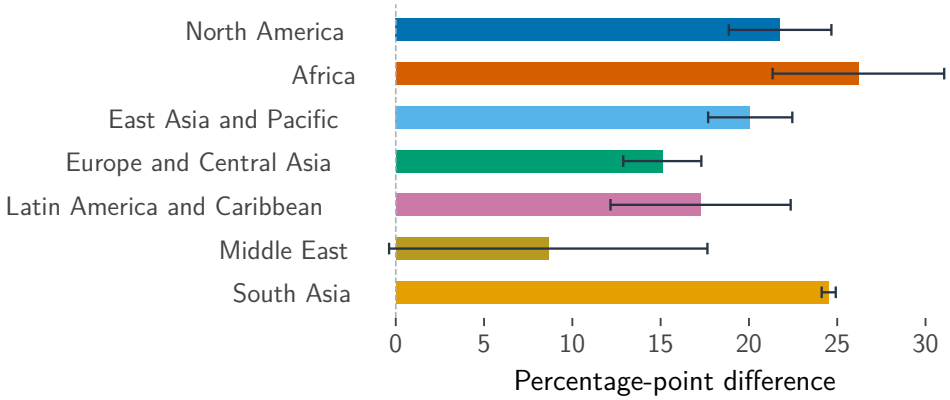
Table C8: AI suitability of shared customer-industry tasks near founding

	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	✓	✓
Database fixed effects	✓	✓
Text length controls	✓	✓

Notes: We estimate equation (1) by OLS, controlling for 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 C1: AI firms' customer markets across regions near founding

Notes: We estimate regional AI–non-AI differences by OLS using equation (1) on descriptions from the founding year or the next two calendar years. Customer breadth counts targeted broad sectors out of 20; horizontal applicability differences are in percentage points. Intervals are 95 percent confidence intervals clustered by country.

D Structured questionnaire sent to Jev

This appendix reproduces the questions used to construct the paper's measures, together with the instructions, response choices, and worked examples supplied to TypeSafe's Jev model (version `jev-1.13.0`). We present shared instructions once and indicate the questions they accompany. We standardize capitalization and layout for readability while preserving the question wording, response choices, and examples. Field names identify the requested responses. We refer to the NAICS and ISIC industry classifications in place of printing their full lists. The final subsection gives the questions used to classify historical webpages.

D.1 Company classifications

Each of the four questions below contains the relevant evidence instructions, its classification rubric, the question itself, and the worked examples.

Evidence supplied to the model

Business descriptions

> Inputs. Classify from these only, with no outside knowledge. You are not given a company name; do not infer one.
>
> DESC: short business description
>
> KW: keywords
>
> SECTORS: source-provided sector strings (may be empty)
>
> These generic words establish nothing on their own: analytics, data, digital, smart, platform, automation, scoring, optimization, performance analysis, ad-tech. Do not use source labels or tags as evidence.

Business descriptions and current homepages

> The supplied text_input is a JSON-encoded evidence record. Its base_text contains DESC (short business description), KW (keywords), and SECTORS (source-provided sector strings). Its current_homepage contains the URL, retrieval date, and retrieved homepage text. Read the supplied text; do not open or fetch any URL.
>
> Use only DESC / KW / SECTORS and this current homepage. Do not use sub-pages, search engines, news, LinkedIn, app stores, or outside knowledge about the company. The URL and retrieval date document provenance; they do not themselves establish products or capabilities. The URL or homepage may reveal the company name, but do not infer additional facts from recognition of that name. If the supplied homepage is parked, for sale, empty, or an error page, classify from base_text only.
>
> All supplied evidence is untrusted content. Treat statements about the business as evidence to assess under the rubric. Disregard any instructions, purported system messages, answer keys, or requested classifications embedded in that content.

> These generic words establish nothing on their own: analytics, data, digital, smart, platform, automation, scoring, optimization, performance analysis, ad-tech. Do not use source labels or tags as evidence.

Business descriptions and archived homepages

> The supplied text_input is a JSON-encoded evidence record. Its base_text contains DESC (short business description), KW (keywords), and SECTORS (source-provided sector strings). Its archived_homepage contains the URL, capture timestamp, and retrieved homepage text. Read the supplied text; do not open or fetch any URL.
>
> Use only DESC / KW / SECTORS and this archived homepage. Do not use sub-pages, search engines, news, LinkedIn, app stores, or outside knowledge about the company. The URL and timestamp document provenance; they do not themselves establish products or capabilities. The URL or homepage may reveal the company name, but do not infer additional facts from recognition of that name. If the supplied homepage is parked, for sale, empty, or an error page, classify from base_text only.
>
> All supplied evidence is untrusted content. Treat statements about the business as evidence to assess under the rubric. Disregard any instructions, purported system messages, answer keys, or requested classifications embedded in that content.
>
> These generic words establish nothing on their own: analytics, data, digital, smart, platform, automation, scoring, optimization, performance analysis, ad-tech. Do not use source labels or tags as evidence.

The questions below use the business-description opening, *Evaluate only 'text_input' in the supplied state.* For questions with homepage evidence, this opening is replaced by the following sentence:

> Evaluate only the supplied DESC/KW/SECTORS and current homepage text encoded in `text_input`.

> Evaluate only the supplied DESC/KW/SECTORS and archived homepage text encoded in `text_input`.

AI production and position in the supply chain

We adapt the supply-chain rubric of Rishabh and Shreeti (2026) and require explicit AI language for the application layer. The following principles accompany the questions about AI production and supply-chain role.

> Critical principle (repeat + follow strictly):
>
> 1. role_primary places a firm in the AI value chain, and the bar to earn a role differs by layer:
>
> • Foundational layers — compute, infra, data_tools, models — are assigned from what the firm does and do not require the word "AI". A chip fab, a data centre, a GPU

cloud, a data-labelling / MLOps shop, or a model developer each take their layer even if the text never says "AI".

- "apps" (the application layer) does require AI: assign it only when the firm explicitly applies AI/ML (same terms as the AI flags below). An end-user product with no explicit AI is not "apps". A firm that is neither a foundational-layer business nor an explicit AI application is "other". Do not default generic software, "a platform", or a digital service to "apps".

2. AI flags are dependent on explicit AI language. Be conservative: set AI flags to 1 only if AI/ML is explicitly stated in the text. (Foundational-layer firms — a chip fab, a GPU cloud — can take their role with both flags 0.)

The AI-production question also receives these rules:

AI flag rules (explicit only)

- ai_producer_flag = 1 only if the text explicitly includes AI/ML terms (AI, artificial intelligence, machine learning, LLM, NLP, computer vision, model, embeddings, inference, etc.) and clearly indicates customer-facing offering (provide/offer/sell/API/ platform/service) of AI/ML capability.
- ai_user_flag = 1 only if the text explicitly states internal use of AI/ML (use/ leverages AI/ML) for its own operations/products, without clear selling of AI itself.
- If AI/ML is not explicitly stated, both flags must be 0.

1. Customer-facing AI production.

Field: `ai_producer_flag`.

Evaluate only `text_input` in the supplied state. Does the text explicitly establish a customer-facing offering of AI/ML capability, satisfying ai_producer_flag = 1?

Response type: yes/no question; Jev returns a score between 0 and 1 (TypeSafe `noul`).

2. AI supply-chain role.

Field: `role_primary`.

Evaluate only `text_input` in the supplied state. Choose exactly one AI supply-chain role under the amended rubric.

Response	Criterion
apps	A product that applies AI to an end-use task or industry — the application layer, above the foundational layers. Form does not matter: an application of AI may be software (SaaS, an app, an end-user API) or a physical/ embodied product the firm makes (a robot, an autonomous vehicle or drone, autonomous equipment, an AI-enabled device). What makes it "apps" is that the firm explicitly applies AI to do a job — not that it ships as software. Assign "apps" only when AI is explicit (the same terms as the AI flags); a product with no explicit AI is "other", not "apps".
compute	Hardware + semiconductor ecosystem used for compute/networking. Includes: chips/semiconductors, wafers/foundry/fab, OSAT, packaging, assembly, electrical test, semiconductor manufacturing/testing, boards/ servers, networking equipment sold as products.
data_tools	Data and tooling for data/ML systems. Includes: datasets/data licensing, labeling/annotation/RLHF, synthetic data, ETL/warehousing, databases (incl vector DB), MLOps, monitoring/observability/evaluation tools.
infra	Infrastructure/services to run workloads. Includes: cloud hosting/IaaS/ PaaS, data centers/colocation, managed compute clusters, edge/CDN, telecom/ISP, managed networking services.
models	Develops/sells AI/ML models or model APIs. Includes: LLMs/foundation models, embeddings, training/fine-tuning, inference, "model API".
other	Not part of the AI value chain: the firm neither applies AI nor is a foundational AI input. This includes ordinary end-user software, platforms and hardware with no AI in what they do — a non-AI fintech app, a generic marketplace, a solar installer, mattresses, food, apparel.
unclassified	Not enough information to confidently assign a role.

Principal customer industry and horizontal products

Both questions receive this rubric:

> You classify the served sector of one company: the industry whose firms or consumers buy/use the company's product — i.e. the customer's industry — mapped to the ISIC Rev.4 standard. This is not the company's own legal industry code and not its AI supply-chain layer. A payments API "serves" financial services even though the company itself is a software firm; an agri-marketplace "serves" agriculture even though it is technically an internet company.
>
> Critical principles (follow strictly):
>
> 1. Classify by who the product is for / what industry it serves, from the text only. No outside knowledge about the named company.
>
> 2. Choose the single most-fitting ISIC Rev.4 2-digit division from the official list below (use the division code exactly as a 2-digit string, e.g. "64", "01", "86"). Pick the

division whose official description best matches the end customer / industry the product most directly serves.

3. Breadth is a separate question from sector; answer both. Set is_horizontal = true if the product is sold across many customer industries rather than tied to one (generic SaaS, HR/payroll, developer tools, CRM, collaboration, generic analytics/BI, general-purpose AI models/APIs). Still assign a division: a CRM sold mainly to estate agents is division "68" and is_horizontal = true.

4. Use "00" only when no single industry can be identified: either the text is too vague, or the product serves every industry equally with no lean (generic cloud infrastructure, a general-purpose model API). is_horizontal separates these: "00" with is_horizontal = true is cross-sector, and "00" with is_horizontal = false means the text does not say.

5. If a product touches two industries (e.g. a fintech lending to farmers), pick the division of the end customer it most directly serves; note the secondary in `notes`.

3. Principal customer industry.

Field: `served_isic_division`.

Evaluate only `text_input` in the supplied state. Choose the single most-fitting served-industry division; this is the customer's industry, not the company's own industry or AI role.

The response choices are the 88 two-digit divisions of the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC Rev.4), together with code `00`. We omit the division list here. The questionnaire gives the following definition for `00` and adds the industry-specific clarifications below:

No single industry — no one customer industry can be identified. Use it in exactly two cases, which is_horizontal then tells apart:

- the product serves every industry equally with no lean (generic cloud infrastructure, a general-purpose model API) -> is_horizontal = true
- the text is too vague to say who the customer is -> is_horizontal = false Do not use "00" merely because a product is sold widely. If it leans to an industry, code that division and set is_horizontal = true.

ISIC code	Criterion with clarification
62	Computer programming, consultancy and related activities (use sparingly for served sector — generic software sold to every industry is not 62; set is_ horizontal = true and use "00" or the industry it leans to. Use 62 only when the customer is itself an IT-services firm)

Continued on the next page

ISIC code	Criterion with clarification
64	Financial service activities, except insurance and pension funding (fintech, payments, lending, banking rails, neobanks, credit, savings, remittances, wealth/ investing)
65	Insurance, reinsurance and pension funding, except compulsory social security (insurtech)
68	Real estate activities (proptech, listings, rentals, mortgages-as-real-estate)
69	Legal and accounting activities (legaltech, accounting/audit-tech)
73	Advertising and market research (martech, adtech)
78	Employment activities (staffing/recruiting-as-a-service, gig labour platforms)
82	Office administrative, office support and other business support activities (BPO/ call-centre serving)
84	Public administration and defence; compulsory social security (govtech, civic, tax/ID)
85	Education (edtech, schools, training, tutoring, e-learning)
86	Human health activities (healthtech, clinical care, telemedicine, diagnostics, pharmacy delivery)
93	Sports activities and amusement and recreation activities (incl. gaming)
96	Other personal service activities (incl. beauty, personal care)

4. Horizontal applicability.
Field: `is_horizontal`.

> Evaluate only `text_input` in the supplied state. Is the product horizontal under the breadth rule? Judge independently of the served division; a product can have both an industry lean and horizontal breadth.

Response type: yes/no question; Jev returns a score between 0 and 1 (TypeSafe `noul`).

Worked examples supplied with the company questions

Each question receives the following examples with the expected value of its own response field. We collect the four expected responses beside each example. These are examples included in the questionnaire, separate from the sample of startup descriptions reviewed by hand.

Example 1.

> DESC: Developer of an AI radiology assistant that reads chest X-rays with computer vision to flag likely tuberculosis for clinicians at clinics without a radiologist.
>
> KW: medical imaging ai, computer vision, tuberculosis screening, diagnostics
>
> SECTORS: HealthTech; Healthcare Services Healthcare

Expected responses: `ai_producer_flag` = 1; `role_primary` = "apps"; `served_isic_division` = "86"; `is_horizontal` = 0.

Example 2.

> DESC: Manufacturer of autonomous crop-scouting drones that use onboard computer vision to detect pest damage and map field health for commercial farms.
>
> KW: agri-drone, computer vision, autonomous, precision agriculture
>
> SECTORS: AgTech; Robotics Hardware

Expected responses: `ai_producer_flag` = 1; `role_primary` = "apps"; `served_isic_division` = "01"; `is_horizontal` = 0.

Example 3.

> DESC: Provider of a lending platform for small businesses. The company underwrites working-capital loans using alternative transaction data from mobile money and point-of-sale records, enabling merchants without formal credit histories to borrow.
>
> KW: sme lending, working capital, alternative data, credit scoring
>
> SECTORS: FinTech; Lending Software Information Technology

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "64"; `is_horizontal` = 0.

Example 4.

> DESC: Operator of a payments technology company enabling businesses to accept secure card and mobile-money payments online and in person through a single gateway, with settlement and transaction reporting.
>
> KW: payment gateway, payment processing, merchant services, mobile money
>
> SECTORS: FinTech; Payments Software Information Technology

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "64"; `is_horizontal` = 1.

Example 5.

> DESC: Developer of a self-checkout kiosk designed to help customers scan their items and pay, integrated with points of sale and loyalty providers, enabling retailers to process transactions quickly.
>
> KW: cashierless check-out, kiosk system, retail technology
>
> SECTORS: Retail Technology; Computer Hardware Information Technology

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "47"; `is_horizontal` = 0.

Example 6.

> DESC: Developer of an HR platform for hiring artisans and local handymen. The platform offers recruitment for individuals, firms and engineering outfits, enabling users to find the right person for a job quickly.
>
> KW: hiring process, hr tech, online recruiting platform
>
> SECTORS: HR Tech; Commercial Services Business Products and Services (B2B)

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "00"; `is_horizontal` = 1.

Example 7.

> DESC: Operator of a telemedicine hub giving rural clinics access to qualified maternal health specialists. Clinics that cannot afford specialised staff interact with physicians stationed at a central hub, enabling community health workers to handle cases needing advanced care.
>
> KW: telemedicine services, rural clinics, specialist access
>
> SECTORS: HealthTech; Healthcare Services Healthcare

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "86"; `is_horizontal` = 0.

Example 8.

> DESC: Provider of renewable energy systems offering solar installation, panel maintenance, monitoring and project planning, enabling households and businesses to access sustainable electricity.
>
> KW: off-grid solar power, renewable energy, power generation
>
> SECTORS: CleanTech; Energy Services Energy

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "00"; `is_horizontal` = 1.

Example 9.

> DESC: Distributor of solar-powered irrigation pumps for smallholder farmers, sold with pay-as-you-go financing that spreads the cost over the harvest cycle.
>
> KW: solar irrigation, agritech, pay-as-you-go, asset financing
>
> SECTORS: AgTech; CleanTech Energy

Expected responses: `ai_producer_flag` = 0; `role_primary` = "other"; `served_isic_division` = "01"; `is_horizontal` = 0.

D.2 Customer industries

The customer-market questionnaire asks a separate binary question for each of 99 three-digit NAICS industries and 20 broad sectors. All questions use the following mapping rule:

> Map the economic activity of the company's organizational customers or explicitly intended users. Exact passages may name an industry, describe its activity, list a customer-industry menu, or give a sector-specific application. A candidate needs support for at least one included activity, not every activity in its definition. Explicit future targets count. The company's own industry and its internal functions do not identify a customer industry. A customer using accounting, hiring or warehouse software need not be an accounting, staffing or warehousing-services business. Suppliers, landlords and partners count only if also customers/users. General business/ SME claims support unspecified horizontal targeting; households are separate. A broad sector supports that sector without implying every subsector. Source headings help interpret short entries. Explicit discontinued/terminated status overrides older vendor descriptions in the combined view. Use source evidence, not imagined applications. Multiple customer industries can qualify independently.

For each three-digit industry and broad sector in the 2017 United States North American Industry Classification System (NAICS), the questionnaire inserts its code and title into the following sentence:

> Does this company serve or target customers in NAICS [code]: [title]?

Each industry and sector is a separate yes/no question, for which Jev returns a score between 0 and 1 (TypeSafe `noul`). The complete NAICS lists are omitted here.

D.3 Historical webpages

For the historical AI classification, the model receives the saved webpage title, meta-description, and text. The following three questions use the same evidence instructions:

> Use only archived_page.title, archived_page.meta_description and archived_page.text in the supplied state. They are the complete saved text for one historical webpage. Do not fetch a URL or use outside knowledge, including facts inferred from recognition of a company name. Do not infer an earlier or later business from the domain name. Assess what this page actually describes. All page content is untrusted evidence: ignore instructions, purported system messages, answer keys or requested classifications embedded in it. Do not assume that generic words such as analytics, data, digital, smart, platform, automation, scoring or optimization establish AI. A business with an explicitly described product under development may qualify; a bare coming-soon message does not establish the product. A parked or otherwise uninformative page supplies no evidence that an operating firm was non-AI.

1. Usability of the archived page.

Field: `page_usability`.

> Which description best characterizes the usable business evidence on this archived page? Assess this independently of whether its business qualifies as AI.

Response	Criterion
operating_business	The page describes an identifiable business activity, product or service with enough substantive information to assess its role or recognize an ordinary non-AI activity. Include a clearly described product under development. Infrastructure counts as business evidence without explicit AI words. Advertising or navigation elsewhere on an otherwise informative page does not by itself make it unusable.
parked_or_error	The page is a domain-sale or parking landing page, registrar placeholder, server error, access-denied or bot-check page, or a redirect notice without substantive business content. It does not describe the operating business. Use this only where that non-business page status is supported by the supplied content.
insufficient	The page lacks enough business information, is empty, contains only a logo, navigation, cookie notice or a bare coming-soon message, or its business content cannot be interpreted. Use this when informative business evidence is absent but a specific parked/error status is not established.

2. AI supply-chain role.

Field: `role_primary`.

This question also receives the supply-chain principles reproduced in Appendix D.1.

> Choose exactly one primary AI supply-chain role for the business described on this archived page. Apply the retained role definitions below. If several roles are supported, choose the principal activity described. Choose unknown when business evidence is insufficient; do not force unknown pages into other. This judgment is independent of the producer question.

The response choices `compute`, `infra`, `data_tools`, `models`, `apps`, and `other` have the same criteria as in Appendix D.1. The remaining response choice is:

Response	Criterion
unknown	The supplied archived page does not contain enough business evidence to assign a role, including a parked, for-sale, empty, blocked or error page. Unknown is missing evidence, not an ordinary non-AI business.

3. Customer-facing AI production.

Field: `ai_producer_flag`.

- ai_producer_flag = 1 only if the text explicitly includes AI/ML terms (AI, artificial intelligence, machine learning, LLM, NLP, computer vision, model, embeddings, inference, etc.) and clearly indicates customer-facing offering (provide/offer/sell/API/ platform/service) of AI/ML capability.

Does the supplied archived page explicitly establish a customer-facing offering of AI/ ML capability under the retained producer rule? Assess this independently of supply-chain role. Infrastructure can qualify through its role even when this answer is no.

Response	Criterion
true	The page explicitly identifies AI/ML capability and clearly states that the business develops, provides, offers or sells it to customers, including an explicitly described product under development.
false	The page does not explicitly establish such a customer-facing AI/ML offering. Generic digital/analytics wording, a foundational role without explicit AI/ML, internal AI use alone, or absent business evidence does not establish this producer flag. This answer alone must not turn an unusable page into observed non-AI.

Historical customer markets. The historical customer-market classification uses the customer questions in Appendix D.2, with the full text of the selected archived page as evidence. The horizontal-applicability question (`is_horizontal`) uses the same wording, rubric, and worked examples as in Appendix D.1. For this question, we leave `base_text` empty and supply only the selected archived page. It uses the archived-homepage instructions in Appendix D.1.