Appropriate Entrepreneurship?
The Rise of China and the Developing World

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Abstract

Global innovation and entrepreneurship have traditionally been dominated by a handful of high-income countries, especially the US. This paper investigates the international consequences of the rise of a new hub for innovation, focusing on the dramatic ascent of high-potential entrepreneurship and venture capital in China. First, using comprehensive global data, we show that as the Chinese venture industry rose in importance in certain sectors, entrepreneurship increased substantially in other emerging markets. Using a broad set of country-level economic indicators, we find that this effect was driven by country-sector pairs most similar to their counterparts in China. The estimates are similar when exploiting Chinese sector-specific policies that affected the likelihood of entrepreneurship. Second, turning to mechanisms, we show that the baseline findings are driven by local investors and by new firms that more closely resemble existing Chinese companies. Third, we find that this growth in emerging market investment had wide-ranging economic consequences, including a rise in serial entrepreneurship, cross-sector spillovers, innovation, and broader measures of socioeconomic well-being. Together, our findings suggest that many developing countries benefited from the more "appropriate" businesses and technology that resulted from a rise of an innovation hub in an emerging economy.

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1 Introduction

A small set of high-income countries have historically accounted for the bulk of global investment in innovation and entrepreneurship. Slow or absent diffusion of this innovation and entrepreneurship to the rest of the world is a dominant explanation for vast global differences in income and productivity (Keller, 2004). How would the rise of an emerging economy as a new center of global innovation affect international technology transfer?

A first perspective suggests that the concentration of innovation has had little impact on access to technology, and hence there is no clear benefit of shifting the geography of innovation. In this view, innovation in high-income countries is broadly applicable and local barriers to technology adoption — independent from where the technology is developed — are the main obstacle to development. "Leapfrogging" to frontier technology can even lead countries to accelerate their development trajectory.[1] A second perspective, however, suggests that the concentration of innovation has led to the development of technology and business models that are well-suited to the factor endowments, tastes, geography, or culture of the countries that develop them but often "inappropriate" elsewhere.[2] Thus, the rise of a new center of innovation could have major consequences by shifting the global focus of innovation toward technologies better suited to other parts of the world.

We investigate this question by studying the rapid rise of innovation in China, focusing in particular on fast-growing entrepreneurial firms and venture capital (VC) investment. We study this area for four reasons.[3] First, venture capital investment has been vital to the growth of entrepreneurship — not only in the United States, where the VC model was pioneered, but also across other developed and emerging markets. Second, the rise of VC investment in China was dramatic, providing stark time-series variation. While in 2001, 85% of global venture dollars were invested in the US and only 5% in all developing countries, by 2019, China had surged to account for 38% of global investment. Third, global data on VC investment and firm outcomes make it possible to systematically measure entrepreneurship and its consequences around the world. Finally, the idiosyncratic factors that drive Chinese investment across sectors, along with the differences in the "appropriateness" of Chinese technology in other nations and sectors, make it possible to isolate the international consequences of China's rise as an R&D hub while controlling for

[1] Parente and Prescott (1994, 2002) argue that local impediments to technology adoption are the main barriers to growth. Lee and Lim (2001) and Tonby et al. (2020) argue that leapfrogging can drive development.

[2] Inappropriateness driven by skill and capital differences is described by Basu and Weil (1998) and Acemoglu and Zilibotti (2001). Moscona and Sastry (2025) studies inappropriate technology in agriculture.

[3] These fast-growing entrepreneurial firms can be contrasted with the "subsistence" entrepreneurial ventures that make up the bulk of the small businesses in the emerging economies. For a discussion of this distinction, see Schoar (2010).

global, country-specific, and sector-specific trends in entrepreneurship.

Anecdotally, this transformation already has had far-reaching, global impacts: Christopher Schroeder, an investor focused on the Middle East, writes that companies in China have faced "challenges not contemplated in the West — navigating particularly hard last mile logistics, dealing with rapidly changing regulatory regimes, educating millions of consumers to use FinTech [...] It should come as no surprise that massively successful companies in China [have become] models for how it is done to the rest of the world."[4]

In this paper, using a global database of entrepreneurial activity and novel measures of the potential appropriateness of Chinese technology in foreign markets, we document that the rise of China led to a substantial increase in emerging-market entrepreneurship. This was driven entirely by country-sector pairs where our measure predicts Chinese technology is especially suitable. The rise in investment is fueled by local investors, rather than US- or China-based groups, and by the creation of new firms that closely resemble pre-existing counterparts in China. Moreover, this rise had far-reaching economic impacts, leading to a rise in serial entrepreneurship, innovation, and development more broadly. Together, these findings indicate that the rise of new centers of R&D can shift the global focus of innovation, generating large potential benefits in parts of the world that currently lack technology or business models suited to their local contexts.

Background VC investment was responsible for $340 billion (in current dollars) of investment worldwide in 2021 and is critically important for the development of innovation, employment, and economic activity more generally.[5] VC investments are disproportionally responsible for successful entrepreneurship and innovation outcomes.[6]

Traditionally, highly successful US firms have served as templates for companies elsewhere. This trend may result from a combination of *entrepreneurs* seeking inspiration from visible examples, from *investors* relying on parallels to earlier successes, and from the interaction between entrepreneurs and their financiers (venture capitalists could shape funded businesses into proven models). This focus on emulating proven "benchmark companies" in the US is a key feature of VC investment that can be explained (in part) by the substantial information asymmetries that often exist, particularly in contexts where contract enforcement is less well established (e.g. Gompers and Lerner, 1999; Lerner and Schoar, 2005). However, business models suitable for the US may not be appropriate

[4]Source: `https://tinyurl.com/44bh55da`

[5]See, among others, Kortum and Lerner (2000), Samila and Sorenson (2011), Puri and Zarutskie (2012), Bernstein et al. (2016), and Akcigit et al. (2022), and Section 2 of this paper.

[6]Evidence from the US is presented in Kortum and Lerner (2000), Lerner and Nanda (2020), and Akcigit et al. (2022), among other sources.

elsewhere, and those that would thrive in other regions might not have suited the US market in the first place. This misalignment could be especially pronounced in low- and middle-income countries.

While VC investment was heavily concentrated in the US for much of its history—for instance, as we show in Figure 1, 85% of global venture investment in 2001 flowed to the US—the past decade has seen a dramatic surge in China, unmatched by any other country. Similar to the US, virtually all of China's most successful entrepreneurial ventures can trace their origins to venture backing. While the Chinese government has played an active role, both by establishing government-sponsored venture funds and by investing as an LP, many of the country's leading venture funds have roots in predecessors from the US. The government's overall footprint in China's venture capital market was relatively small during this period: between 2010 and 2023, 82.8% of venture-backed companies had private VC investment, representing 70.6% of the financing raised.[7]

A range of qualitative evidence — in areas ranging from education technology to social commerce to "super apps" — suggests that China's rise as a counterpoint to the US has reshaped entrepreneurship across emerging markets (Lerner et al., 2025b, and Section 2). New Chinese entrepreneurs focus on solving different problems than US firms, and Chinese startups have become benchmarks for entrepreneurs and investors, especially in other developing countries. Local entrepreneurs actively emulate and adapt Chinese business models to their markets, while local investors often use these models to identify promising funding opportunities. However, beyond a handful of cases, little is known about the international impacts of China's R&D take-off, in this or other contexts.

Measurement To study the global consequences of the rise of VC investment in China, we combine several sources of data and measurement strategies. First, we compile comprehensive records on venture deals around the world between 2000 and 2019 using PitchBook, a venture capital database designed from its inception to have global coverage.[8] In total, we compile data on 169,505 venture deals involving 88,267 firms in 152 countries.

Second, we use deep learning neural network tools to categorize firms into 263 sectors, using text data from PitchBook's company descriptions and its existing hand-curated mappings as a training set. Each sector is also categorized by PitchBook into fifteen

[7]We will explore the distinction between government and non-government venture funds, as well as sectoral investments shaped by regulatory decisions, in Sections 4.2 and 4.4.

[8]PitchBook includes a description of each company and the size and providers of each infusion of capital. (Due to uncertainty and information asymmetries, venture investors do not typically fund startups in a single transaction. Rather, they typically make a series of investments of increasing size. These are termed financing rounds.) It has become the industry gold standard for the analysis of global venture transactions. Data are gathered through firm and VC contacts, news stories, and regulatory filings (see Section 3).

"macro-sectors" (e.g., EdTech, FinTech). The sectoral composition of Chinese companies does *not* mimic that in the US, a first indication that the rise of China shifted the global focus of entrepreneurship: China dominates several sectors in which US firms have limited or no involvement, and China does not enter other sectors with many US companies. These investment sectors are our primary units of analysis, and we define sectors with above-median Chinese participation (relative to the US) as "China-led" sectors.

Third, we exploit variation across country-sector pairs in the potential appropriateness of Chinese entrepreneurship to identify how the rise of China affected other global markets. To do so, we compile all country-level social and economic indicators from the World Bank's World Development Indicators (WDI) database, measured during the pre-analysis period. We then link each of these variables to one or more of the macro-sectors in the PitchBook data (e.g., literacy and teacher-pupil ratio are linked to the EdTech macro-sector) and construct a one-dimensional measure of similarity to China for all country-sector pairs, aggregating across all indicators relevant to each sector. This serves as an *ex ante* measure of socioeconomic similarity to China that varies at the country-sector level. Thus, our main analysis fully absorbs any trends in country-specific (e.g., proximity to China) and sector-specific (e.g., the rise of AI) characteristics, exploiting only differences in *ex ante* similarity to China across sectors and within countries. We validate this measure of appropriateness by showing that it predicts proxies for technology transfer and technology similarity using global patent data.

Finally, we systematically query the top Chinese economics and finance news sources to identify constraints to sectoral growth in China driven by specific policy interventions. We compile a sector-level data set of these policy constraints — for example, restrictions on private access to meteorological data that limited firm growth in Climate/Earth Data sector — and show that they throttled entrepreneurship and investment in China. Importantly, such domestic policies are plausibly uncorrelated with the sectors' investment potential in China or elsewhere in the world.

Main Results We begin with our core result: that the rise of China was followed by a surge in entrepreneurship in other countries, especially in country-sector pairs where we predict Chinese entrepreneurship would be most appropriate. Using a triple-difference design, we compare entrepreneurship across all country-sector pairs before versus after the take-off of Chinese venture activity, inside versus outside of the sectors in which China took off, and across high versus low values of the appropriateness measure. This specification includes all two-way fixed effects, making it possible to fully absorb any country-level trends (country-by-year effects), sector-level trends (sector-by-year effects), and any average differences in the direction of VC investment across countries (country-by-sector effects). Our baseline result suggests that a one standard deviation increase in measured appropriateness is associated with tripling of venture investment deals among China-led sectors. Aggregating these estimates across all country-sector pairs implies that the rise of China increased emerging market venture activity outside of China by 42%. The effects are similar if we instead define China-led sectors only based on the investment behaviors of venture groups with non-China (mostly US-based) fund investors (also known as limited partners or LPs), alongside a broad set of additional robustness checks, and seem to also extend to financing deals outside VC.

We next investigate whether the results are consistent with a causal effect of China's emergence as an entrepreneurial hub. Given the fixed effects in the baseline specification, the main concern is a spurious correlation between *trends* across markets (country-sector pairs) with similar values of the appropriateness measure and trends in some omitted characteristic that causes entrepreneurial take-off. To help rule out this possibility, we exploit idiosyncratic domestic policies in China that constrained certain sectors from emerging in China but are likely independent from potential investment success elsewhere in the world. Importantly, we find no relationship between the presence of a policy constraint in China and a broad set of global and emerging market pre-period entrepreneurial outcomes or trends. Using the presence of a policy constraint as an instrument for sector-level take-off in China, we find very similar results to our baseline findings. These estimates dovetail with a series of falsification exercises showing that only measured country-sector appropriateness of *Chinese* technology, and not an analogous measure for any other country, strongly predicts entrepreneurship following China's rise. This series of placebo tests helps rule out the possibility that spurious correlation drives the result.

Turning to dynamics, we find no evidence that pre-existing market-level trends are correlated with the appropriateness measure. Our measure of the appropriateness of Chinese enterprise has no relationship with venture activity *prior* to the rise of China. Instead, and consistent with qualitative accounts, early in our sample period only socioeconomic similarity to the US is positively associated with entrepreneurship around the world. After 2013, however, appropriateness to China becomes a strong predictor of venture activity, especially in sectors that China comes to dominate. Appropriateness relative to the US remains a strong predictor of venture activity in areas that the US continues to dominate.

Mechanisms We then explore the mechanisms that drive the main results. First, we investigate which sectors and investors drive the main result. We find that the effects are concentrated in non-tradable sectors—where successful Chinese firms cannot simply enter foreign markets—though the effect on tradable sectors remains positive albeit insignificant, inconsistent with large negative innovation spillovers. The effects are also predominantly driven by *local*, rather than Chinese and American, investors.[9]

Second, using Natural Language Processing tools to measure similarity in business description across company pairs, we show that the rise of China was accompanied by an increase in textual similarity between the descriptions of new firms and of Chinese firms founded in the same sector during the preceding five years. Consistent with our main result, this is only the case in country-sector pairs with high appropriateness. This finding indicates that entrepreneurs were not only working in similar technology areas, but also directly emulating their Chinese predecessors.

Third, we show that the results are driven both by an increase in the number of young firms and an increase in investment in existing firms. Thus, VC success in China not only led to the development and diffusion of new business ideas, but also helped validate existing ideas that could then more easily attract investment elsewhere in the world.

Fourth, we investigate whether political ties to China mediate our results. We find no evidence that political links between China and other countries, measured either using similarity in UN voting patterns or regime characteristics, drive our main results. The estimates are also similar after excluding sectors that are on the Chinese government's published lists of strategic sectors.

Finally, we decompose the sources of Chinese ventures' appropriateness to other countries into vertical and horizontal components. The vertical component captures the extent to which a Chinese venture is appropriate for a particular economy due to similarities in income level (as measured by GDP per capita). The horizontal component, by contrast, reflects the dimension of appropriateness that is orthogonal to income. We find that our baseline results are driven by both components, with a larger impact from the horizontal component. In other words, Chinese entrepreneurship influences ventures in emerging markets not only because it is appropriate for their current income level — which may prove transitory as countries develop — but also because of similarities that are uncorrelated with income and development stage, and thus potentially more persistent.

Broader Impacts In the last section of the paper, we study the broader economic consequences of our main results. Increased entrepreneurial activity alone does not guarantee positive outcomes. New firms may not have gained traction and failed quickly, or invest-

[9] A one standard deviation increase in appropriateness leads to a 116% increase in local investment. The effects on Chinese and US investments are about a quarter the size and neither is significant. This is consistent with the limited overall investment by Chinese VC firms abroad — just 2.5% of the emerging market deals outside of China involve a Chinese investor, and just 0.5% involve exclusively Chinese investors.

ments may have created "lock-in" to technologies well suited to low-income settings but less productive as countries develop. Thus, further empirical analysis is necessary.

First, we focus on firm-level effects and find large positive effects on the number of firms that are acquired or go public but no effect on firms that have failed. In other words, the positive effects that we identify are not driven by failures or short-run fads.

Second, we document an increase in the number of serial entrepreneurs: individuals who found multiple startups and are especially important for the growth of local centers of entrepreneurship (e.g. Mallaby, 2022). We also find that these serial entrepreneurs start subsequent companies in sectors that are *not* led by China. This suggests that there were also potentially important cross-sector spillover effects, as serial entrepreneurs branched out from the China-dominated sectors in which they started.

Third, we present suggestive evidence that this rise in entrepreneurship was associated with improved development outcomes. We find a strong, positive correlation between predicted post-period entrepreneurial activity for each country-sector pair and a composite country-sector measure of well-being constructed from the WDI database.

Fourth, we show that this growth in entrepreneurship was associated with a rise in broader forms of innovative activity. Turning to global, city-level data on entrepreneurship and innovation, we show that cities with a higher pre-existing share of firms in China-led sectors experienced an increase in the number of new firms and in patenting after the rise of China. These effects are also present in sectors with few existing Chinese firms, consistent with the aforementioned cross-sector spillover effects driven by serial entrepreneurship.

Finally, we decompose the aforementioned results by vertical versus horizontal differences that contribute to the appropriateness of Chinese ventures. If the "lock-in" hypothesis is true, we might expect new business models matched to vertical differences across countries to have weaker (or even adverse) economic effects, especially in the medium or long run. Strikingly, we find that the positive effects are primarily, and in some cases, exclusively, driven by horizontal differences across countries. That said, we find no evidence that appropriate technology on the vertical dimension has a negative effect.

Taken together, our results indicate that the concentration of entrepreneurial innovation in the US may have limited firm growth in developing countries. The rise of China led to a shift in the direction of business innovation and, in turn, an increase in entrepreneurship in emerging markets that most closely resembled China. More broadly, these findings suggest that new centers of R&D, by increasing the availability of appropriate technology and business models for the developing world, could have large, global productivity impacts.

Related Literature This work builds on three strands of existing literature. First, we extend a large body of work on the determinants of international technology diffusion (e.g., Eaton and Kortum, 2002; Keller, 2002, 2004). We build especially on a small set of papers studying how the uneven focus of innovation results in "inappropriate technology" for developing countries (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006; Moscona and Sastry, 2025). These studies have focused on the consequences of direction of innovation reflecting the characteristics of high-income markets. This paper, on the other hand, studies the consequences of a shift in the geography of R&D by analyzing the impact of a dramatic recent transformation in global innovation: the rise of China. We argue that entrepreneurs in large emerging economies like China may endogenously develop technology suited to contexts beyond their borders, especially other developing countries. Central to our story is the focus of Chinese entrepreneurs on meeting local needs, which builds existing work documenting innovation "home bias" in other areas (e.g., Costinot et al., 2019; Moscona and Sastry, 2025; Akerman et al., 2025). Finally, while existing studies have identified important mechanisms of technology transfer — including the role of governments (Giorcelli, 2019), academia (Aghion et al., 2023), and supply chains (Bai et al., 2025)—this study highlights the less-explored role of financiers. In doing so, it extends existing work on technology transfer to the study of entrepreneurship and venture capital, which have transformed global R&D in recent years.

A second strand of related literature is the growing body of work on innovation in China (Holmes et al., 2015; Aghion et al., 2015; Wei et al., 2017; Chen et al., 2021; König et al., 2022; Beraja et al., 2023). We focus on the impact of the rise of innovation in China on entrepreneurial activity beyond China's borders.

Finally, we build on the small existing set of work on venture capital in emerging economies (e.g., Lerner and Schoar, 2005; Colonnelli et al., 2024, 2025). While there is a large body of knowledge about venture capital in developed countries, especially the US, relatively little is known about the economics of venture capital in other parts of the world. This field is a potentially important gap to fill since, as we show below (Figure 1), venture-backed firms represent a large and increasing share of young public firms, market capitalization, R&D investment, and patenting in low- and middle-income countries.

Outline This paper is organized as follows. The next section describes the recent history of VC, focusing on its rise in China and expansion in emerging markets. Section 3 describes our data and measurement strategy. Section 4 presents our main results and Section 5 presents our evidence on mechanisms. Section 6 investigates the broader economic implications of the growth of entrepreneurship in emerging markets. Section 7 concludes.

2 Background: the rise of China and VC investment

2.1 Origins of the venture investment model

The VC industry was a predominantly American phenomenon in its initial decades. It had its origins in the family offices that managed the wealth of high-net-worth individuals beginning in the early 20$^{\text{th}}$ century. Families such as the Phippses, Rockefellers, Vanderbilts, and Whitneys invested in and advised a variety of business enterprises, including the predecessor entities to AT&T, Eastern Airlines, and McDonnell-Douglas.

Over time, these families increasingly involved outsiders to select and oversee these investments. VC activity gradually formalized with the emergence of dedicated funds after World War II, the rise of the limited partnership structure in the late 1950s, and the US Department of Labor's rule change in 1979 that allowed pension funds to invest substantial amounts of money into high-risk asset classes.[10]

For much of its history, the VC industry was concentrated in the US, where it had substantial economic impacts. Up until the early 2000s, the US made up at least 80% of the entire global market. It continued to grow in size — though at a slower pace than other markets, notably China, as we will describe in the next section — reaching $1.2 trillion under management (or $0.9 trillion if excluding uninvested capital) by the end of 2024.

It is important to note that even after decades of growth, the US venture capital remains small relative to other financial pools. The trillion-dollar venture capital pool is substantially smaller compared to (as of mid-2025) the $62.2 trillion in US public equity markets, $47.8 trillion in fixed income, or the $21.5 trillion commercial real estate market.

But venture capital's economic impact has been profound. The eight most valuable US companies at the end of 2025 were all originally venture-backed. When one examines all recently publicly listed firms — likely a key source of economic dynamism (Haltiwanger et al., 2013; Ayyagari et al., 2017) — the out-sized role of VC is apparent. Despite the fact that under one-tenth of one percent of US business starts are venture funded, VC-backed firms account for 88.8% of all R&D spending by young publicly traded firms in the US, as shown in Panel C of Figure 1 (see Appendix A for details).

2.2 China's venture investment take-off

The take-off One of the most drastic shifts in the landscape of global innovation was the emergence of China in the 2010s. This paper focuses on a particularly stark component

[10]The VC sector also benefited from government support in other ways. Small Business Investment Companies, federally guaranteed risk capital pools, proliferated during the 1960s before fading in subsequent decades. Similarly, many of the pioneering venture-backed firms relied heavily on military contracts.

of that take-off: venture-backed firms and startups.[11] Panel A of Figure 1 displays the changing distribution of VC investment around the world between 2001 and 2021. Panel B of Figure 1 plots the total amount of investment worldwide during the same time period, all expressed in 2011 US dollars (as are the numbers in this section).[12] Venture investment in China started at 0.27% of the global share (US$ 81 million) in 2001 and remained relatively low (4.39% in share and US$ 3.06 billion in amount) at the eve of its take-off in 2013. This has changed rapidly since then: between 2014 and 2021, China captured an average of 22.01% of global venture dollars, second only to the US, amounting to US$ 63.04 billion in average annual investment. These totals represented a 501% and 2,060% increase compared to the 2013 share and level.

The size of China's venture industry is unprecedented and unique among emerging economies. This makes it an exciting natural experiment to study the consequences of an emerging economy rising as a new center of global innovation. To convey this point, we fix China's GDP per capita at its 2015 level (US$ 12,244) and compare China's share of global VC investment at this income level to that of other emerging and recently developed countries in the year that they reached about the same level of GDP per capita (Table A.1). China constituted 13.44% of the world's venture investment when it reached US$ 12,244 GDP per capita. In contrast, none of the other emerging or recently developed countries represented more than 1% of the global venture investment when they reached this level of income. A similar pattern is also observed among other dimensions of innovation — such as the share of the world's scientific publications, R&D expenditure, and filed patents — but China's rise to global leadership is most pronounced in venture investment.

Private vs. government funds The take-off of China's venture sector had numerous drivers, including the willingness of global investors to contribute both capital and expertise to local managers, favorable government policies (such as the creation of robust public markets), and the return of seasoned Chinese entrepreneurs and investors from abroad.

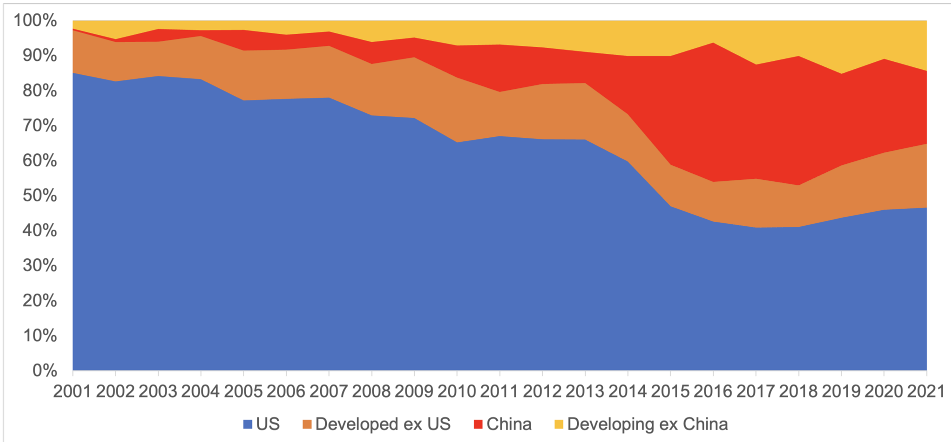
Many of the leading venture funds in China built off experiences in the US and had strong American affiliations during the period under study. Sebastian Mallaby's (2022) history supports this assertion: "China's technology boom was forged to a remarkable extent by American investors, and the Chinese VCs who emerged beside them were themselves quasi-American — in their education, professional formation, and approach to venture

[11] The recent rise of Chinese venture investment reflects, in part, a broader rise in Chinese innovation. Figure A.1 illustrates China's growing share of global R&D investment and scientific publications. While the share of innovation happening in China has increased using both measures, the pattern is less extreme.

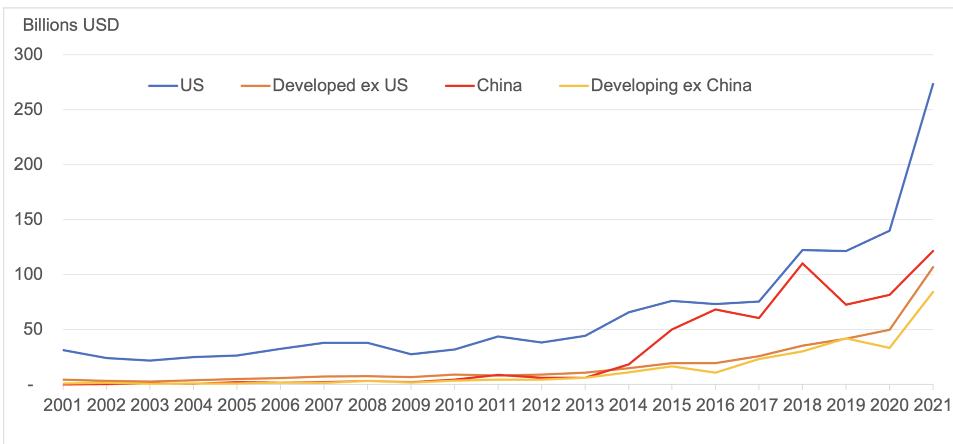
[12] Figure A.2 shows the same plot expressed in total number of unique deals instead of deal value. The pattern is very similar except that the timing of China's rise shifts slightly earlier.

Figure 1: Venture Investment Overview

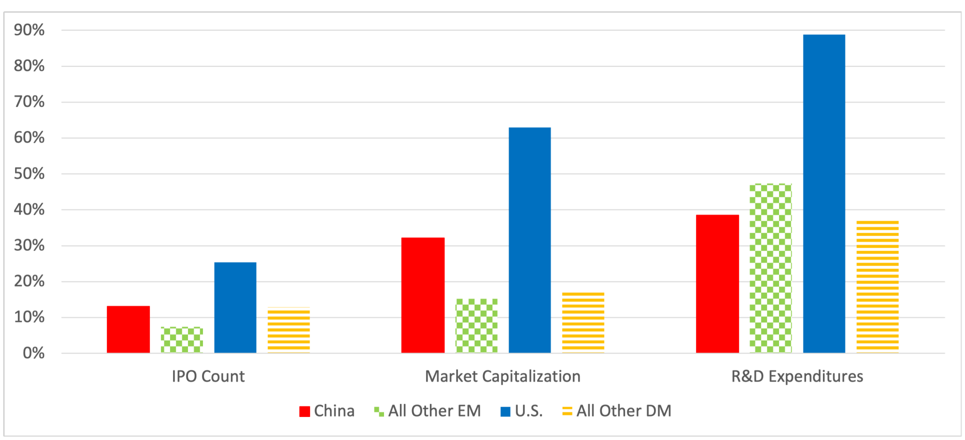
(a) Share of Global VC Investment



(b) Value of Global Investment



(c) VC-Backed Firms as a Share of Young Public Firms



Note: This figure provides an overview of venture investment worldwide. We define developed countries as countries in the OECD by 1980 and the rest as developing/emerging markets. Figure 1a shows the changing mixture of venture capital investments worldwide. Figure 1b displays the value of venture capital investment worldwide in billions of 2011 dollars. Figure 1c presents VC-backed firms' share of publicly traded firms that went public between 2003 and 2022 along various metrics. Data for Figure 1a and Figure 1b are from PitchBook; the data sources for Figure 1c are discussed in Appendix A.

Table 1: Facts about Chinese Venture Industry

Panel A: Characteristics of Five Most Active China/Hong Kong Venture Groups, 2001–2019

	Number of Deals	US Parent/ Co-Manager	Founder (or Co-Founder) with	
			US Education *and* Work Experience	US VC Experience
IDG Capital	897	Yes	Yes	No
Sequoia Capital China	761	Yes	Yes	Yes
Matrix Partners China	606	Yes	Yes	No
Qiming Venture Partners	578	No	Yes	Yes
ZhenFund	526	Yes	Yes	No

Panel B: Funding Sources of Chinese Companies Receiving Government and/or Private VC Funding, 2010–2023

	Received Any? (%)	Share of Total Funding (%)
Government VC	27.4	18.9
Private VC	82.8	70.6

Panel C: Financial Performance of VC Funds by Region, 2005–2024

	China	India	U.S.	Europe	Middle East	Canada
IRR (%)	15.04	13.47	10.88	6.72	6.22	-8.17
KS PME	1.15	1.03	1.09	0.94	0.97	0.53

Panel D: Share of Chinese Billionaires from VC-Backed Firms

	Top Ten	Next Two Deciles (11–30)	Next Two Deciles (31–50)	Next Five Deciles (51–100)
Share (%)	40.0	45.0	36.7	24.0

Notes: Panel A reports the tabulation of the top venture groups, drawn from the cases and references in Lerner et al. (2025b); US work and VC experience exclude individuals working for U.S. organizations located in China. Panel B reports the tabulation of funding sources of Chinese firms, based on data from Beraja et al. (2025). Panel C reports tabulations of venture returns by region (internal rates of return and Kaplan-Schoar public market equivalents), based on unpublished tabulations of the State Street custodial databases. Panel D reports the tabulation of Chinese billionaires, based on Hurun Research Institute's *Hengchang Shaofang·Hurun China Rich List 2020* and the sources cited in the main text.

capital. They had studied at top US colleges, worked at US companies, and carefully absorbed the US venture playbook." This claim can be supported by the examination of the five VC firms most active in China during our sample period (Table 1, Panel A). These results, described at greater length in Lerner et al. (2025b), suggest a substantial degree of integration between the Chinese and other venture industries, especially that in the US.

The Chinese government has had an important, but historically limited, footprint in the VC industry. The government has an ownership stake in 50.1% of the Chinese-domiciled limited partners, representing a total ownership of 28.9% (Colonnelli et al., 2024). They have a stake in (or invest in funds associated with) 38.6% of the Chinese venture groups, totaling 12.5% of their capital. When we look at a complementary analysis in Panel B of Table 1 at the capital structure of all firms domiciled in China that have ever received funding from either government or non-government venture capital, only 27.4% had government venture investment, in contrast to 82.8% of firms that received private VC investment. Government VC represents 18.9% of the total capital firms received.[13]

Were China to have a venture industry only because of state-connected institutional investors, we might expect the performance of the funds would be modest.[14] Data from global asset custodian State Street suggests that this is not the case in China: they estimate that during the period that we study (from the mid-2000s, when Chinese funds began appearing in their client's portfolios, to the end of 2019), Chinese venture funds outperformed those of every other nation or region with a significant group of dedicated funds, with an internal rate of return of 15.04% (see Panel C of Table 1). Moreover, the presence of substantial government funding *per se* does not sharply distinguish China from many Western markets. Akin to the Chinese Government Guidance Fund program, many other nations have directed substantial influxes of government capital into their venture industries to promote economic development.

On the other hand, it is important to acknowledge that from the beginning, venture capitalists in China have paid close attention to government regulatory and industrial incentive policies and responded accordingly (a trend that has intensified in recent years). We exploit idiosyncratic variation generated by Chinese VCs reacting to government regulations in the paper to identify the impact of the VC sector in China on other emerging markets' entrepreneurs. We also restrict our attention to Chinese venture capital funds with explicitly Western LPs as a robustness exercise.

Pivotal to successful entrepreneurship Similar to the VC market in the US, the rise of VC in China contributes disproportionately to successful entrepreneurship and innovation.

Venture capitalists have played a key role in the creation of economically significant new firms in China. As of August 2025, five firms have an equity market capitalization of at least one trillion RMB (approximately $140 billion USD) that were founded since the establishment of the first Chinese venture capital fund in 1985 (Tencent, Alibaba Group, CATL, Xiaomi, and Pinduoduo). All five were backed by venture capitalists before going public.[15] This pattern generalizes: Figure 1, Panel C, shows that venture-backed firms

[13] These figures are based on data from Beraja et al. (2025), which compiles comprehensive investment records from primary sources including Zero2IPO, CVSource, and Tianyancha firm registration data of all companies in China that received funding from either government or private VCs between 2010 and 2023.

[14] The experience of nations such as Canada and France, where the government has provided extensive public venture funding, has been one of mediocre returns.

[15] Were we to include private firms, ByteDance and Ant Financial would also be included (see, for instance,

account for 40% of all R&D investment by young, publicly listed firms in China.

Similarly, when we looked at the Hurun Research Institute's Hengchang Shaofang Hurun China Rich List 2020,[16] we identified individuals on the list who had earned their wealth primarily through firms that were backed by venture capital firms prior to going public. As Panel D of Table 1 reports, of the top 100 wealthiest individuals or families on this list, there were 36 clear cases where an individual had become a billionaire through a company that received venture capital before going public. Four of the top ten had gained the bulk of their wealth through venture-backed firms.

2.3 Venture capital in other emerging economies

In recent years, venture investment has begun to play an increasingly important role in emerging markets more broadly.

To make this point systematically, we again return to our analysis of young, publicly traded firms around the world in Panel C of Figure 1. About 10% of the young, publicly listed firms in emerging markets outside of China are venture-backed, representing 15% of total market capitalization and (strikingly) almost 50% of R&D spending. Venture investments have become a non-trivial component of firm growth in emerging markets and an even larger share of R&D.

To investigate the significance of the innovation carried out by venture-backed firms, we examine US patents awarded between 2013 and 2022 to all institutional (non-individual) assignees based in emerging markets outside of China.[17] We use the same definition of emerging markets outside of China as in Figure 1, except for deleting patent awards to assignees based in the Cayman Islands and Korea (see Appendix A for details). We find that venture-backed firms represent 31.32% of citation-weighted awards (21.32% when unweighted). When we concentrate on patents with a primary assignment to the knowledge-intensive patent sub-classes identified in Lerner et al. (2024), the weighted share rises to 41.66%. Thus, venture-backed companies represent a substantial share of overall innovation in low- and middle-income countries.

`https://tinyurl.com/mpsmppu2`), both of which were also venture backed. For spun-out firms, we use the founding dates of the original parent.

[16]We chose to examine the 2020 list as it was the list compiled soonest after the end of the main analysis sample (December 2019) `https://tinyurl.com/y68abyk8`.

[17]We focus on US rather than domestic awards due to the consistency of US patent policy, and due to the likelihood that cases where assignees incurred the cost of US patent prosecution were likely to represent more significant innovations than domestic-only awards.

2.4 Emulating Chinese ventures

Chinese ventures have demonstrated genuine innovative accomplishments, not merely copying business models from elsewhere. Many Chinese companies feature "recombinant innovations" (see Weitzman, 1998), as they reconfigure and combine existing ideas (see the discussion of social commerce below). In other areas, such as unmanned aerial vehicles, Chinese manufacturers excelled through manufacturing techniques, frequent product updates, strict quality control, and close relationships with key suppliers.

In recent years, Chinese firms have been increasingly emulated, especially in emerging markets (Lerner et al. (2025b) presents four short case studies). This could be in part a result of entrepreneurs in developing countries actively seeking business inspiration from Chinese companies that learn to solve problems relevant to their local context. Such emulation may also be, in part, because venture investors frequently look for indications that new ventures correspond in important ways to ones that have proven successful in the past. This focus on emulating proven successes characterizes a large share of VC investment in emerging markets, in large part because venture capitalists invest in situations characterized by substantial information problems (e.g., Gompers and Lerner, 1999; Lerner and Schoar, 2005). It can be difficult to assess whether a new business will be able to supplant existing incumbents, how daunting regulatory barriers will be, and whether the many necessary complements will be provided by other firms at a reasonable price point. While these proven "benchmark companies" used to consist almost entirely of US firms, they increasingly include Chinese ones.

Social commerce is one clear area where business models that originated in China spread to startups in other emerging markets. Pinduoduo broke into the Chinese e-commerce market by introducing the concept of "social commerce," where customers can purchase items as a group at lower prices and pitch products to one another. This model soon attracted imitators in developing markets, especially where food spending (as a share of income) is high and where last-mile food delivery logistics are complex. The Indonesian firm Super, which dubs itself "Pinduoduo for Indonesia," combined the agent-led group buying model introduced by Pinduoduo with a logistics backbone, reflecting the infrastructure conditions in Indonesia. Pinduoduo's business model has also been the inspiration for Latin American firms Facily and Favo, localizing e-commerce in general and social commerce in particular to a large market that was previously underserved. Similarly, the startup Tushop followed Pinduoduo and brought social commerce to Kenya. Figure A.3 plots the timeline of investment milestones of major social commerce firms, where one again sees that the rise of the Chinese firm (Pinduoduo, in this case) precedes the take-off of similar ventures in other emerging markets.

There are ample other examples of prominent startups across developing countries that followed the lead of specific Chinese companies' business models, some of which are highlighted in our cases. The startup PhonePe sought to emulate WeChat in developing a "super-app" for India; the Indian company Groww, a wealth management firm, shared important elements with Ant Financial's Yu'e Bao; the Indonesian delivery unicorn, J&T Express, aimed to solve the country's last-mile delivery services and was motivated by its co-founder's experience while serving as a country manager for a major Chinese electronics firm. Chinese ventures in education technology, especially the subset geared toward elementary and secondary education, have been highly influential in India.

These examples of businesses emulating Chinese ventures suggest three observations. First, while founders followed different routes to generate their business ideas, all were exposed to Chinese business models and explicitly acknowledged the role these models played in shaping their own ventures. Second, few of these examples involve direct overseas investments by Chinese VCs themselves — instead, local entrepreneurs and investors around the world learn from and adapt businesses first developed in China. Third, while in each case the entrepreneurial team found inspiration in China, in no case could the business be ported over in its entirety to another emerging market. Some degree of adaptation was required to tailor for local conditions.

We can also point to many examples where emerging market venture firms grew out of Chinese and US firms, akin to how—as discussed in Section 2.2—the nascent Chinese venture industry was shaped by the US venture sector. In one of the companion case studies in Lerner et al. (2025b), for instance, we discuss how the founder of the southeastern Asia-focused Insignia Venture Partners, Yinglan Tan, was trained at Carnegie-Mellon, Stanford, and Harvard and then worked for Sequoia Partners in Singapore. Similarly, there are numerous examples of individuals deeply steeped in the Chinese venture environment shifting their focus to emerging economies.

3 Data and measurement

3.1 Venture deals around the world

The main data source we use to track global venture deals and investments is PitchBook, one of the major databases of venture capital investment.[18] From its founding in 2007, PitchBook was designed to have a worldwide focus. The information in the PitchBook

[18]We use various auxiliary data sets throughout the paper, such as patent filing records. We describe these auxiliary data sources in Appendix A.

database is gathered from contacts with funds and portfolio firms, news stories, and regulatory filings. Due to its global reach, PitchBook has been used for international comparisons by the National Venture Capital Association, US National Science Board, and others. It also includes a range of additional information about each deal and company, including the dates, size, and participants in each financing round; short (averaging 44 words) descriptions of each company; and additional company-level characteristics, including location, founders, and outcome as of mid-2022 (e.g., went public, bankruptcy), among other information. Our main analysis sample includes all global venture investment deals included in PitchBook from 2000 to 2019.[19,20]

In Table A.2, Panel A, we present a series of summary statistics. The compiled data cover 88,267 companies from 152 countries that received 169,505 venture deals in total for the period from 2000 to 2019. On average, companies in the US receive 2.23 venture investments during their life cycles, as compared to 1.90 for companies in China, and 1.54 for companies in other emerging markets. The average amount for each deal is US$ 13.67 million. 44.55% of the companies receive more than one venture capital financing.

In Appendix B, we describe potential data quality concerns and a range of checks that we conduct to assess the validity of the data. For example, Kaplan and Lerner (2017) highlight some inconsistencies between commercial venture databases, such as disparities introduced by various data sourcing approaches and varying definitions of what constitutes a venture capital transaction.[21] We compare our measure of reported Chinese venture capital activities — where data access and definitional issues are likely the most severe (Chen, 2023) — with that reported by other commercial databases that specialize in Chinese VC. Reassuringly, the PitchBook coverage on Chinese VC activities is consistent with and lies generally between the other two estimates (Figure A.4).

3.2 Constructing a global sector-level database

Our main analysis treats the country-sector pair as the main unit of observation. This requires us to categorize all relevant firms into as detailed an industry classification

[19]We begin in 2000 because coverage before 2000 is spotty and end our main analysis in 2019 in order to make sure that none of our findings are driven by COVID-19. However, our findings are very similar when we include 2020 and 2021 in the sample.

[20]We define "venture investment deals" as those categorized by PitchBook as "Early-Stage VC" or "Later-Stage VC," and drop failed or canceled deals.

[21]In our conversations with practitioners, many felt that PitchBook was the best database for the purposes of this study. A number of respondents believed that the data had more human auditing and data cleansing than PitchBook's competitors. Others noted that many of the earlier incumbent databases only gradually expanded their coverage to include emerging markets, resulting in a variety of potential selection biases. These conclusions are also broadly consistent with a comparison study of venture capital databases by Retterath and Braun (2022), though it focuses on European transactions.

scheme as possible. To do so, we use PitchBook's "market map" categorization, which divides firms into a three-level structure consisting of markets (most broad), segments, and subsegments (the most detailed). Throughout our analysis, we define sectors as the "subsegments" in the PitchBook structure and define macro-sectors as the fifteen "markets" in the PitchBook structure. Many of the sectoral categories are extremely narrow, such as the *Natural Language Technology* sector in the *AI and ML* macro-sector, or the *Crime Surveillance and Fraud Detection* sector in the *FinTech* macro-sector.

PitchBook analysts have assigned 26,524 companies to these sectors by hand. To assign the remaining companies, we fine-tune Bidirectional Encoder Representations from Transformers (BERT) models for each sector using these human classifications and the paragraph-long text that describes each company's business mission, business model, and area of business as the training set.[22] We then use our models to predict the relevant sector(s) for all firms in the database. In the end, 88,267 companies, or 93.73% of the companies that have venture capital deals in PitchBook, are classified into 263 sectors.

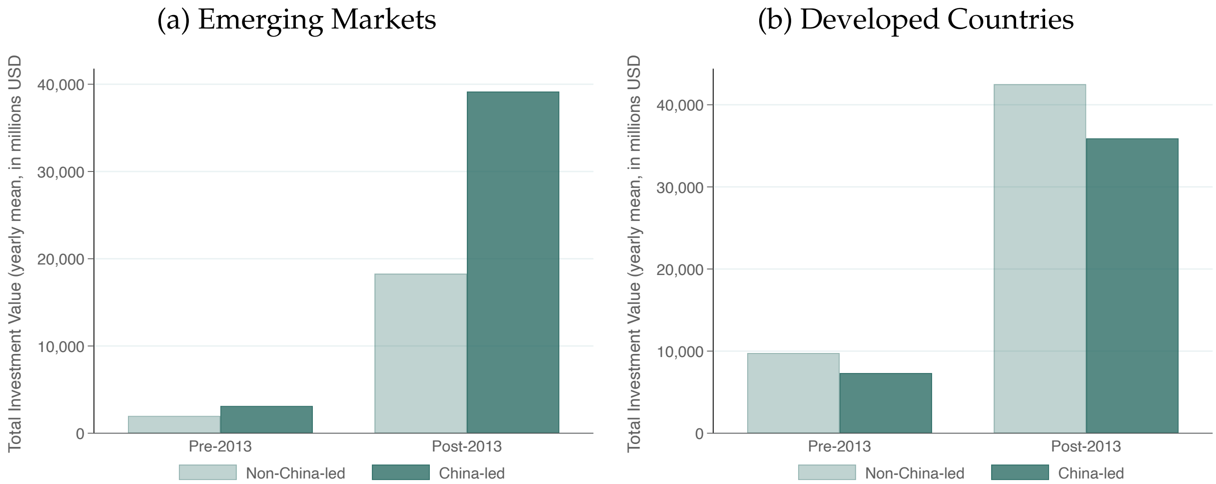
Table A.2, Panel B.1, provides summary statistics of the sector-level data. On average, each sector has 1021 firms. Categorization into each sector is treated as a binary and independent task; thus, companies may be assigned to multiple sectors. About 17.36% of the firms are categorized into just one sector. Conditional on being categorized into multiple sectors, the average number of sectors is 3.51.

Identifying sectors led by China Once we categorize firms into sectors, we can define whether global investment in a given sector is "led by China." Figure A.5 displays a histogram of deals in China in each sector from 2015 to 2019 as a share of total deals in both China and the US. In some sectors, there are very few (or zero) deals that take place in China; in others, several of which are described in Section 2.4, a greater number of deals take place in China than in the US. There are several sectors in which China's share of deals is close to one, meaning that US firms are almost completely uninvolved in the technology area. This is a first indication that, even looking at aggregate differences across sectors, the rise of Chinese venture capital shifted the global focus of entrepreneurship.

In our baseline analysis, we define a sector to be China-led if the ratio of the number of VC deals received by Chinese companies relative to that of US companies for the 2015 through 2019 period is above the median among all sectors. By construction, half of the sectors are China-led following the baseline definition. As an alternative definition, we define the stricter China-led sectors as those where the total number of venture investment

[22] These descriptions are written in English by a team of analysts at PitchBook headquarters using a standardized template, to avoid differences in structure or content across regions or types of companies.

Figure 2: Investment Trends in Emerging vs. Developed Markets



Note: Figure 2a shows the total VC investment for emerging markets (defined as countries not in the OECD by 1980), separated by China-led sectors. Figure 2b displays the total VC investment for developed markets (defined as countries in the OECD by 1980), separated by China-led.

deals received by that sector in China is greater *in absolute terms* than that in the US for 2015 to 2019. These are the sectors with a share greater than 0.5 in Figure A.5. A smaller but still substantial number (69) are China-led following our stricter definition.[23,24]

The rise of China and its focus on very different technology areas has led to a sharp re-direction of overall entrepreneurship across these two "benchmark countries." Figure A.6a plots the (log of the) total number of deals in both the US and China in China-led and US-led sectors over time. While deals in US-led sectors remain on a similar trend throughout the sample period, China-led sectors have substantially fewer deals early in the sample period but then rapidly catch up between 2013 and 2015, coinciding with China's take-off. Figure A.6b shows directly that total deals in China-led sectors grew dramatically faster than deals in US-led sectors after 2013. Thus, the rise of China shifted the overall focus of entrepreneurship within these two superpowers.

[23]The choice to define Chinese sector-level leadership based on its share of venture activity compared to the US (and not the rest of the world) is motivated by (1) the fact that, outside of the US and China, no single country represents a large share of global investment and (2) case study evidence, described in Section 2, that the benchmark companies that investors look to when making investment decisions are from the US or China. Nevertheless, all results are very similar if we use the share of global deals (see Section 4.3).

[24]Another possibility may have been to adjust for population size when determining the China-led sectors. Our baseline measure, which uses the median as the threshold, is population invariant. Moreover, given China's large population size, only two sectors would be considered "China-led" using our stricter definition if we weight by population. Keeping the measure population invariant is also consistent with the general presumption that new technology and business models are largely non-rival.

Global investment trends: emerging vs. developed markets Moving beyond investment in China or the US, and consistent with the cases outlined in Section 2.4, the rise of China was followed by a dramatic increase in business formation in *other* developing countries, driven by sectors in which China led the US.

Figure 2a displays the total value of venture investment in developing countries (excluding China) in China-led and US-led sectors, both before and after the rise of China. There was a dramatic increase in investment in China-led sectors compared to sectors in which China did not take a leading role. We do not observe similar trends in developed countries, where new Chinese business models and technology may have been less relevant (Figure 2b). If anything, the pattern is the opposite. Table A.2, Panel B.2, presents a broader set of summary statistics, all consistent with China's rise coinciding with greater investment in other emerging economies.

3.3 The appropriateness of Chinese entrepreneurship

To systematically investigate the hypothesis that venture investments in China-led sectors spurred entrepreneurship in places where Chinese technology is likely to be appropriate, we construct a country-by-sector measure of socioeconomic similarity to China.

To do this, we first compile all of the nearly 1500 country-level socioeconomic and development indicators from the World Bank's World Development Indicators (WDI) database. We calculate the average value of each indicator for each country c in the decade prior to 2013 (China's "take-off" year). We denote these characteristics as x_c and normalize each characteristic to be in comparable, *z-score* units: $\hat{x}_c = (x_c - \mu(x_c))/\sigma(x_c)$.

Second, we determine which socioeconomic indicators are most relevant to each of the fifteen macro-sectors in the PitchBook data.[25] We use these broader sector groupings because it is straightforward to assign social and economic indicators to the most relevant macro-sector(s). For example, school enrollment rates are relevant to the Education Tech macro-sector, and data related to land cultivation and crop production are most relevant to Agriculture Tech and Food Tech. We view these indicators as capturing both features of technology supply (i.e., characteristics that affect the supply of particular technology) and features of demand (i.e., characteristics that affect the demand for particular technology) that are specific to country-sector pairs — both can shape the applicability of Chinese businesses and their relevance in a particular context. While it would be interesting to separately identify how supply-side and demand-side similarity to China shapes business

[25]The 15 macro-sectors are Artificial Intelligence and Machine Learning (AI&ML), Agriculture Tech, Blockchain, Carbon and Emissions, Development and Operations (DevOps), Education Tech, Enterprise Health, Fintech, Food Tech, Information Security, Insurance Tech, Internet of Things (IoT), MobilityTech, Retail HealthTech, and Supply Chain Tech. All sectors belong to one of these macro-sectors.

diffusion, that is beyond the scope of this paper.

Members of our team assigned indicators to macro-sectors using three methods, with different levels of coder freedom. In a first method (baseline), coders were fully free not to assign indicators that they deemed of limited relevance to any of the macro sectors. In a second method (restricted), coders were only free to choose across broader "Topic" categories defined by the World Bank; once they assigned one indicator within each Topic, all indicators in the Topic were assigned to the same sector. In a third method, designed to be most restrictive, coders were asked to classify *all* indicators to at least one macro-sector (all assigned).[26] In the end, these three measures are highly correlated with one another, yet there are still some differences across measures (see Table A.4).[27]

Third, we aggregate all characteristics to create a measure of the socioeconomic mismatch with China at the country-by-macro-sector level, where $\mathcal{S}_i$ denotes the set of all characteristics assigned to macro-sector S_i:

$$M_{cs} = \frac{1}{|\mathcal{S}_i|} \sum_{x \in \mathcal{S}_i} |\hat{x}_c - \hat{x}_{China}|$$

This measure captures, in comparable units, how different each country and macro-sector is from the same macro-sector in China. Finally, to convert to a relative appropriateness measure, we subtract M_{cs} from its maximum and define this as $Appropriateness_{cs}$.

Variation in appropriateness The appropriateness measure captures variation both across countries—since it is constructed using country-level indicators—and across macro-sectors within countries, since only certain indicators are assigned to each macro-sector. Figure A.7a displays the $Appropriateness_{cs}$ value for each country, averaged across sectors. The set of countries with the highest values includes parts of South and Southeast Asia, Latin America, and Eastern Europe. However, not *all* low- and middle-income countries have a high value. In Figure A.7b, each country is color-coded based on the *difference* between its average $Appropriateness_{cs}$ and its average US-appropriateness, calculated in an analogous manner. Emerging market countries are 0.565 standard deviations more similar to China than they are to the US, suggesting that they might stand to benefit on average from new technologies designed for the Chinese market.

There are also major differences across sectors within countries. For most countries,

[26] Table A.3 gives examples of the indicators chosen for specific macro-sectors.

[27] We also pursued a fully hands-off approach by assigning OpenAI's GPT o3-pro model, the most intelligent at the time of this exercise, the task of assigning indicators to macro sectors. While we prefer making this classification by hand since it avoids the "black box" nature of LLM-based assignment, this measure is highly correlated with our baseline measure (Table A.4) and all of our main results are similar using this LLM-based approach (see Section 4.3).

there is a large gap in appropriateness between the most and least appropriate sectors (Figure A.8). Zooming in on specific markets, we display histograms of $Appropriateness_{cs}$ for AgTech (Figure A.9a) and FinTech (Figure A.9b), after subtracting average appropriateness across all other sectors. While Figure A.7a shows that India is very similar to China on average, Figures A.9a and A.9b document that the appropriateness measure is far higher in FinTech compared to AgTech. The same is true for Indonesia. Afghanistan, on the other hand, has far higher measured appropriateness in AgTech compared to FinTech. Canada is also very similar to China in AgTech, highlighting that Chinese technology may be suitable in certain high-income countries as well.

In our empirical analysis, we exploit this within-country, cross-sector variation in the potential appropriateness of Chinese R&D. This makes it possible to absorb all country-level or sector-level trends, as well as any cross-country differences in specialization.

A question that we return to throughout the paper is the extent to which the results are driven by variation in appropriateness that is spanned by differences in per-capita income. To operationalize this empirically, we regress $Appropriateness_{cs}$ on average per-capita income during the sample period. We refer to the component of $Appropriateness_{cs}$ that can be explained by income as its "vertical" dimension and the component that cannot be explained by income (i.e., the regression residual) as its "horizontal" dimension.

Figure A.10 provides a series of examples of the difference between these dimensions, focusing on EdTech. Japan and South Korea have very high values of horizontal appropriateness. Despite being wealthier than China, there are features of the education system and educational institutions that are similar and cannot be explained by income. The WDI indicators that drive this "horizontal" similarity are the relatively low student-teacher ratio and low government expenditure (relative to family expenditure) on education. Nigeria and Columbia, on the other hand, have lower values of appropriateness on average, and especially when we focus on the "horizontal" component that accounts for the fact that these two countries and China had similar income during the sample period.

Validation To validate that $Appropriateness_{cs}$ captures the applicability of technology across country-sector pairs, we show using independent data that it strongly predicts cross-sectional patterns of technology transfer and technology similarity. We compile comprehensive patent and inventor location data from the US Patent and Trademark Office's PatentsView database and train BERT models using patents linked to companies already assigned to PitchBook sectors, and then in turn predict a random sample of patents to one (or multiple) of the PitchBook sectors s. We then link these data to information from the European Patent Office's PATSTAT database on patent families: i.e., instances in which the inventor seeks patent protection of an invention in multiple patent offices, a commonly used metric for technology transfer (e.g., Dechezleprêtre et al., 2011). We also compute the pairwise similarity of all patent abstracts within the same sector as an alternative measure for the applicability of technology designed for one market in another.

We estimate the following regression specification:

$$y_{cks} = \beta Appropriateness_{cks} + \gamma_{ck} + \delta_{cs} + \alpha_{ks} + \epsilon_{cks} \tag{1}$$

where $Appropriateness_{cks}$ is the socioeconomic similarity of countries c and k for sector s; y_{cks} is a measure of technology transfer or similarity between c and k for sector s; and the remaining terms are two-way fixed effects. We find strong evidence that $\beta > 0$ (Table A.5). That is, our measure of appropriateness strongly predicts technology transfer and technology similarity across markets, proxies for differences in the applicability of technology. This relationship holds conditional on country-pair fixed effects (γ_{ck}) which capture all variation in proximity or other drivers of technology transfer across countries, making it possible for us to zoom in on the within-country, cross-sector variation that underpins our main analysis. In an additional analysis, we find that appropriateness with respect to China is associated with emerging market citations to Chinese patents (Table A.6). As a placebo test, we show that there is no relationship between appropriateness with respect to China and citations to US patents, indicating that our measure precisely captures the usefulness of Chinese technology and not foreign technology more generally.[28]

4 Main results

4.1 Empirical strategy

In this section, we investigate whether the rise of China led to global growth in entrepreneurship, driven by the "appropriateness" of new Chinese business models and technologies in markets around the world. Our baseline specification estimates differential effects of the rise of China in country-sector pairs whose *ex ante* socioeconomic conditions more closely match those of China. Specifically, we estimate:

$$y_{cst} = \beta\,(ChinaLed_s * Post_t * Appropriateness_{cs}) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + X'\Gamma + \epsilon_{cst}, \tag{2}$$

[28]We do not use citation patterns in the full sample, which would include Chinese citations to foreign patents, given existing evidence that Chinese inventors rarely cite foreign patents. Comparisons of US and Chinese awards to domestic inventors suggest that citations are five-to-ten times more common in the US (Lerner et al., 2025). Even when Chinese inventors apply for patents in the US, the bulk of the citations are added by the patent examiners, which may be quite different in nature from those that are added by the inventors, making citation information challenging to interpret.

where c indexes countries, s indexes sectors, and t indexes years. $ChinaLed_s$ is a sector-level indicator for Chinese leadership described in Section 3.2. $Appropriateness_{cs}$, as described in Section 3.3, varies at the country-by-sector level. While we investigate dynamics in more detail below, here we set $Post_t$ equal to one for all years after 2013, the year in which VC investment in China took off.[29] The outcome of interest, y_{cst}, is the number of deals in the country-sector-year, normalized by the total number of pre-period deals in the country.

Our hypothesis is that β>0. If entrepreneurship has an important context-specific component and diffuses disproportionately where it is most "appropriate," then the rise of China could precipitate a rise in global entrepreneurship, especially in markets where Chinese business ideas and technology are most suited. That said, there are a range of reasons why we may find that $\beta = 0$. Chinese technology may not depart substantially from technology developed in the US; the most transformative new businesses may not be specific to any context; or barriers to all technology diffusion could be sufficiently high that the specific characteristics of technology are unimportant. Moreover, China's economy may be sufficiently different from other emerging economies, or so beholden to political pressures, that businesses developed there are not broadly relevant beyond its borders.

The specification includes three sets of fixed effects that account for several important forces. First, $country * year$ fixed effects control for country-specific trends. These effects capture, for instance, shifts in country-level growth rates, overall entrepreneurship, or connections to China, as long as these changes do not disproportionately affect the specific sectors in which Chinese VC investment specializes. Second, $sector * year$ fixed effects control for global trends in entrepreneurship for each sector. These interactions capture any sector-specific trends (e.g., the rise of AI) that affect all countries. In a more stringent specification, we also include sector-year fixed effects interacted with country-level economic development, thereby allowing for separate sector-specific trends for developed vs. developing countries. Thus, we can fully absorb any sector-level trends that are specific to developing countries (e.g., internet penetration, the rise of e-commerce), and β only exploits variation in appropriateness within developing nations. Finally, $country * sector$ fixed effects control for differences in entrepreneurial specialization by country.

The main identification threat, therefore, is that there is an omitted driver of *country-sector specific trends* in entrepreneurship that is spuriously correlated with trends in more versus less appropriate markets in sectors that are led by China. While it is unclear *ex ante* why this would be the case, we pursue three strategies to rule out this possibility. First,

[29] We define 2013 as the start of the "post-period" because it is the start of the two-year period with the highest growth rate. In Section 4.5, we discuss this timing in more detail and exploit as additional variation the fact that each sector began to grow in China at a slightly different time.

we control directly for a range of potential drivers of common sector-country trends in entrepreneurship. Second, we use sector-specific policy constraints to Chinese investment to generate idiosyncratic variation in $ChinaLed_s$ that is plausibly fully independent from sector-specific trends in the rest of the world. Finally, we present a series of falsification tests that are inconsistent with the results being driven by any common sector-specific trend, even trends that are unique to emerging markets.

4.2 Main estimates

Columns 1 and 2 of Table 2 present the baseline estimates of Equation 2. The estimates of β are positive and statistically distinguishable from zero ($p < 0.01$). A one standard deviation increase in sector-specific appropriateness is associated with a 214% increase in venture deals among China-led sectors during the post-period.[30] In column 2, we add to the two-way fixed effects an interaction between the emerging market indicator and the full set of sector-by-year effects. This fully absorbs any differences in sector-specific trends between developed and developing countries. The similar estimate of β, even within emerging markets, suggests that the results are not only driven by diffusion from China to less-developed countries (i.e., down a "ladder of development"); instead, the effect is driven by sector-specific similarity to China *within* emerging economies.[31] Column 3 includes year fixed effects interacted with the appropriateness measure, thereby absorbing any trends specific to markets more (or less) similar to China; the estimate is again similar.

Columns 4 and 5 of Table 2 replace $Appropriateness_{cs}$ in Equation 2 with an indicator that equals one for emerging markets, but restricts the sample to $country * sector$ sets with low (column 4) vs. high (column 5) values of the $Appropriateness_{cs}$. While we showed above that entrepreneurship in China-led sectors increased substantially in developing countries following China's take-off (Figure 2a), these columns show that this effect is entirely driven by country-sector pairs that are more socio-economically similar to China.

All estimates are similar and, if anything, larger in magnitude if the regression is weighted by the total number of deals in each sector or if the outcome is measured in

[30]This effect is large, but consistent with the small number of existing estimates suggesting that venture-backed US businesses have large spillover effects and that many of these benefits accrue outside of the US (Myers and Lanahan, 2022; Schnitzer and Watzinger, 2022). Schnitzer and Watzinger (2022), for example, argue that spillovers from venture capital are on average almost seven times larger than those from corporate innovation spending. Moreover, the 214% effect is consistent with the very high average growth rate of venture deals during the sample period; non-China led sectors grew by nearly 300% during this period, the same order of magnitude, and many markets started the period with a small baseline number of deals.

[31]Table A.7 further makes this point by controlling for $ChinaLed_s * Post_t$ interacted with country-level income (or income relative to China). In all cases, the effect of the income interactions does not attenuate our coefficient of interest. These results are inconsistent with a mechanism in which appropriateness is only "vertically" differentiated by development stage. We return to this point in Section 5.4.

Table 2: Appropriateness of Chinese Technology Increases Entrepreneurship

	Dependent Variable: Number of Deals (Normalized)				
	(1)	(2)	(3)	(4)	(5)
Regression Sample:	Full	Full	Full	Bottom Quartile	Top Three Quartiles
China-Led × Post × Appropriateness	8.238***	7.827**	8.414***		
	(2.902)	(3.023)	(2.951)		
China-Led × Post × EM				0.149	4.976***
				(1.697)	(0.961)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year × EM FE	No	Yes	No	No	No
Appropriateness × Year FE	No	No	Yes	No	No
Number of Obs	552300	552300	552300	124440	475200
Mean of Dep. Var	3.588	3.588	3.588	3.033	3.726
SD of Dep. Var	44.979	44.979	44.979	38.363	47.572

Note: The unit of observation is a country-sector-year. EM countries are defined as countries not included in the OECD as of 1980. The first three columns use the full sample and the fourth and fifth columns are based on sample split of appropriateness quartiles. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

terms of total investment value or even investment value per deal (Panel A of Table 3). Thus, the findings are not driven by economically unimportant sectors or small financing rounds. Intuitively, the results are also stronger using the stricter definition of China-led sectors to construct the independent variable, restricting attention to the sectors in which China's rise in entrepreneurship was most dramatic (Panel B of Table 3).[32] We report more robustness and sensitivity results in Section 4.3.

Together, these findings indicate that venture investments are substantially more likely to follow China's lead if local sector-specific economic conditions are more similar to China. They indicate that the potential appropriateness of entrepreneurship plays a major role in shaping its diffusion around the globe.

Magnitudes To assess the effect of China's rise on overall entrepreneurship in emerging markets, we use Equation 2 to predict the total number of deals, both with and without the effect of China captured by β (see Appendix D for details). We find that the rise of China increased emerging market venture deals by 42%. An important assumption is that the rise of China did not come at the expense of venture investments in the US, which are likely to have international spillover effects of their own. The dramatic rise of investment in the US in absolute terms during this period (see Figure 1)—as well as the relatively limited

[32]Table 3 also shows that the result is similar using alternative parameterizations of the outcome variable.

Table 3: Appropriateness of Chinese Technology: Robustness

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log($/deal)
Panel A: Baseline China-led measure					
China-Led × Post × Appropriateness	8.414***	10.686***	0.107**	0.209**	0.284**
	(2.951)	(3.839)	(0.044)	(0.086)	(0.139)
Panel B: Strict China-led measure					
China-Led (Strict) × Post × Appropriateness	11.009***	14.439***	0.133***	0.279***	0.480***
	(3.339)	(4.554)	(0.031)	(0.083)	(0.158)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479

Note: The unit of observation is a country-sector-year. Panel A presents results using our baseline China-led sector measure, where a sector is defined as China-led if it has an above-median ratio of the number of deals received by Chinese companies to that of US companies for the period of 2015 to 2019. Panel B uses a stricter China-led measure, where a sector is defined as China-led only if the number of deals received by Chinese companies is strictly higher than that of US companies during the same period. The outcome variable and parameterization changes across specifications and is noted at the top of each column. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

flows of US funding sources into Chinese venture deals as a share of the total US venture market—makes this assumption seem plausible.[33] Moreover, to the extent that our inappropriateness measure is an imperfect proxy for the suitability of Chinese entrepreneurship across markets—or that some Chinese technology was "general purpose" and had benefits in foreign markets regardless of their level of appropriateness—our estimates likely understate the true effect of China's rise on emerging market entrepreneurship.[34]

[33]The total volume of flows into Chinese venture deals between 2010 and 2019 from US sources was $43 billion (Lysenko et al., 2020). During the same decade, US-based venture-backed firms raised nearly $762 billion, whether from US or foreign sources. Moreover, especially after the first years of our sample period, much of the investment in China was financed by returns from prior venture investments in China itself.

[34]We also investigate the potential impact of additional countries rising to entrepreneurial leadership (see Table A.8). This makes it possible to benchmark the effect of China *per se* against the potential spillover effects of growth in other emerging markets. This analysis is described in Appendix D.

4.3 Robustness and extensions

Excluding government-selected winners in China In contrast to much of our sample period, during the 2020s the Chinese state has become more directly involved in venture capital investment[35]. If our results were driven by Chinese businesses that were selected and funded by the government, the interpretation of our baseline results would be different. We repeat our entire analysis after restricting attention only to "Western-backed" deals in China, defined as deals in which one of the investors has an LP headquartered outside of China or Hong Kong, or one of the fund investors is headquartered outside of China or Hong Kong. While this is a conservative definition, it allows us to fully rule out direct involvement by the Chinese government.[36] Using this restricted sample of deals to define sector-specific take-off in China generates estimates that are similar to our baseline (Table A.9), suggesting that our main results are not driven by state involvement in Chinese venture capital.

Beyond VC investment Our main results focus on venture capital investment because of its central role in modern innovation, its dramatic rise in China, and substantial case study evidence about the importance of "benchmarking" and cross-border spillovers (Section 2). One potential concern with focusing only on VC investment, however, is that other sources of funding could substitute for VC investment. If this were the case, it might lead us to overstate the effect size. More generally, exploring the effects on other sources of funding conveys whether or not the baseline results generalize.

We repeat our baseline analysis using different outcome variables capturing non-VC sources of investment, all constructed from PitchBook (Table A.10). We first investigate individuals investing not through a fund, also known as angels. Like venture groups, they fund startups, typically at the earliest stages. Angel investments are interesting to examine for two reasons. First, angels are closely linked to VC, and as such might display the substitution effect delineated in the prior paragraph. Second, the role of the Chinese government in angel investing appears to be considerably less than in VC (aside from tax incentives), reflecting the modest size and informal nature of angel investments.[37] We find positive effects when we examine angel deals, which are especially large and precisely estimated using the "strict" definition of China's sector-level leadership (Panel B). We also investigate private equity (PE) and growth deals (Panels C and D). These investments

[35]See, e.g., `https://tinyurl.com/4urjs7p8`

[36]In particular, this exercise excludes deals with only non-government VCs in China without Western LPs, even if the same company has received a Western financing round before or after.

[37]For a discussion of the limited role of the Chinese state in the angel sector, see Xiao and Anderson (2022).

frequently occur in the same firms at some point after VC financings. We estimate positive effects that are smaller in magnitude. We finally examine corporate investments (Panels E and F) and again find positive effects that are similar in magnitude to the effect on PE and growth deals, though less precise.[38]

While admittedly speculative, these results suggest that our findings may apply beyond VC investment, especially in the sectors where China was most involved (our "strict" definition). Certainly, the positive coefficient estimates across specifications suggest that our baseline estimates are not driven by negative spillovers across investment classes.

Additional sensitivity analysis We conduct a range of sensitivity analyses, all reported in the Appendix. In particular, the results are similar after including the years 2020 and 2021, which we exclude from the baseline analysis due to COVID (Table A.11, Panels A and B), or extending the sample period through 2024, after the VC downturn (Table A.11, Panels C and D). And the results are similar if we define China-led sectors using China's share of global deals (Table A.12). The results are also robust to a range of sensitivity checks of our construction of the appropriateness measure (see Appendix C for details), such as alternative strategies for assigning indicators to macro sectors (Table A.13, Panels A and B), including an LLM-based approach (Table A.14); using different thresholds for dropping countries or indicators with missing data (Table A.13, Panels C-F); and randomly dropping sets of indicators from the analysis (Figure A.11).

4.4 Threats to identification

The main empirical concern throughout this part of the analysis is that some sectors grew in emerging markets for reasons *unrelated* to China's growing dominance in those sectors. If an unobserved characteristic affected both growth rates and appropriateness at the country-sector level, our interpretation of β in Equation 2 might be problematic. One example of a threat to identification would be a version of the "reflection problem" (Manski, 1993), in which the results are driven not by the transfer of knowledge and know-how from China to foreign markets but rather by common responses across similar markets to the same global trend or underlying conditions. Section 2 described a number of reasons — including the history of venture capital in emerging markets and the importance of "benchmarking" — that make this threat unlikely. The goal of this section is to empirically

[38]The size of the later-stage transactions in Panels C and D is much larger, as the table suggests. The capital here is typically not provided in multiple transactions as in venture deals: rather, there is often a single financing. Moreover, deal sizes are missing in many of the later-stage financings in the PitchBook database. While the total investment amounts in column 4 increase as anticipated, the interpretation of results about deal sizes in column 5 is challenging for the growth and expansion deals.

rule out this concern.

4.4.1 Accounting for common trends due to information and trade connections

To the extent that trends affecting sector-specific entrepreneurial activity in China and other emerging markets are reflected in their connectedness with information and networks, we can control for these observed features directly. Specifically, we control for internet penetration rate (Table A.15), trade with China (Table A.16), and the triple-difference term interacting with the trade volume (Table A.17). Our baseline estimates remain similar. As a hands-off strategy to account for common trends, we also control directly for the emerging market sector-level growth rate during the sample period interacted with country-by-year fixed effects (Table A.18). The coefficient of interest is again similar, indicating that even the differential country-specific effect of common sector-level trends do not drive the results.

4.4.2 Policy shocks to Chinese take-off in specific sectors

We next exploit specific regulatory policies implemented by Chinese leadership and bureaucracy that limited growth in some sectors and provide plausibly exogenous variation in sector-level take-off in China. Since these policy restrictions were likely motivated by the Chinese government's own economic and political considerations, they are arguably independent from trends in potential investment opportunities and success elsewhere in the world. If our baseline results capture the causal effect of investment take-off in China, we should observe no effect on entrepreneurship sectors that were constrained by government policy. If we *do* observe an effect, it would suggest that our estimates could be driven by spurious differential trends across markets (i.e., the reflection problem).

We systematically search top Chinese economics and finance news sources for discussions of each of the 263 sectors and identify descriptions of all policy constraints that might hinder development (see Appendix E). For example, many reports highlight policies in China that restricted access by individuals and companies to basic hardware facilities for meteorological data, potentially limiting firm growth in climate data and ecosystem monitoring.[39] Similarly, sources note the high degree of control of low-altitude airspace and the major obstacle that these policies posed to firm development in air mobility services.[40,41]

Importantly, these policies seem specific to China's administrative, bureaucratic, and political environment. We search for the presence of each policy in all other emerging

[39] For instance, Felix Wu, founder of Seniverse, said in a Stanford GSB China interview, "Due to the closure of China's commercial meteorological market [...] the value of natural big data such as meteorology is difficult to apply to industries and enterprises in the Chinese market, hindering the refined operation and efficient growth of enterprises." Source: `https://tinyurl.com/48uaz54r` (in Chinese).

[40] As Caixin recently reports, "The biggest obstacle [to any development of low-space technology firms] is the high degree of control of low-altitude airspace." Source: `https://tinyurl.com/4347ny3z` (in Chinese).

[41] Table A.19 provides a full list and description of the policy constraints.

Table 4: Exploiting Variation in Sector-Level Policy Constraints in China

	China-Led? (0/1)		Number of Deals (Normalized)			
	(1)	(2)	(3)	(4)	(5)	(6)
Policy-Constrained	-0.388***	-0.321***				
	(0.071)	(0.080)				
Policy-Constrained × Post × Appropriateness			-5.381**	-8.760***		
			(2.547)	(2.684)		
$\widehat{\text{China-Led}}$ × Post × Appropriateness					11.091**	27.890***
					(5.153)	(8.832)
Macro-Sector FE	No	Yes	-	-	-	-
Sector × Country FE	-	-	Yes	Yes	Yes	Yes
Country × Year FE	-	-	Yes	Yes	Yes	Yes
Sector × Year FE	-	-	Yes	Yes	Yes	Yes
Macro-Sector × Year × Country FE	-	-	No	Yes	No	Yes
Model	1st Stage	1st Stage	RF	RF	IV	IV
Number of Obs	263	263	552300	552300	552300	552300
Mean of Dep. Var	0.490	0.490	3.588	3.588	3.588	3.588
SD of Dep. Var	0.501	0.501	44.979	44.979	44.979	44.979

Note: The unit of observation is a sector for columns 1 and 2 and a country-sector-year for columns 3 to 6. Dependent variables are reported at the top of the respective columns. Columns 1 and 2 report the first stage results, columns 3 and 4 and report the reduced form results, and columns 5 and 6 report the IV results. The triple interaction term is instrumented by not-policy-constrained sectors interacted with post and appropriateness in Columns 5 and 6. Robust standard errors are reported for columns 1 and 2 and standard errors are clustered by country for columns 3 to 6. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

markets in our sample, and we find that, on average, a policy resembling the constraint we identify in China is present in only 7 out of 117 countries.[42] Moreover, presence of similar sector-constraining policies that we do identify is not associated with socioeconomic similarity to China (Table A.20, column 1). Consistent with the idiosyncratic nature of these constraining policies in China, we find no evidence that constrained sectors differ from unconstrained sectors along many important aspects of global investment, including the pre-period level or growth rate in the number of deals, average deal size, total number of companies, and total number of countries with at least one deal (Table A.21, Panel A). These differences remain insignificant when we focus only on venture activity in emerging markets (Panel B) or even when we focus only on China itself (Panel C).

We exploit these sector-specific policy constraints in China as idiosyncratic shocks to Chinese take-off (Table 4). First, we show that the presence of constraining policies in China strongly reduces the probability that a sector is led by China (column 1); this relationship holds even within macro-sectors (column 2). Thus, these constraining policies

[42]We employ a team of RAs to search each of the 15 constraints we identified in China within each of the 117 emerging markets in our sample by searching online news, media reports, and legal databases.

indeed substantially restricted sectoral development within China itself.

Second, we estimate Equation 2 after replacing the China-led sector indicator with the policy constraint indicator (columns 3 and 4, Table 4). We estimate a large, negative coefficient on the triple interaction term, indicating that foreign venture activity growth is substantially lower if a constraint exists in China. Columns 5 and 6 of Table 4 report consistent estimates from an instrumental variable specification where the China-led sector indicator is instrumented using the absence of constraining policies in China. The results also hold if we fully exclude any policies that appeared in an emerging market other than China from the construction of the instrument (columns 2 and 3, Table A.20).

Thus, policy constraints that affected sector-specific growth in China, but were plausibly independent from sector-level trends in the rest of the world, strongly predict the global spread (or lack thereof) of entrepreneurship. These estimates are consistent with a causal effect of China's rise on the growth of entrepreneurship in other parts of the world.

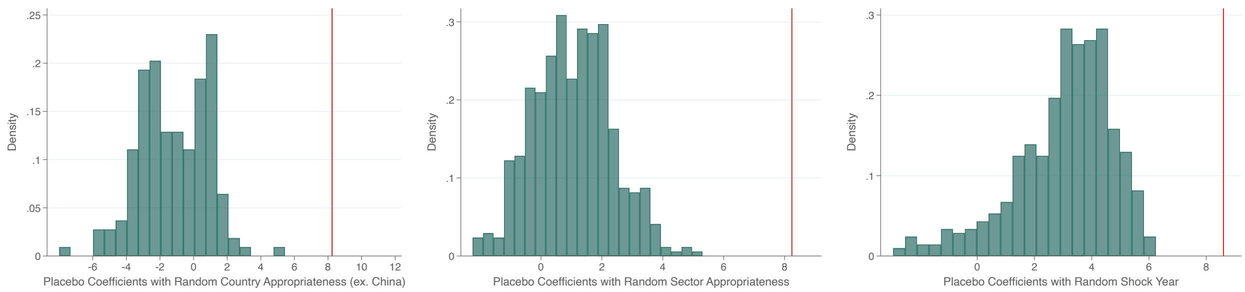
4.4.3 Falsification tests

As a final strategy to validate our interpretation of the main result, we conduct a series of falsification tests. If the findings are driven by some common shock to emerging economies—or even to markets with similar economic conditions to China—rather than the rise of China itself, we would expect socio-economic similarity to *other* emerging markets to also be correlated with a rise in entrepreneurial activity. To investigate this possibility, we compute socio-economic similarity of each $country * sector$ to its counterpart in every other country. We then successively re-estimate Equation 2 in which we replace $Appropriateness_{cs}$ with the analogous appropriateness measure for every other country. Figure 3a presents the histogram of placebo coefficients in green and our main coefficient estimate from Table 2 with a vertical red line. The placebo coefficients are centered near zero and our estimate is the largest, consistent with a causal interpretation of our findings.

A second potential question is whether the results capture the effect of average, country-level differences in appropriateness—which may be more likely to correlate with investment trends—rather than differences across sectors, within countries. To investigate this, we estimate a series of placebo versions of Equation 2, now randomizing the sectoral component of $Appropriateness_{cs}$ within each country.This keeps all country-level variation the same while randomizing variation across sectors within countries. Our estimate is again larger than all placebo estimates, suggesting that our appropriateness measure is not only capturing broad differences in similarity to China across countries, but also within-country differences in similarity to China across investment sectors (Figure 3b).

Figure 3: Falsification Tests

(a) Random Country (b) Random Sector (c) Random Post-Year



Note: Figure 3a reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which $ChinaAppropriateness_{cs}$ is replaced with an analogous appropriateness measure for each other country. Our main estimate of β from Equation 2 is displayed with a red vertical line. Figure 3b reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which the sector component of $ChinaAppropriateness_{cs}$ is drawn at random each time. Our main estimate of β from Equation 2 is displayed with a red vertical line. Figure 3c reports a histogram of coefficient estimates from a series of estimates of Equation 2, in which we use a sector-specific post-period identifier and the post-period start year is randomized across sectors. Again, our main estimate of β from using this specification is displayed with a red vertical line. All histograms summarize the results from 500 separate regressions.

4.5 Dynamics

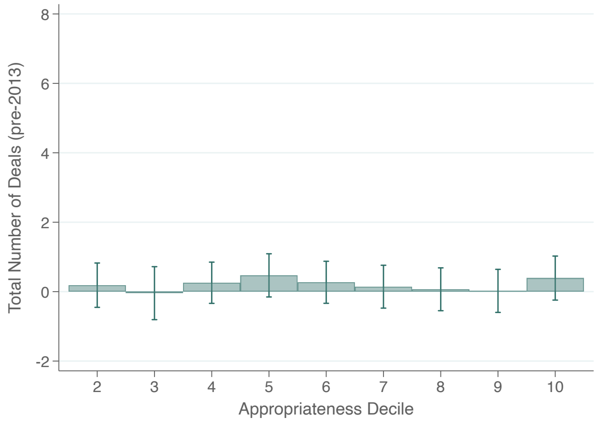
Rise of China: Effects Over Time Next, we turn to dynamics and study drivers of entrepreneurship prior to the rise of China, as well as how they changed over time. Figure 4 reports the relationship between the China-led sector indicator and venture deals, separately for each decile of our appropriateness measure, both for the pre-period (before 2013) and post-period (after 2013). The results in each sub-figure are from a single regression in which the first decile is the excluded group and all bars display estimates of the interaction between $ChinaLed_s$ and the appropriate decile indicator. There is no difference between country-sector pairs with different values of the appropriateness index prior to the rise of China (Figure 4a). Thus, there are no pre-existing trends in the relationship between the potential appropriateness of Chinese R&D and entrepreneurship. After 2013, however, there is a positive relationship between the appropriateness decile and venture activity: with two exceptions, the bars increase from left to right (Figure 4b).

Our main results are also consistent with the timing of *sector-specific* investment take-off in China. We identify a separate surge year for each sector in China, defined as the start of the two-year window with the highest growth rate.[43] While the modal surge year is 2013, which is why we use this year in our baseline analysis, there is also variation

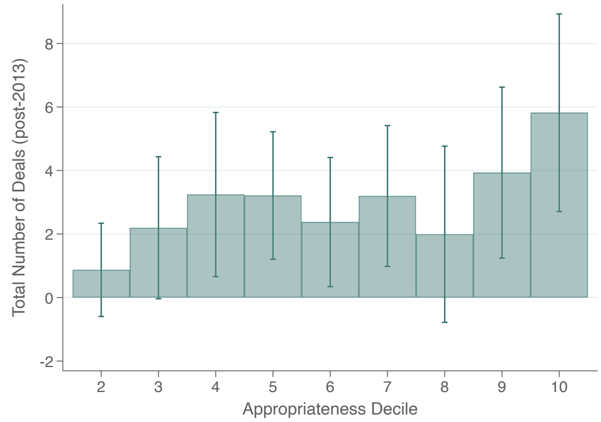
[43] Figure A.12 shows the number of Chinese deals over time for several sectors, with the surge year marked.

Figure 4: Effect of Appropriateness by Decile: Pre vs. Post Period

(a) Pre-period (before 2013)



(b) Post-period (2013 and after)



Note: Figure 4a shows estimates of appropriateness decile indicators interacted with $ChinaLed_s$. The outcome variable is total (normalized) deals in the country-sector during the pre-period. Figure 4b shows estimates of appropriateness decile indicators interacted with $ChinaLed_s$. The outcome variable is total (normalized) deals in the country-sector during the post-period. Standard errors are clustered by country and 95% confidence intervals are reported.

across different sectors (Figure A.13).[44] Estimates of Equation 2 using a sector-specific post-period definition are slightly larger than our baseline results (Table A.22). Moreover, if we randomize the surge year across sectors and re-estimate the regression, our main estimate is larger than all other estimates (Figure 3c). The global spread of entrepreneurship in China-led sectors thus exactly followed the sector-level timing of growth in China.

Whither the US? What drove patterns of entrepreneurship *prior* to China's rise? The premise of our analysis is that the US was the dominant center of VC investment, suggesting that socioeconomic similarity to the US should correlate with market-level investment. We construct a country-by-sector measure of similarity to the US, analogous to the measure of $Appropriatness_{cs}$ and, focusing on years before 2013, we estimate:

$$y_{cs} = \phi_1(Appropriate_{cs}^{US} * USLed_s) + \phi_2(Appropriate_{cs}^{US} * ChinaLed_s) + \alpha_c + \gamma_s + \epsilon_{cs} \quad (3)$$

where $USLed_s = 1 - ChinaLed_s$ are the sectors that the US dominates. ϕ_1 captures the effect of US appropriateness on sectors dominated by US firms. ϕ_2 captures the effect of US appropriateness on deals in sectors that would come to be dominated by China.

Our estimate of ϕ_1 is positive and significant (Figure A.14a), consistent with qualitative accounts that during the early part of our sample period, new entrepreneurial ideas diffused almost exclusively from the US. In sectors where US firms were active, markets

[44] 2013 also satisfies the requirements used to determine the sector-specific surge year for the full sample.

with similar socioeconomic conditions to the US were more likely to invest in startups. Our estimate of ϕ_2 is about half the magnitude of ϕ_1 and statistically indistinguishable from zero (Figure A.14b), consistent with there being less activity in these sectors prior to the rise of China. Moreover, Figures A.14c and A.14d confirm that socioeconomic similarity to China did not predict entrepreneurship *prior* to the rise of China—the US was the dominant (if not only) benchmark country during this period. Finally, we investigate whether the global diffusion of entrepreneurship from the US changed after 2013 (Figure A.15). If anything, the effect of US appropriateness *increased* over time for US-led sectors. In other words, China's rise did not replace the US's role; instead, it offered a new set of potential business models for different sectors and suited to different contexts.[45]

5 Mechanisms

5.1 Mirroring Chinese businesses

The previous section documented that emerging market entrepreneurship grew disproportionately where Chinese businesses and technology would be most "appropriate." Our hypothesis is that part of this pattern is driven not just by investment in the industries led by China, but also by directly adapting businesses that were successful in China. We next investigate whether — within each sector — the businesses founded in emerging markets resemble companies previously founded in China.

In order to capture the emulation of Chinese companies, we use Natural Language Processing tools to measure similarity in business description across all company pairs within each sector.[46] We then calculate the pairwise similarity for all companies in each sector. This method captures patterns consistent with case study analysis. For example, a range of analysts have noted that Indian EdTech firm Byju's drew inspiration from the business model pioneered by China's Yuanfudao. Consistent with this, we estimate a high (80.11%) level of textual similarity between Byju's and Yuanfudao. However, Byju's is not similar to many other Chinese companies in its sector, including Yundee (28.59%), a Chinese EdTech company focused on expanding educational tools for autistic children.

Using the pairwise similarity measures, we compute each company's average textual

[45] This figure reports the difference in the effect of $(USAppropriateness_{cs} * USLed_s)$ and $(USAppropriateness_{cs} * ChinaLed_s)$ between the pre and post-periods. We estimate this difference from a single regression, a version of Equation 3 that includes both the pre-period and post-period in the sample. We interact both $(USAppropriateness_{cs} * USLed_s)$ and $(USAppropriateness_{cs} * ChinaLed_s)$ with a post-period indicator and include all two-way fixed effects.

[46] We use SentenceTransformer (SBERT), a framework for state-of-the-art sentence embeddings standard for similarity comparison, to tokenize business descriptions and calculate pairwise cosine similarity. SentenceTranformer is especially suitable for textual similarity comparisons because the resulting embeddings are directly comparable for cosine similarity calculations.

Table 5: Increasing Business Model Similarity to China

	Text similarity to Chinese companies in the sector	
	(1)	(2)
	Mean Similarity	90th Percentile Similarity
China-Led Sector × Post × Appropriateness	0.010**	0.014***
	(0.005)	(0.005)
Sector × Country FE	Yes	Yes
Country × Year FE	Yes	Yes
Sector × Year FE	Yes	Yes
Number of Obs	42536	42536
Mean of Dep. Var	0.506	0.614
SD of Dep. Var	0.094	0.099

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Only Chinese companies existed before a given company are considered. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

similarity with existing Chinese companies in the same sector that were founded during the preceding five years. For each country-sector pair, we measure both the average similarity to recent Chinese companies as well as the 90$^{\text{th}}$ percentile of the similarity distribution, to capture the fact that companies may closely follow a small number of Chinese companies in the sector but not be similar to others. We then estimate versions of Equation 2 with company similarity to China as the dependent variable.

Table 5 presents the results. Country-sector pairs with higher values of $Appropriateness_{cs}$ experience a rise in business description similarity to Chinese companies during the post-period (column 1). The estimate is larger and more precise when focusing on the right tail of the company similarity distribution (column 2). Not only did high-appropriateness country-sector pairs grow in response to the rise of China, but companies in these sectors became more similar to their Chinese counterparts. Fixing the level of appropriateness, the estimates suggest that businesses became roughly 0.15 standard deviations more similar to recent Chinese companies in China-led compared to non-China-led sectors. Like our baseline results, these findings are similar if we restrict attention to Western-backed Chinese companies when constructing the similarity measures (Table A.23), suggesting that the estimates are not driven only by state-sponsored companies or government investment.

To further assess whether the baseline results are driven by entrepreneurs around the world learning from Chinese successes, we return to our baseline specification and separately estimate the effect on the number of first investments in companies and of follow-on deals. In principle, both could be affected by the rise of Chinese venture capital. If new startups are founded by entrepreneurs learning from businesses and technology developed in China, we might expect the effect primarily in early-stage deals. Alternatively, if the results are driven by sophisticated investors' piling in" to finance existing firms once there is a proven benchmark in China, we might expect the effect in later-stage deals.

Columns 1 and 2 of Table 6 report estimates in which first deals and follow-on deals are included as separate independent variables. We find effects on both types of deals, but substantially larger effects for first deals, suggesting that the rise of China led to the development of new companies in emerging markets. The growth of initial funding opportunities seems to be an important mechanism driving the baseline result.

5.2 Investor and sector heterogeneity

The nature of who provides the funding for entrepreneurship is a critical question. One possibility in our context is that investment is driven by Chinese VCs, who may try to replicate their domestic successes by investing in similar areas abroad. Such a result might have substantial implications for the governance and flow of profits from these firms. Alternatively, funding could be drawn from local groups or from third countries, who deduce that Chinese business models will be good fits for the local context.

Columns 3 to 5 of Table 6 report estimates in which the dependent variables are the number of deals with an investor from US (column 3), with an investor from China (column 4), and with an investor from the same country as the firm (column 5). While all three are positive, the largest effect is for local investors. This finding indicates that the growth of Chinese venture capital promoted local investment in emerging markets. The effect of Chinese investment is the smallest in magnitude and one-fifth the effect size on investment by local venture groups, suggesting that Chinese VCs play a limited role.

The results could also be very different across different sectors. While it is natural to think that China's rise in non-tradable sectors had positive effects on business formation elsewhere, China's rise in tradable sectors might have had a more limited effect if new Chinese businesses simply exported their products or technology overseas. The effect in these areas could even be negative, to the extent that new Chinese products crowded out local entrepreneurship elsewhere.[47] To investigate these possibilities, we determine whether each investment sector is tradable or not, following the definition introduced by Mian and Sufi (2014).[48] Figure A.16 displays trends in Chinese deals in tradable and non-

[47] Consistent with this possibility, Gentile et al. (2025) provide evidence that Chinese industrial policy in solar photovoltaic manufacturing had a negative effect on innovation elsewhere in the world.

[48] We follow Mian and Sufi (2014)'s sectoral split into tradable, non-tradable, and others. We define sectors with clear products as tradable and retail and local services as non-tradable; the remaining sectors are classified as others. Since VC investment sectors do not fall strictly into NAICS codes, we use our reading of the PitchBook data to determine whether each sector has tradable products or not. To be conservative, we combine "other" sectors with non-tradable sectors in our analysis. We identified 57 tradable sectors and 196 non-tradable or other sectors. If we use only explicitly non-tradable sectors, our coefficient of interest is even higher and also significant ($\beta = 20.849, S.E. = 8.631$).

Table 6: Deal Types, Investors, and Sector Tradability

	(Normalized) number of		(Normalized) number of deals from investors from			(Normalized) number of deals for the sample of	
	(1) First deals	(2) Follow-on deals	(3) US	(4) China	(5) Local	(6) Tradable Sectors	(7) All Other Sectors
China-Led × Post	5.517***	2.897**	0.966	0.936	4.656***	1.553	10.195***
× Appropriateness	(1.992)	(1.272)	(1.364)	(0.574)	(1.688)	(2.630)	(3.562)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	552300	552300	552300	552300	119700	432600
Mean of Dep. Var	2.772	0.816	0.803	0.079	1.716	3.646	3.572
SD of Dep. Var	39.463	17.930	19.497	4.150	26.571	44.037	45.237

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Columns 1 and 2 report the effect on first deals versus follow-on deals. Columns 3 to 5 report the coefficients on deals with different investor origins where Local is defined as the same HQ country investor as the invested company's HQ country. Columns 6 and 7 report the results when splitting the sample by tradable sectors and other sectors. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

tradable sectors respectively, as well as in the full global sample; while there is a marked rise in both after 2013, the rise is much larger in non-tradable sectors, both within China and in global VC more generally. Columns 6 and 7 of Table 6 report the effect on venture activity in tradable and non-tradable sectors separately. Consistent with the hypothesis above, the effect on tradable sectors is positive but small in magnitude, suggesting weaker effects in these areas but no obvious crowding out, while the effect for non-tradable sectors is larger and more statistically precise than our baseline estimate.

5.3 Political pressures and incentives

So far, our results have been silent about the role of international politics. It is possible, for example, that our main findings are partly driven by disproportionate technology diffusion to China's political allies. The direction of entrepreneurship in China has also been driven in part by top-down initiatives that target key strategic sectors, which may have been responsible for the development of some strategic sectors.

To investigate these issues, we develop two proxies for political proximity to China: *(i)* voting similarity on UN resolutions, which captures countries' international political stance;[49] and *(ii)* the similarity of political regime as measured by the Polity Project, which

[49]This measure is based on an "ideal point scale" derived from voting behavior from 1946 to 2012 in the UN General Assembly, as documented by Bailey et al. (2017).

captures countries' political institutions[50] We find no evidence that the results are driven by more politically aligned countries (Table A.24, columns 1 to 4). The baseline effect is positive, significant, and similar in magnitude when focusing on the samples of aligned and non-aligned countries, using both measures.

We then identify state-supported sectors by compiling lists of strategic technologies from two high-profile government technological blueprints—*(i)* "Made in China 2025," a national strategic plan for industrial policy as part of China's Thirteenth and Fourteenth Five-Year Plans and *(ii)* "China's Stranglehold Technologies"— and hand-linking them to the sectors in our baseline analysis. We estimate a smaller effect for the government-prioritized sectors and a larger effect for the non-prioritized sectors (Table A.24, columns 5 and 6). These findings suggest that "top-down" investment did not lead to the development of successful business models with international applications. The sectors that grew in China with limited government involvement seem to generate the largest spillovers to other emerging markets.

Finally, we investigate whether political links to China could be an independent mechanism leading to the diffusion of Chinese entrepreneurship. We estimate a version of Equation 2 in which we also include $ChinaLed_s * Post_t$ interacted with both UN voting distance from China and Polity score distance to China (see Table A.25). The coefficients of both terms are negative — countries more politically aligned with China are more likely to invest in China-led sectors — but our main coefficient of interest is unaffected.

5.4 Vertical vs. Horizontal Appropriateness

Our main measure of appropriateness captures both differences across countries that can be explained by income ("vertical" differences) and differences across countries that are unrelated to income ("horizontal" differences). Are the main results driven by similarity to China along vertical or horizontal dimensions? If they are driven only by the former, it could raise the concern that these new technologies and business models could become less relevant as countries develop, and even limit future productivity growth or upgrading to the extent that they cause technology "lock in."

To investigate this set of issues, we separately estimate the effect of the horizontal and vertical components of appropriateness (see Section 3.3). Both components seem to matter for our results (see Table A.26). If anything, the effect is larger for the horizontal component, which is consistent with our earlier results that differences in per-capita income alone do not drive our baseline findings (Table A.7). This distinction between vertical versus

[50] Polity scores each country's institutions from -10 (authoritarian) to 10 (full democracy) by amalgamating data on key features such as checks and balances on the executive and election competitiveness.

horizontal differences will be important when assessing the broader economic implications of our findings, which we turn to in the next section (Section 6).

6 Broader impacts

In this section, we investigate the broader economic impacts of this rise in emerging market entrepreneurship. So far, we have shown that the rise of China led to an increase in venture deals and total investment in markets where Chinese technology and business models would be most appropriate. In and of itself, this does not imply economic benefits.

There are several potential reasons that this rise in venture activity may not have translated into clear economic gains. First, these new businesses may have had limited success if they were following international trends without clear local potential. Second, and more subtly, investing disproportionately in entrepreneurial models developed in China may have led to "lock-in" to particular markets and technologies. Certain technologies may be appropriate at lower income levels but become less productive as countries develop. Firms that market these technologies may ultimately fail or, more perniciously, adoption of these technologies could impose development costs. For example, Basu and Weil (1998) develop a model of appropriateness determined by the local capital-labor ratio (i.e., a vertical difference). While technology that is well-suited to a low capital-labor ratio may be productive in the short run, it may also become less productive over time (as the country accumulates its capital stock) or cause lock-in to a low-capital equilibrium, limiting future adoption of capital-complementing technologies.

To evaluate the broader economic consequences of rising entrepreneurship activities in emerging markets, we assess outcomes of firms (Section 6.1), entrepreneurs and their subsequent ventures (Section 6.2), socioeconomic outcomes associated with the entrepreneurship sector (Section 6.3), and aggregate effects on innovation at the city and regional levels (Section 6.4). Throughout this section, we decompose the effects between the vertical and horizontal differences that contribute to the appropriateness of Chinese ventures (see Section 5.4). If the "lock-in" hypothesis is true, we might expect new business models matched to vertical differences across countries may have weaker economic benefits.

6.1 Firm outcomes

We first investigate outcomes at the firm-level. We use PitchBook data to count the number of funding rounds in each sector-year pair for firms that end up failing, firms that end up acquired or going public (rough but frequently used proxies for investment success), and firms that have not yet exited. Panel A of Table 7 presents estimates of Equation 2, in which the dependent variables are the (normalized) number of deals associated with each exit

Table 7: Company Outcomes

	Outcome is (normalized) number of deals for companies that end up		
	(1) Failing	(2) Acquired or IPO	(3) Neither (yet)
Panel A: Baseline Appropriateness Results			
China-Led × Post × Appropriateness Z-score	0.143	0.327**	1.769***
	(0.215)	(0.151)	(0.609)
Number of Obs	552300	552300	552300
Mean of Dep. Var	0.507	0.496	2.584
SD of Dep. Var	16.311	13.803	38.142
Panel B: Vertical versus Horizontal Results			
China-Led × Post × Appropriateness	0.256**	0.124	0.945**
(GDP component Z-score)	(0.126)	(0.088)	(0.369)
China-Led × Post × Appropriateness	-0.015	0.286*	1.369**
(Residual component Z-score)	(0.265)	(0.154)	(0.651)
Number of Obs	547040	547040	547040
Mean of Dep. Var	0.508	0.500	2.601
SD of Dep. Var	16.341	13.860	38.283
Sector × Country FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. To facilitate comparison, we take the Z-score for both our baseline appropriateness and its GDP and residual components. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

type (or no exit). When the outcome is the number of failures (column 1), the coefficient estimate is small in magnitude and statistically indistinguishable from zero. This result suggests that our findings are not driven by failures or short-run fads. When the outcome variable is the number of acquisitions or IPOs, we find a positive and significant effect, suggesting that many of these new investments ended in (proxies for) success (column 2). Finally, when the outcome is the number of deals associated with companies that have not yet exited as of mid-2022, the estimate is again positive (column 3). This group is the largest in our sample, reflecting the recent growth of venture investing in many emerging economies and the lengthening of VC holding periods (Davydova et al., 2022).

Next, we separately estimate the effect of horizontal and vertical similarity of China using an augmented version of Equation 2 that includes both measures of appropriateness on the right hand side (Table 7, Panel B). Vertical similarity to China led to a positive and significant effect on the number of failing firms (column 1) though it also had a positive effect on the number of successful exits and still-existing firms (columns 2-3). Horizontal similarity to China, on the other hand, had no effect on the number of failing firms and a larger positive effect on the number of firms with successful exits and the number of firms that have not yet exited. This difference is despite the fact that both measures have comparable effects on the number of deals (see Table A.26). This result is a first indication that the benefits of appropriate entrepreneurship are driven by technologies adapted to horizontal differences across countries rather than those purely determined by income.

6.2 Serial entrepreneurs and cross-sector spillovers

Next, we move beyond the firm level and investigate local entrepreneurial ecosystems. On one hand, the rise of China as a successful entrepreneurial model led other emerging markets to focus only on the areas in which China was successful. This could lead to counterproductive concentration of investment or under-exploration of potential opportunities in other areas. On the other hand, local entrepreneurial success is often associated with the emergence of repeat ("serial") entrepreneurs or investors. Existing work has documented that these serial players are more successful (e.g., Lafontaine and Shaw, 2016) and can take greater risks (Gompers et al., 2010), potentially making it possible to branch out beyond the areas in which they started. More generally, qualitative work suggests that serial entrepreneurship contributes to regional development (Mallaby, 2022).

To study these possibilities, we investigate whether our findings are accompanied by repeat entrepreneurship. We then investigate whether these serial entrepreneurs branched out from the China-led markets that they initially followed.

We estimate the following augmented version of our baseline specification:

$$y_{cst} = \beta \left(ChinaLed_s * Post_t * Appropriateness_{cs} \right) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + \epsilon_{cst}, \tag{4}$$

where y_{cst} is the number of serial entrepreneurs whose first company was in sector s, and whose second was founded in year t.[51] We also estimate the effect separately for repeat entrepreneurship in China-led and non-China-led sectors.[52]

We find that the rise of China led to a larger number of serial entrepreneurs in similar emerging markets (Table 8, Panel A, column 1). This is an indication that the patterns identified in our baseline results led to the creation of local entrepreneurial ecosystems. Moreover, these effects are driven by serial entrepreneurs entering sectors that are *not* led by China. This pattern is the opposite of what one would expect if following Chinese benchmarks constrained local creativity or led to market lock-in. When the outcome is the number of serial entrepreneurs whose subsequent company (or companies) fell into

[51] If the founder is listed, we define the founder as the CEO at the time of the first investment.

[52] Focusing on each serial founder's second company's sector is largely without loss, since 93% of serial founders have founded exactly two companies.

Table 8: Serial Entrepreneurs

	Number of Serial Entrepreneurs			Serial Entrepreneur Indicator		
	(1) All	(2) Only CL	(3) Any non-CL	(4) All	(5) Only CL	(6) Any non-CL
Panel A: Baseline Appropriateness						
China-Led × Post × Appropriateness	0.005**	0.001	0.004**	0.003***	0.001*	0.002**
(Z-score)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Number of Obs	552300	552300	552300	552300	552300	552300
Mean of Dep. Var	0.007	0.002	0.005	0.006	0.002	0.004
SD of Dep. Var	0.105	0.049	0.085	0.076	0.043	0.066
Panel B: Vertical versus Horizontal						
China-Led × Post × Appropriateness	-0.002	-0.003**	0.001	-0.001	-0.002**	0.000
(GDP component Z-score)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
China-Led × Post × Appropriateness	0.007***	0.003***	0.004**	0.004***	0.003***	0.002**
(Residual component Z-score)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Number of Obs	547040	547040	547040	547040	547040	547040
Mean of Dep. Var	0.007	0.002	0.005	0.006	0.002	0.004
SD of Dep. Var	0.105	0.049	0.086	0.077	0.043	0.066
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. A founder is coded as "only in CL sectors" if her second company only falls within the China-led sectors (as defined in our main analysis), and as "any non-CL sectors" if her second company falls into at least one non-China-led sector. In Panel B, both GDP component of appropriateness and residual component appropriateness are normalized to z-scores. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

China-led sectors (column 2), the coefficient estimate is very close to zero. However, when the outcome variable is the number of entrepreneurs whose second company (or companies) did not (column 3), the estimate is positive and significant. We observe a similar pattern on the extensive margin when the outcome variable is an indicator for the presence of any serial entrepreneur in the relevant category (columns 4 to 6).

We next decompose the effects of vertical and horizontal differences that contribute to appropriateness of Chinese ventures (Table 8, Panel B). Strikingly, the positive effects are entirely driven by horizontal similarity to China, which is associated with a positive and precise effect on serial entrepreneurship on both intensive and extensive margins. This is further evidence that business models matched to a particular level of development are less likely to generate local spillovers than those matched to other local characteristics.

6.3 Socioeconomic outcomes

So far, our results in this section have focused on how the expansion of emerging market entrepreneurship led to the development of successful firms, serial entrepreneurs, and innovation ecosystems. However, the effects of a rise in entrepreneurship may (and ought to) extend beyond the innovation economy. After all, greater investment in EdTech startups, for example, may be beneficial not only because it fuels entrepreneurship, but also because it leads to improved educational outcomes. Direct evidence of positive effects on these socioeconomic outcomes would be further evidence that the rise in appropriate entrepreneurship improved local well-being.

To investigate this possibility, we first use the World Bank development indicators described in Section 3.3 to construct proxies for socioeconomic well-being for each country-macro-sector pair. We turn each indicator into a z-score, where higher values correspond to improved outcomes. We then compute the average z-score across all indicators assigned to each macro-sector during the post-period (2013 to 2019). Higher secondary school enrollment will increase this measure for the educational technology macro-sector, for example, while greater agricultural output will increase it for agricultural technology.

We next use the coefficient estimates from Equation 2 to predict the total number of deals in each country-sector pair during our post-period induced by the rise of China. We aggregate these predicted values to the country-macro-sector level and use this as a proxy for induced entrepreneurship in each country-macro-sector pair. Finally, we estimate the following regression specification:

$$y_{cm} = \phi \text{PredictedDeals}_{cm} + \alpha_c + \delta_m + \epsilon_{cm}, \tag{5}$$

where m indexes the 15 macro-sectors, c indexes countries, and y_{cm} is average of the development indicator z-scores for each country-macro-sector pair. All specifications include both country and macro-sector fixed effects. An estimate of $\phi > 0$ would indicate that the rise in entrepreneurship was associated with improved socioeconomic well-being.

We find that higher predicted entrepreneurship is associated with a higher overall socioeconomic well-being (Table A.27, Panel A, column 1). Column 2 restricts the sample to emerging markets: the coefficient estimate increases by 60%. When we restrict attention to macro-sectors of agricultural technology, education technology, and health technology — areas in which we can most clearly track improvements in well-being using the WDI database—the coefficient estimates increase by ten-fold (Table A.28).[53]

[53]Combined with the fact that our main results are driven by entrepreneurship in non-tradables (Table 6), these positive effects on economic outcomes are consistent with recent work highlighting that services and other non-tradable sectors can be a source of economic growth (Fan et al., 2023; Peters et al., 2026).

Next, we decompose whether these effects are driven by the horizontal or vertical component of appropriate entrepreneurship. As discussed above, new business models matched only to vertical differences across countries may have weaker economic benefits if they become less productive as countries develop or (more perniciously) make countries less able to benefit from future technological progress. We develop two separate measures of PredictedDeals$_{cm}$, one using only the vertical dimension of appropriateness and the other using only the horizontal dimension. We then estimate Equation 5 using each of these measures. Deals predicted by the vertical dimension have no effect (Table A.27, Panel B); in contrast, deals predicted by the horizontal dimension have a positive and significant effect that is larger than the baseline estimates (Panel C). While we find no evidence that deals predicted from the vertical dimension had a significant *negative* effect, studying these effects over a longer time horizon could be important to fully assess their implications.

6.4 City-level effects and geographic spillovers

Finally, we investigate the effects of the rise of emerging market entrepreneurship at the city level. This builds on a large body of work emphasizing the importance of local research spillovers and the geographic clustering of entrepreneurship (Jaffe et al., 1993). Moreover, by developing a measure of city-level exposure to new entrepreneurship, we can study the effect of the rise of China on measures of innovative activity beyond venture investment (e.g., new patenting). This city-level analysis requires a different empirical approach to identify the effect of China's entrepreneurial take-off. To measure the exposure of each city to the rise of China, we compute the share of its VC-backed companies in China-led sectors during the pre-analysis period. We then estimate whether the rise of China increased entrepreneurship and innovation in the locations that were best able to capitalize on the growth of China using the following specification:

$$y_{it} = \gamma(ShareChinaLed_i * Post_t) + \alpha_i + \delta_t + \epsilon_{it} \tag{6}$$

where i indexes cities and t continues to index years. y_{it} is a measure of venture activity in city i and year t. As outcome variables, we focus on both the number of VC-backed companies founded in each city and the number of patents assigned to firms in each city.[54]

We first restrict attention to cities in emerging economies. We find a positive city-level effect on the number of new companies (Table A.29, column 1).[55] While the effect size is larger when the outcome is companies in China-led sectors (column 2), it remains

[54]We geo-locate the headquarters of all PitchBook companies using SimpleMaps, supplemented with Opendatasoft, and use patent assignee location information from PatentsView. We link both to the nearest city from Natural Earth and restrict attention to cities with at least 20 companies during the pre-period.

[55]In Table A.29, the outcome is parameterized as the normalized level of deals or patents; however, the results are very similar if we instead use the inverse hyperbolic sine or log transformation (see Table A.30).

positive for companies outside China-led sectors (column 3). These findings dovetail with the results from Section 6.2, which documented the rise of serial entrepreneurs who branched out from the sectors that had clear Chinese predecessors. Using the full sample of countries, we find that the positive effect on overall entrepreneurship is larger in developing compared to developed countries (column 4). The city-level effect for emerging markets is nearly eight times as large as it is for non-emerging markets.

Finally, we turn to the effect on patenting, one proxy for overall innovative activity. We estimate a positive effect on patenting activity in emerging markets (column 5). Using the full sample of countries, we again find that the effect of the rise of China on innovation is stronger in emerging markets than in developed countries. Figure A.17 reports event study estimates corresponding to these estimates and, in all cases, we see no evidence of different pre-existing trends in more China-exposed (as compared to less China-exposed) cities. Together, these results suggest that the rise of Chinese entrepreneurship had impacts beyond the companies that it directly inspired, affecting sectors in which Chinese firms had little involvement, as well as overall innovative activity.

7 Conclusion

This paper investigates how the rise of a new R&D hub affects the global diffusion of business ideas and technology. We focus on the unprecedented growth of entrepreneurship in China since 2010, and find that it was associated with a surge in business formation in other emerging markets around the world. This was driven by country-sector pairs with socio-economic conditions closely resembling their counterparts in China, consistent with an "appropriate technology" story in which new technology was most productive in contexts resembling the ones for which it was designed. This global rise in investment had wide-ranging consequences, including increases in successful firm exits, serial entrepreneurship, patenting activity, and broader measures of economic well-being.

Our study is a first step towards evaluating the consequences of "spreading innovation out" more evenly across the globe. Our results suggest that there could be large benefits, especially if new innovation hubs shift the focus of technology toward applications that have been ignored by the existing system. This hypothesis is not unique to the rise of China. As technology investment increases in India or Brazil, for example, it too may have consequences far beyond their borders by developing technologies that are appropriate for other emerging regions. A key challenge will be accomplishing this "spreading out" without sacrificing the benefits of economies of scale and well-aligned incentives between entrepreneurs, investors, and asset owners that exist in current centers of innovation. How entrepreneurship can help realize human and social capital in emerging economies is a trillion-dollar question, with much of humanity's growth potential on the line.

These findings raise a variety of questions for future research. First, what are the political and geo-political consequences of the rise of Chinese innovation? The entrepreneurial success of Chinese business models may also lead to more credibility for "the Chinese model," at the expense of US or Western influence. Israel's entrepreneurial success, for instance, has long been reputed to give it more influence on the global stage than a country with a similar GDP and population would enjoy otherwise (Senor and Singer, 2009). Understanding the consequences of Chinese entrepreneurial success for "soft power"—especially in the long run—is an important question for further investigation.

Second, did 2020, the end of our study, mark the end of the golden era of entrepreneurship in China? The Chinese government in the early 2020s appears to have reversed its largely "hands off" approach towards the venture capital industry and become much more interventionist. As a result, many venture firms have swung to "politically correct" investing, with an emphasis on technologies directly aligned with government objectives. As the results in Section 5.3 suggest, this shift may make China less relevant as a role model for aspiring entrepreneurs in other countries going forward.

Third, how might the benefits of "spreading innovation out" differ across sectors or time horizons? While our analysis in Section 6 suggests that the spread of entrepreneurial leadership to China had global economic benefits, it is not clear that this would be the case in all contexts; it depends on the extent to which appropriateness shapes the impact of new innovation. While appropriateness may matter a lot for many technology startups—as well as in fields like agriculture (Akerman et al., 2025) and medicine (Kremer and Glennerster, 2004; Costinot et al., 2019) where technology needs to be tailored to local environmental or ecological conditions—this may be less true in areas like robotics, where the impact of returns to scale dominates. Moreover, there is the possibility that the development and adoption of appropriate technology in the short run could affect longer-run factor accumulation and the returns to future factor accumulation. Exploring these trade-offs empirically would be an interesting area for future work.

Finally, was the diffusion of business ideas to the developing world accelerated by the growth of venture capital? Successful startups can often be readily emulated, because there is greater information about them available through either securities filings or media coverage, in a way that may be very different from corporate innovations. Venture investors themselves highlight that they are able to arbitrage entrepreneurial insights across geographies, and the mobility of entrepreneurs appears to be far higher than among corporate executives. We leave it to future work to identify whether or not the venture model itself accelerates the global diffusion of ideas.

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Online Appendix for: Appropriate Entrepreneurship? The Rise of Chinese Venture Capital and the Developing World

by Josh Lerner, Junxi Liu, Jacob Moscona, and David Y. Yang

Appendix A Additional Information on Sourcing of Data

Appendix A.1 Venture capital investment

The main challenges with constructing a time series of venture capital data are two-fold:

- The inconsistencies in measuring venture capital investment activity across data providers. For instance, providers differ in whether the investments are classified by the nationality of the fund or the portfolio company, where the line between venture capital and growth investments are drawn, and if the investments by non-venture actors in venture deals counted.
- The changing quality of data vendors over time. For instance, PitchBook was established in 2007, and its data prior to the early 2000s are understated. Other once-high quality data providers (e.g., Thomson Reuters/Refintiv) seem to become less comprehensive over time.

We try to use as consistent a series as possible. For the period from 2000 to 2021, we use a tabulation of our own PitchBook data.

Since PitchBook did not begin data collection until 2007, years before 2000 seem to have severe "backfill bias." For data from 1969 to 1999 (used only in Table A.1), we tabulate data from the Refinitiv (also known at various times as Venture Economics, Thomson Reuters, and VentureXpert) database, which appears to be the best coverage of this period (Kaplan and Lerner, 2017). These are again reported in billions of current dollars.

We also did some data cleaning. Several Japanese companies in our November 2022 PitchBook data feed appeared to have amounts reported in yen, not dollars; we used the corrected values available on the PitchBook website. Refintiv data for the Cayman Islands in 1969; Sweden in 1970; the Philippines in 1971; and Kenya in 1973 seemed unreliable. Due to the difficulty in researching these records, they were simply removed. All figures were converted into 2011 US dollars using the GDP deflator series in the Economic Report of the President (`https://www.whitehouse.gov/wp-content/uploads/2023/03/ERP-2023.pdf`).

Appendix A.2 Young public firms

To assess the importance of venture capital in emerging markets and construct Figure 1c, we follow the methodology that Lerner and Nanda (2020) employ using the US data. We focus on companies that went public between 2003 and 2022, given the decreasing data quality in earlier years in many emerging markets.

We identify all initial public offerings using Capital IQ, from which we also obtain data on their market capitalization as of mid-August (emerging markets) or mid-September (developed markets) 2023, and R&D spending in fiscal year 2022. In an ideal world, we would exclude from our calculations "non-entrepreneurial" IPOs, such as spin-offs from corporations and governments, reverse LBOs, and financial instruments (REITs and closed-end funds). Our emerging market data does not allow us to be quite as precise, but we can exclude REITs and other closed end products, as well as firms in industries where IPOs are very likely to be privatizations (banks, extractive industries, insurers, steelmakers, and utilities) (Megginson, 2010). We refer to the remainder as entrepreneurial IPOs, even though we anticipate that this process removes some but not all non-entrepreneurial IPOs.

Capital IQ does not readily identify venture-backed firms, so we match the list of IPOs to the PitchBook data using the ticker symbol and the exchange. Because some firms are cross-listed and the databases are not always consistent in which exchange they list the firm as trading on, we check the tickers and exchanges where cross-listed products are traded (also obtained from Capital IQ) as well. We hand check the 200 largest firms by market capitalization and correct any mismatches due to spelling errors. Because the Indian data was especially problematic in this respect, we also hand-checked the 200 largest Indian IPOs by market capitalization as well. We also reassign large Irish-headquartered firms that have the bulk of their economic activity in another nation (e.g., PDD Holdings, the parent of Pinduoduo).

In some cases, information on R&D spending is missing in Capital IQ for large technology companies where we might anticipate such spending. We hand check the 100 largest firms by market capitalization with missing R&D data for the subset of firms that correspond to the US Bureau of Labor Statistics' (`https://www.bls.gov/advisory/bloc/high-tech-industries.pdf`.) list of "core" high-technology industries:

- Computer and Peripheral Equipment Manufacturing
- Communications Equipment Manufacturing
- Semiconductor and Other Electronic Component Manufacturing
- Navigational, Measuring, Electromedical and Control Instruments Manufacturing
- Aerospace Product and Parts Manufacturing
- Software Publishers
- Data Processing, Hosting and Related Services
- Other Information Services
- Computer Systems Design and Related Services
- Architectural, Engineering and Related Services
- Scientific Research and Development Services

We find that in some cases, R&D spending information is confined to footnotes or in supplemental documents. For instance, Tencent's 2022 annual report (`https://static.www.tencent.com/uploads/2023/04/06/214dce4c5312264800b20cfab64861ba.pdf`) does not include a break-out of its R&D spending from its Sales, General and Administrative (SG&A) spending, but this substantial amount ($7.5 billion) is disclosed in PowerPoint presentations circulated to investors and posted online (`https://static.www.tencent.com/uploads/2023/08/16/fd005676b39a09da4ac60be5889b6ba0.pdf`). In general, the problem is confined to a handful of large cross-listed entities: the sum of missing R&D for the 50th through 100th companies we hand checked was only $241 million. All amounts identified in foreign currency were translated US dollars using the average exchange rate in that year from the OECD.[1]

Appendix A.3 R&D

R&D (used in Figure A.1a) is taken from three sources:

- UNESCO (http://data.uis.unesco.org/) presents gross domestic expenditure on R&D (GERD) as a percentage of GDP on their web site from 2015 to 2021. In other words, they present total intramural expenditure on R&D performed in the national territory during a specific reference period expressed as a percentage of GDP of the national territory. The description of the process of data compilation (https://uis.unesco.org/en/topic/research-and-development) is as follows: "To produce these data, we conduct an annual survey that involves countries and regional partners, such as Eurostat, OECD and RICYT. We also work closely with the African Science, Technology and Innovation Indicators (ASTII) Initiative of the African Union. By working closely with these partners and national statistical offices, we can align and harmonize the surveys and methodological frameworks, such as the Frascati Manual, used at the global, regional and national levels to ensure that resulting data can be compared across countries. This is essential to gain a global perspective on science and technology." We multiply this number by GDP (see below) to obtain total R&D spending.
- The World Bank (https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS) presents R&D as a percentage of GDP from 1996 to 2014. UNESCO is listed as a source. We multiply this number by GDP (see below) to obtain total R&D spending.
- The OECD presents R&D total spending from 1981 to 1996 for selected OECD countries and seven others. We find this in the spreadsheet "Gross domestic expenditure on R&D by sector of performance and field of science," using the total on top of the spreadsheet" (for all fields of science), at https://stats.oecd.org/Index.aspx?DataSetCode=GERD_FUNDS_PRE1981. We download these in constant PPP-adjusted US dollars (2011). We adjust the units as needed. Puzzlingly, for the cases where OECD lists data for selected countries in later periods, it in some cases appears to be inconsistent with the data from UNESCO. For example, in 2011 the World Bank data indicates that in Australia the proportion of GDP on R&D was 2.25%, while the OECD data suggests this is 1.19%. In case of conflict, we use the UNESCO data.

We have (at least in theory) all VC and publication data, so years with blanks should be considered ones with no activity. But the R&D data is based on surveys that in some cases are periodic (every two or more years). We assume that firms did R&D in the years where there were no surveys. We impute missing years as follows:

- If we have R&D in year x and year $x+y$ where $y \leq 5$, we assign to each intermediate year $x+t$ the following amount: $R\&D_{x+t} = R\&D_x + (t/y) * (R\&D_{x+y} - R\&Dx)$. For instance, if there is one missing year, we use the average between the two years, and so forth.
- If the time series ends before 2020, use the value in the last year for the remaining years.

[1] https://stats.oecd.org/index.aspx?queryid=169.

Appendix A.4 Scientific publications

Scientific publications (used in Figure A.1b) from 1996 to 2020 are compiled by the US National Science Board's (NSB) Science & Engineering Indicators 2022 (`https://ncses.nsf.gov/pubs/nsb20214/data`, Table SPBS-2). Article counts refer to publications from a selection of conference proceedings and peer-reviewed journals in scientific and engineering fields from Scopus. Articles are classified by their year of publication and are assigned to a region, country, or economy on the basis of the institutional address(es) of the author(s) listed in the article. Articles are credited on a fractional count basis (i.e., for articles produced by authors from different countries, each country receives fractional credit on the basis of the proportion of its participating authors).

More details about the construction of the data series are here: `https://ncses.nsf.gov/pubs/nsb20214/technical-appendix/`. Blank rows represent countries not included in the NSB tabulation.

Appendix A.5 GDP

The World Bank's World Development Indicators (WDI) data bank (`https://databank.worldbank.org/source/world-development-indicators`) did not begin reporting GDP until 1980. Therefore, we used two databases here.

For GDP estimates from 1963 to 2018, we use the 2020 release of the Maddison Project Database, which provides information on comparative economic growth and income levels over the very long run. The project (`https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2020`) is aimed at standardizing and updating the academic work in the field of historical national accounting in the tradition of the syntheses of long-term economic growth produced by Angus Maddison in the 1990s and early 2000. The 2020 version of this database covers 169 countries. The table presents Purchasing Power Parity-adjusted GDP per capita in 2011 US dollars.

For 2019 to 2021, we use cumulative GDP numbers from the World Bank's World Development Indicators (WDI) data bank (`https://databank.worldbank.org/source/world-development-indicators`). We convert these to comparable numbers to those in earlier years by (a) normalizing WDI GDP data in each country-year (the 2017 constant US dollar series) by population, and then (b) converting from 2017 to 2011 US dollars using the GDP deflator series in the Economic Report of the President (`https://www.whitehouse.gov/wp-content/uploads/2023/03/ERP-2023.pdf`).

Appendix A.6 Patenting

To determine the share of all US patents awarded between 2013 and 2022 to assignees based in the emerging markets outside of China that went to venture-backed entities, we proceeded as follows. We identified the name and location of all venture-backed firms identified by PitchBook based in emerging markets (countries that had not joined the OECD as of 1980), excluding the People's Republic of China, Hong Kong, and Macau. We also used several alternative names provided by PitchBook in addition to the firm's primary name: "company legal name," "company former name," and "company also known as."

We used all US granted utility patents from the September 30, 2023 release of PatentsView, a database supported by the Office of the Chief Economist at the US Patent and Trademark Office (`https://patentsview.org/download/data-download-tables`), which were not solely assigned to individuals and whose assignees satisfied the same geographical criteria as in the previous paragraph. We exclude awards to entities in Cayman Islands (which includes a variety of entities such as GlobalFoundries, a US-headquartered entity that nonetheless issues patents to its Cayman subsidiary, apparently in response to tax concerns of its Emirati major investor). We also exclude Korean patents, which are dominated by its *chaebol*, reflecting the fact that the nation's industrial structure mirrors Japan, rather than those seen in other developing nations. Each remaining patent x institutional assignee pair is an observation. There were 202 thousand such pairs satisfying these criteria.

We then determined if the patent assignees matched the list of venture-backed firms. We first cleaned the company names. We used the "cleanco" package in Python to transform the firm names into lower-case letters, get rid of any legal suffixes, and only keep letters, numbers, and spaces. The cleaning was done on both patent assignees and the PitchBook firm names (including the alternative names). We did the matching using the cleansed company name and the country code, but not cities. Not only did firms sometimes move locations, but many companies assigned patents to subsidiaries in multiple cities. (This may lead to us not capturing patents assigned to foreign subsidiaries, but this would have been much more of a problem were we analyzing established corporations rather than venture-backed firms.) We conducted four rounds of merging for each of the sets of PitchBook names, appending all matches and dropping duplicates.

As discussed in text, PitchBook's coverage of venture-backed transactions prior to 2001 is limited. We thus examined the securities filings and media accounts of all assignees which were (a) coded as non-venture capital backed, (b) with a patent award prior to 2002, and (c) with more than 400 patents cumulatively awarded. We sought to identify the subset of companies that unquestionably received venture financing, eliminating firms funded by the government only, those "bootstrapped" with only the founders' money and operating cash flows, and those only financed by high net worth individuals investing their own money. The unique institutional features of Israeli and especially Taiwanese entrepreneurial finance during that period (see the discussion, for instance, in `https://blog.hardwareclub.co/tsmc-at-0-pre-money-f5f32a67d172`) and the limited English language disclosures by and media accounts from this period make it challenging to characterize these firms as venture-backed or not. Thus, we also consulted local practitioners and academic experts as part of this process. These steps led to the identification of several additional Israeli and Taiwanese firms as venture-backed: Acer Corporation, Asustek Computer, Inventec Corporation, Mellanox Technologies, Macronix International, Marvell International, MediaTek Inc., Taiwan Semiconductor Manufacturing Corporation, Vanguard International Semiconductor Corporation, Via Technologies, and Winbond Electronics Corporation.

To weight the patent awards, we followed the "time-and-technology" adjustment delineated by Lerner and Seru (2022), computing the weight to each patent as the average of the number of citations received by the given patent as of September 30, 2023, divided by the mean number of such citations received as of that date by all US patents with a primary assignment to the same four-digit CPC subclass and awarded in the same year.

Appendix B Validation of PitchBook Data

We verify that the PitchBook data we used was very consistent with the PitchBook tabulations of venture capital investments from the US National Science Board's Science & Engineering Indicators 2020 (Table S8-62, https://ncses.nsf.gov/pubs/nsb20204/innovation-indicators-united-states-and-other-major-economies#venture-capital). The tabulation compiles financing by the location of the portfolio company, company (unlike 2022 National Science Board publication, which presents a PitchBook compilation by the location of the fund).

It is similarly consistent with 2019-21 data from a variety of sources[2]:

- US and World 2019-21: National Venture Capital Association, NVCA Yearbook 2023, https://nvca.org/nvca-yearbook/, source: PitchBook.
- Western Europe 2019-2021: Invest Europe, Investing in Europe: Private Equity Activity 2022, https://www.investeurope.eu/research/activity-data/?keyword=Investing%20in%20Europe:%20Private%20Equity%20activity%202022#search-filter-container. We adjusted this total downward by 2% to control for the inclusion of Eastern European deals. This tabulation is based on their own survey. This tabulation did not include Turkish deals, which are likely to be quite modest.
- Canada 2019-21: Canadian Venture Capital and Private Equity Association, Year End 2022: Canadian Venture Capital Market Overview, https://www.cvca.ca/research-insight/market-reports/year-end-2022-vc-pe-canadian-market-overview. This tabulation is based on their own survey.
- Japan 2019-21, Initial Enterprise, "Japan Startup Funding 2022," https://initial.inc/articles/japan-startup-funding-2022-en. This tabulation is based on their own survey.
- Australia 2019-21, Cut Through Venture and Folklore Ventures, The State of Australian Startup Funding, 2022, https://australianstartupfunding.com. This tabulation is based on their own survey.

We also compare our measure of reported Chinese VC activity with that reported in two commercial Chinese databases, Zero2IPO and the China Venture Institute. We were motivated to undertake the comparison for two reasons.

- First, China likely the setting where data access issues and definitional issues are most severe: e.g., due to the role of public sector and SOE funding (Chen, 2022).
- In addition, Chinese data services use different methodologies, with much greater reliance on government sources.

We find the PitchBook data, as depicted in Figure A.4 lies generally between the other two estimates. The results are also consistent with earlier findings of downward bias in Zero2IPO data (Fei, 2018; Li, 2022).

[2] All other currencies converted into US dollars using average annual exchange rates reported in https://www.irs.gov/individuals/international-taxpayers/yearly-average-currency-exchange-rates. We convert all current dollar figures to 2011 US dollars using the GDP deflator series in the Economic Report of the President (https://www.whitehouse.gov/wp-content/uploads/2023/03/ERP-2023.pdf).

Appendix C Appropriateness Construction

In this section, we describe in greater detail the process of assigning indicators from the World Development Indicators (WDI) database to the macro-sectors in the PitchBook data. This is an important part of the construction of the appropriateness measure used in our main empirical analysis.

Indicator assignment To construct a country-sector level measure of relative appropriateness, we rely on the World Bank's WDI database. The complete database includes 1477 unique indicators, covering a wide range of topics including agriculture, debt, environment, financial markets, government finance, infrastructure, national accounts, social indicators, and trade, among others.

We undertake three approaches for assigning these indicators (by hand) to the fifteen macro-sectors in PitchBook. In the first iteration (full-freedom assignment), which serves as our baseline method, the coding team members went through all indicators and assigned those they deemed most relevant to one or multiple macro-sectors. The coders were also fully free to not assign an indicator to any of the macro-sectors if they felt it was not relevant to the productivity or business model of firms in the sector. In this version, a total of 106 indicators are assigned to at least one of the macro-sectors.

In the second, intermediate approach (restricted-freedom assignment), the coding team members again went through all the indicators, but were required to assign indicators that fell under the same topic heading as any relevant indicator. More specifically, we leverage WDI's three-tiered hierarchical organization of indicators, the most general of which is the indicator "topic" followed by the "general subject."[3] Whenever any indicator within a "topic" was deemed relevant for a particular macro-sector, we required that one indicator from each general subject within that topic heading be assigned to the macro-sector. For example, "Enterprise Health" and "Retail HealthTech" are directly related to the "Social: health" topic, so we assigned an indicator from each subject within "Social: health" to both macro-sectors. This assignment method prevents coders from picking-and-choosing which indicators to include or exclude within each topic. In this version, a total of 142 indicators are assigned to at least one of the macro-sectors.

The final, broadest indicator assignment scheme requires that *all* indicators must be assigned. This leaves coders with no freedom to exclude any indicators in the assignment process. The coding team members went through all indicators and assigned each one to at least one macro-sector. When the indicator was too general, the coder was free to assign it to all macro-sectors. In this version, all 1477 indicators were assigned.

In Table A.13, we show the baseline results are robust to the two broader indicator assignment strategies.

[3] In the WDI database, each indicator is assigned with a unique code, which consists of at least three levels: Topic, General Subject, and Specific Subject. For example, "Arable land (% of land area)" is assigned the code "AG.LND.ARBL.ZS," where "AG" stands for the "Agriculture" *Topic*, "LND" stands for the "Land (area and use)" *General Subject*, "ARBL" stands for the "Arable" *Specific Subject*, and "ZS" stands for the extension denoting "share."

Handling missing values As with most cross-country databases, WDI indicators often contain missing values for certain countries or certain periods. We use a series of strategies to account for the fact that in some cases there is a large number of missing values.

Our first key approach is to use the average for a decade before the treatment (2003-2013) and to skip missing values. This means that for one indicator, as long as one of the eleven years is not missing, this country $\times$ indicator observation is not missing. When all the years are missing for a given country $\times$ indicator, we approximate this value by using *all other countries'* average value for this indicator.

Since this "taking the mean" measure to tackle missing values will inevitably reduce cross-country variation when missing values are prevalent, we apply thresholds to drop certain countries and indicators with poor data availability. Specifically, in our baseline analysis in the paper, for the set of indicators that are assigned to at least one macro-sector, we first drop countries that have at least 25% of the indicators missing. This procedure mainly rules out overseas territories, small island countries, and other countries that have low data availability. Then, we remove indicators that are missing in at least 20% of the remaining countries. As a result, there are 74, 105, and 827 indicators being used in the final appropriateness construction for the baseline, intermediate, and broadest measures, respectively.

To alleviate concerns that these specific missing value-handling criteria might drive our results, in Table A.13, we report our main analysis using different criteria to handle missing data: dropping countries with at least 20% or 30% missing values, and dropping indicators with at least 15% or 25% missing values. Reassuringly, all these results are similar to our main specification. As expected, when the thresholds for dropping observations are lower (for example, dropping countries with 20% missing values or dropping indicators with 15% missing values), the estimates are larger than our baseline results.

Appendix D Magnitudes Calculation

To evaluate the magnitude of the impact of China's rise on venture activity, we conduct the following simulation exercises.

First, we use our baseline specification (Equation 2) to predict the total number of deals in emerging markets, both with and without the effect of China. This allows us to estimate the size of the increase. We estimate the baseline specification and obtain the coefficients for the interaction term $(ChinaLed_s * Post_t * ChinaAppropriateness_{cs})$, a constant term, and fixed effects. We then predict the total number of yearly deals during the post period for each country-sector pair, with or without the interaction term.

The total number of yearly predicted deals for all EM countries with the interaction term is 9130. Using the baseline China-led measure, the China-led effect (the coefficient for the interaction term times the value of the interaction term) for all EM countries is 2683. The percentage increase induced by China's effect is 2683/(9130-2683) = 42%. Using the strict China-led measure, the China-led effect for all EM countries is 1866. The percentage increase induced by China's effect is 1866/(9130-1866) = 26%.

As noted in the main text, this exercise relies on three assumptions. The first assumption is that there was zero effect of China on emerging market entrepreneurship in the sectors that we do not label as "China-led." This likely leads us to under-estimate the true effect, since our own results in Section 6 show that serial entrepreneurs branched out to non-China-led sectors after founding their first company. The second assumption is that there is no effect in country-sector pairs where appropriateness takes value zero. We adjust our appropriateness measure so that this is the case for the minimum value of the appropriateness measure within each macro-sector. We can adjust this assumption and, predictably, increasing the level of the appropriateness measure increases the magnitude and decreasing it decreases the magnitude. However, we view our baseline as a conservative and reasonable approach. The third necessary assumption is that fixed effect estimates are held constant in the counterfactual without the rise of China.

Second, we simulate the hypothetical case of another country X's rise in place of China to evaluate the relative importance of China's rise. We show two versions of the calculation: (i) with a fixed number of country-led sectors and (ii) with a GDP-adjusted number of country-led sectors, where we scale the number of sectors "led" by each country by its GDP as a share of China's GDP. We focus on the "strictly-led" definition of sector-level leadership throughout this exercise, as it has a more intuitive interpretation. In the first version, we fix the number of sectors that another country X can lead to be the same as China (69 strictly-led sectors). Then, we randomly simulate 500 sets of 69 sectors for a country to lead. We replace the $ChinaLed_S$ with one of the 500 sets of sectors and replace the $ChinaAppropriateness_{cs}$ measure with $XAppropriateness_{cs}$, which is our measure of appropriateness with respect to the country X. We assume the same coefficients we obtained from the baseline specification and predict in this hypothetical country X's case what the number of deals will be. We then take the mean of the results from the 500 sets of simulated sectors and use that as our measure of the number of deals resulting from a hypothetical rise of country X. We do this simulation process for all countries. In the GDP-adjusted version, we restrict the number of sectors that country X can lead. In particular, we calculate the number of sectors led in each country as the product of 69 and the ratio of X's GDP to China's GDP in 2019.

We find that without scaling by GDP, the country that generates the highest number of emerging market deals is Pakistan, whose hypothetical rise in place of China would have increased emerging market venture activity by 33% (as opposed to the 26% increase estimated from China), followed by Indonesia (33%) and Nigeria (31%). When scaled by GDP, no other country comes close to China, where China is followed by Japan with a predicted increase of 9%, followed by Germany and India. In Table A.8, we list countries with the highest percentage increase in this simulation exercise.

Appendix E Policy Constraints

Identifying Policy Constraints To comprehensively document policy constraints in China, we asked a team of research assistants who did not know the set of China-led sectors in our main analysis to go through all 263 sectors and search for relevant news articles. Specifically, for each sector, the research assistants searched the sector name (and its variants) combined with "policy" and "constraints" in Chinese. In addition, the research assistants searched the sector name (and its variants) site-by-site in the top 20 most influential Chinese finance and economics news outlets, as ranked by Hurun in 2020, looking for any relevant news. If a news report specifically mentioned that the sector was directly impacted by some policy that was put in place prior to China's take-off year (i.e., 2013), we denoted this sector as "policy-constrained." We identified 15 policy constraints affecting 33 sectors.

Validity Checks To determine whether similar policies can be found in other emerging markets, we again asked research assistants to go through the list of policy constraints we identified for China, and search for the combination of each EM country in our data and keywords related to the policy. The research assistants were required to search for all possible combinations of the constraining policy's keywords and sector's keywords to see if such a policy was present in a given EM. This searching process was repeated for all sector-country (EM) pairs to ensure we were able to identify all information for each country. We documented all similar constraints in other countries and their source at country-sector level.

On average, the results show that there were relatively few similar policy constraints in other emerging markets. On average, an EM has 1.16 similar policy constraints to China's 15 policy constraints, with a maximum of 5. In Table A.20, we document two additional checks. Column 1 shows that whether an EM has a similar policy constraint is not correlated with its appropriateness score with respect to China: the size is very small compared to the mean of the dependent variable. Column 2 demonstrates the IV estimate baseline, and column 3 further restrict the IV's power by only denoting those constraining policies that are unique to China as policy-constrained sectors. Results are again similar and consistent with our IV baseline.

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Fei, Celine Y., "Linking different data sources of venture capital and private equity in China," *SSRN Working Paper no. 3524066*, 2018.

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Li, Jinlin, "Government as an equity investor: Evidence from Chinese government venture capital through cycles," *Unpublished Working Paper, Harvard University,* 2022, `https://ssrn.com/abstract=4221937`.

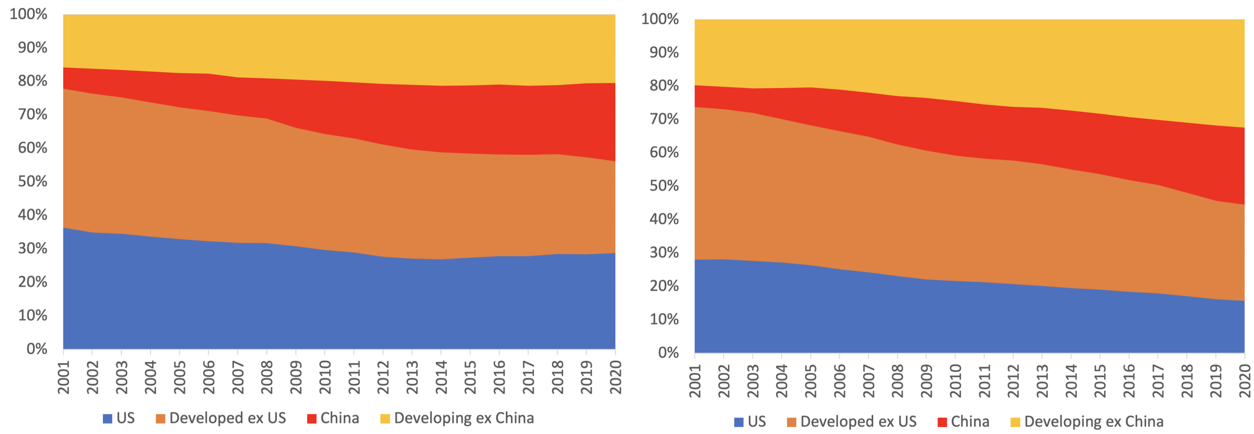
Megginson, William, "Privatization and finance," *Annual Review of Financial Economics*, 2010, *2* (1), 145-174.

Appendix F Additional Figures and Tables

Figure A.1: Global Innovation Trends

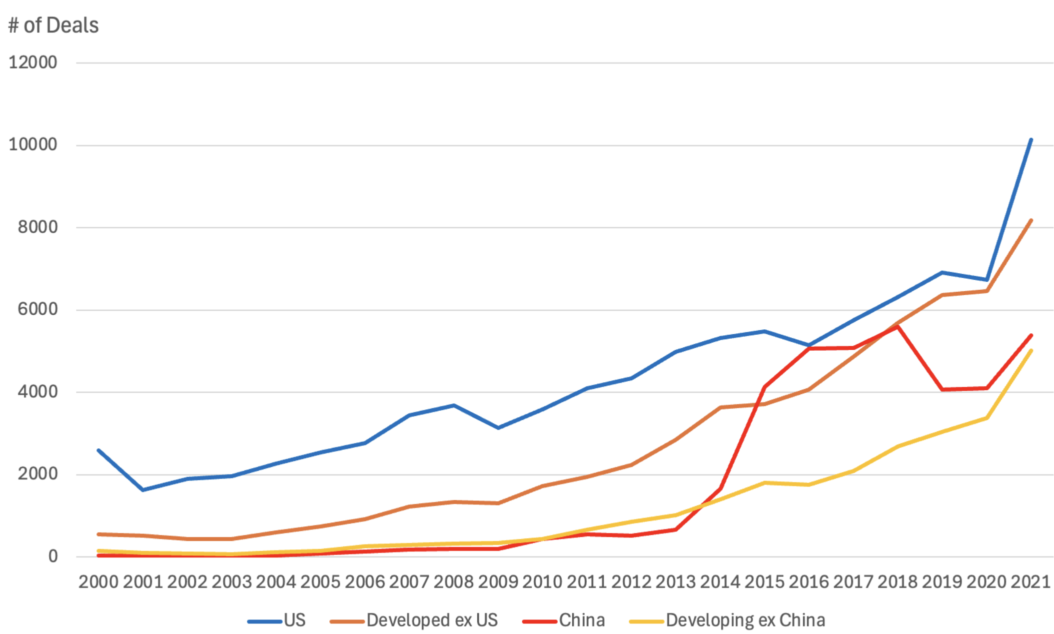
(a) Share of Global R&D Investment

(b) Share of Global Scientific Publications



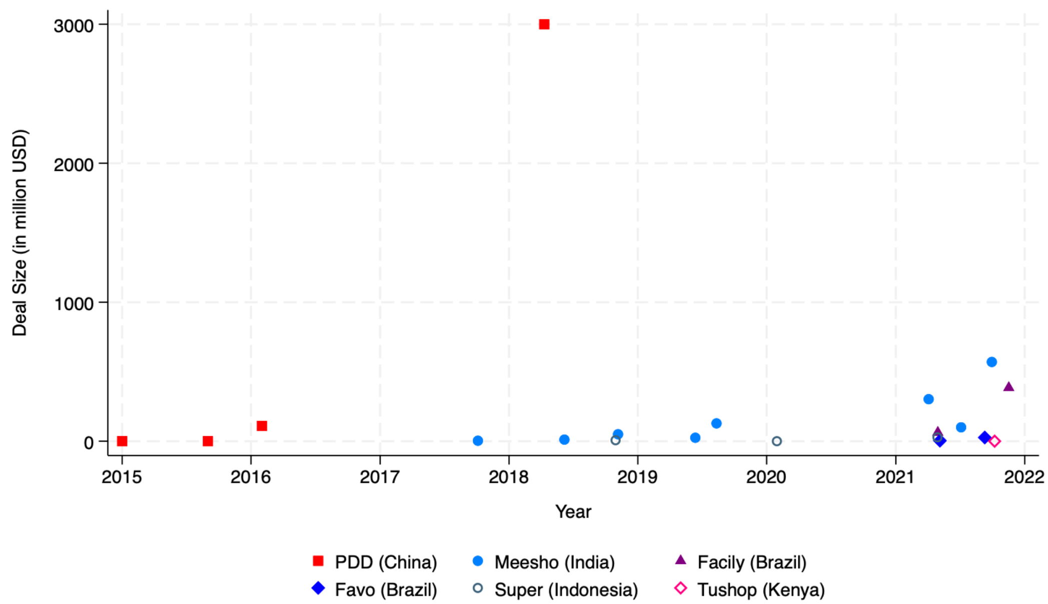
Note: Figure A.1a shows the changing mixture of global R&D investment. Figure A.1b displays the changing mixture of scientific publications. The data sources for this figure are discussed in Appendix A.

Figure A.2: Venture Investment Overview: Deal Numbers



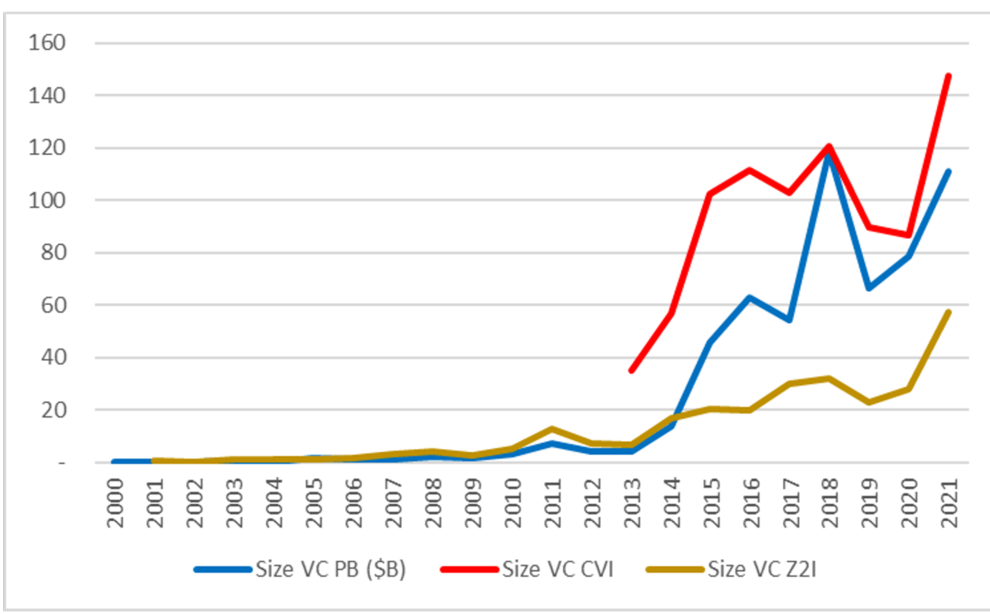
Note: This figure shows the global VC landscape in terms of deal numbers. The data source is PitchBook.

Figure A.3: Social Commerce Case Study: Investment Over Time



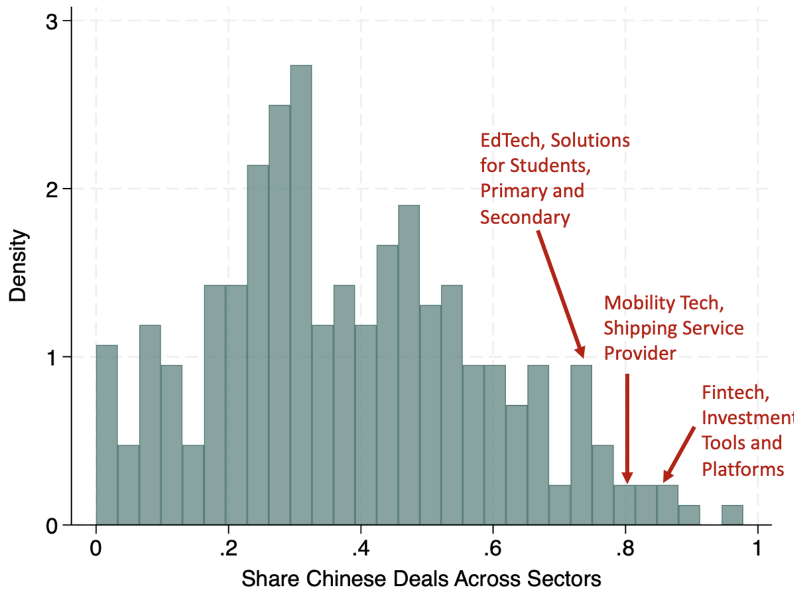
Note: This figure shows all deals for major companies in social commerce. If the deal size is unknown, the dot is plotted as zero deal size. The companies are listed at the bottom of the figure.

Figure A.4: Cross Validation of Chinese VC Data



Note: This figure shows VC transactions in China for three sources: PitchBook, Zero2IPO, and China Venture Institute. Further discussion of the data validation process is in Appendix B.

Figure A.5: China's Share of Venture Deals Across Sectors

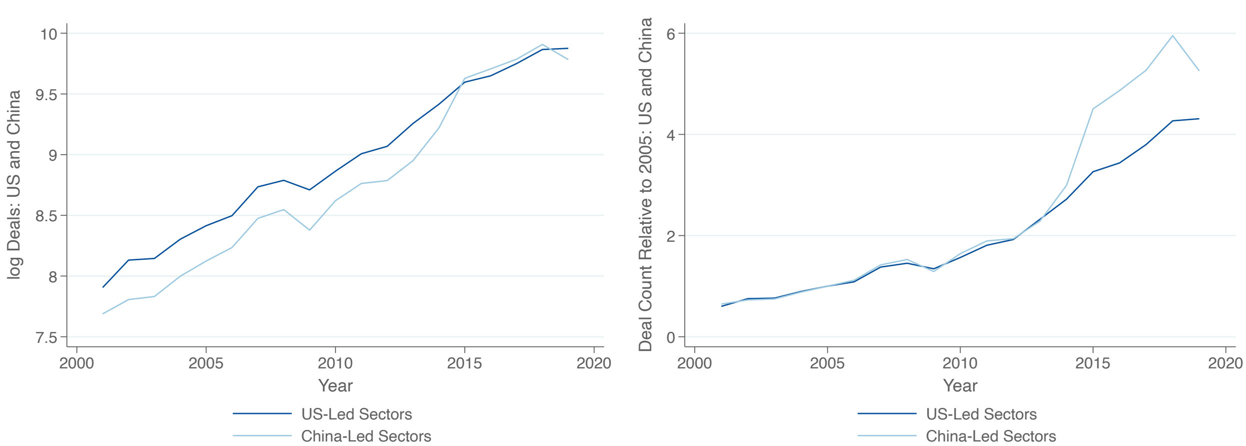


Note: This figure plots a histogram of the ratio of the number of venture deals for Chinese companies to the total number of venture deals for Chinese and US companies in each sector from 2015 to 2019. Values for three example sectors are marked in red.

Figure A.6: Re-direction of Entrepreneurship Toward China-Led Sectors

(a) log Deal Count

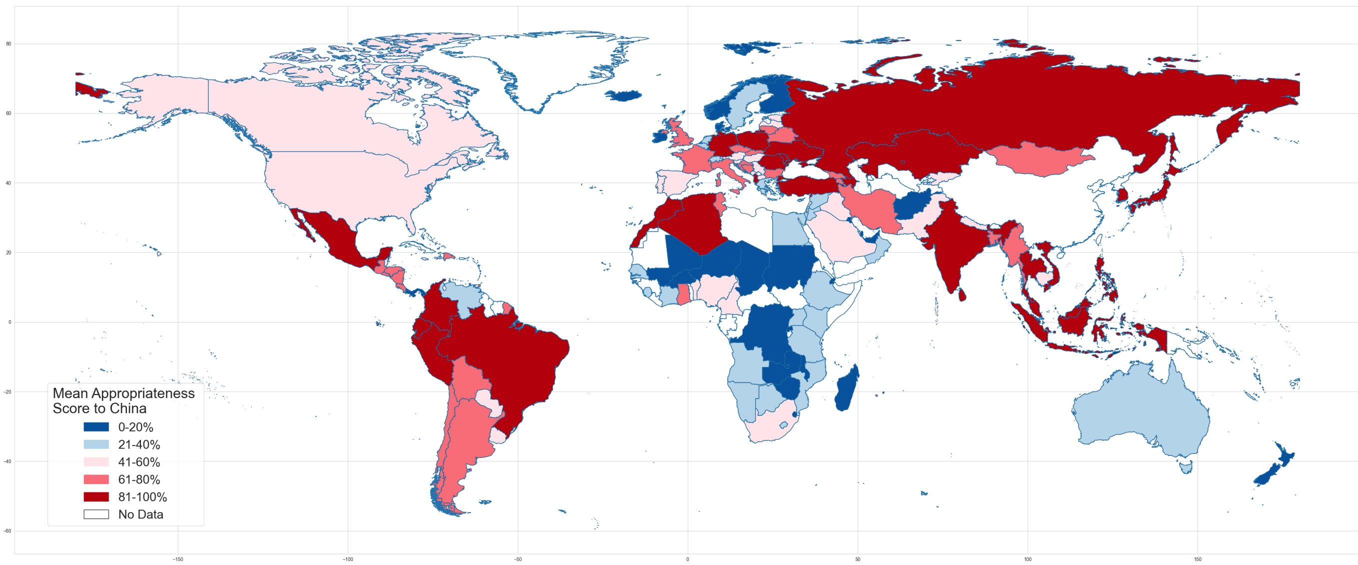
(b) Deal Count Relative to 2005



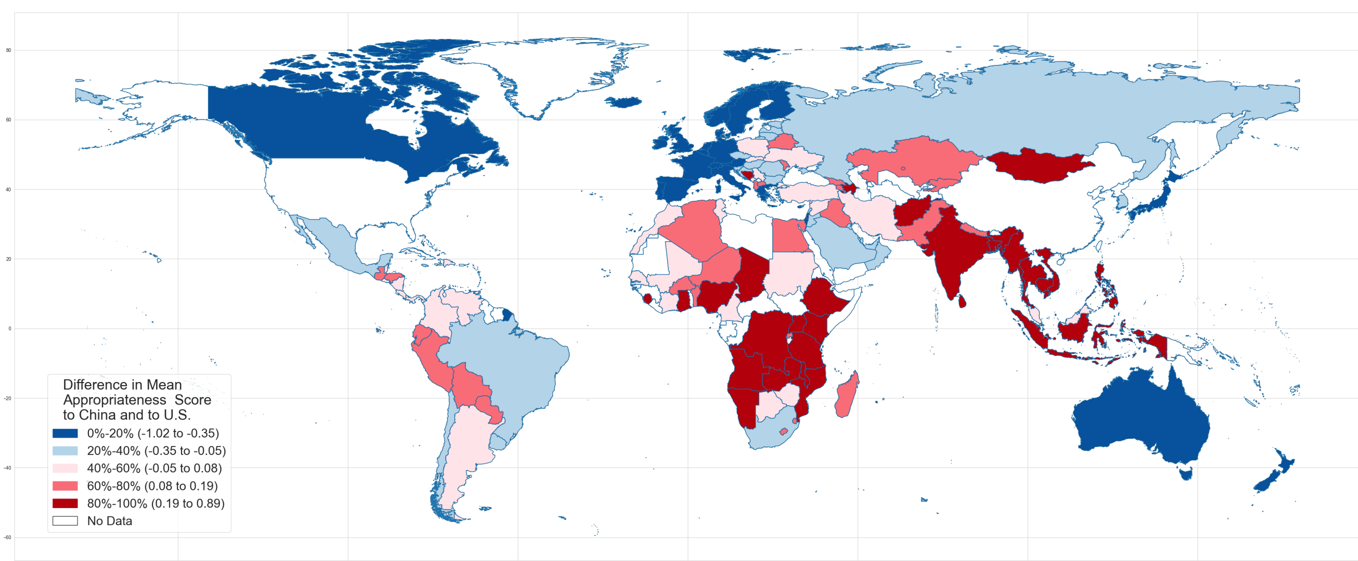
Note: Figure A.6a displays the log of the total number of deals in China-led and US-led sectors in both China and the US, over time. Figure A.6b the total number of deals in China-led and US-led sectors in both China and the US, relative to the total number of deals in 2005, over time.

Figure A.7: Country-Level Variation in Appropriateness

(a) Average China Appropriateness

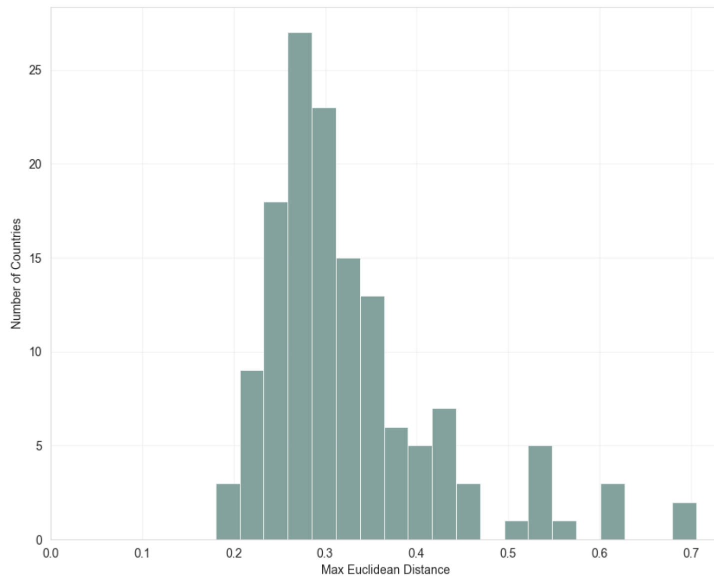


(b) Difference Between Average China Appropriateness and Average US Appropriateness



Note: Figure A.7a displays a world map in which each country is color-coded based on its average China appropriateness, where the average is taken across all fifteen macro-sectors weighted by their share of global pre-period investment. Dark red countries are in the highest quintiles of the China-appropriateness distribution and dark blue the lowest. Figure A.7b displays a world map in which each country is color-coded based on the difference between average China appropriateness and average US appropriateness. Dark blue countries are those that are (on average) most similar to the US (compared to China) and dark red countries are those that are most similar to China (compared to the US).

Figure A.8: Maximum Appropriateness Score Distance between Sectors within Countries

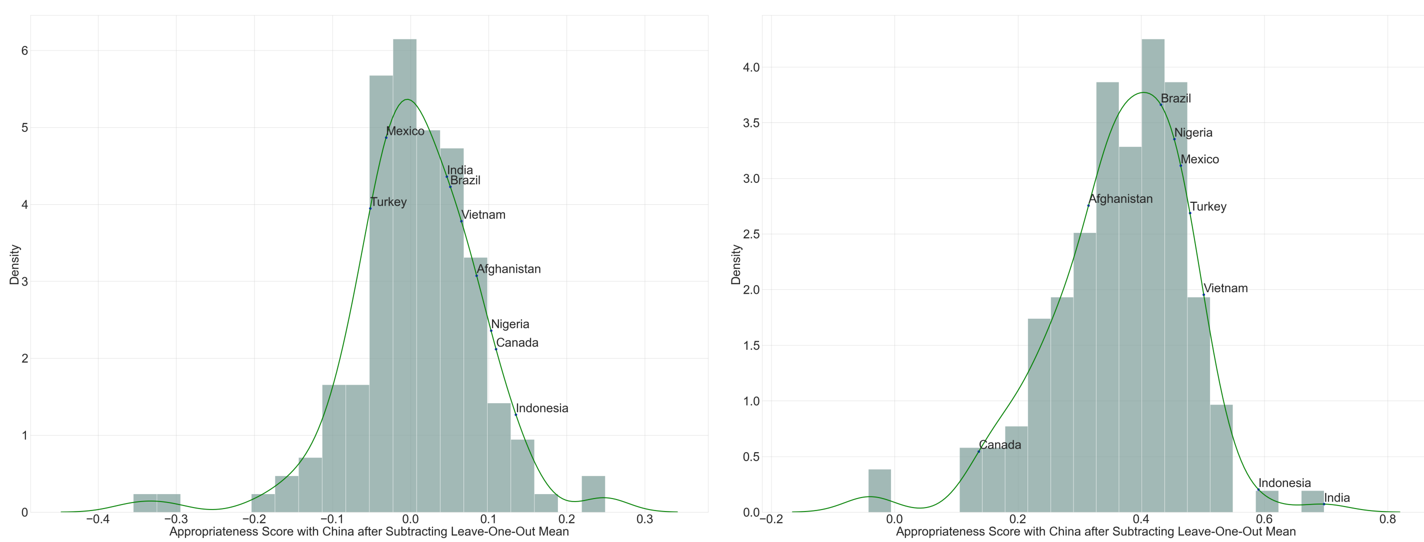


Note: This figure displays a histogram of the maximum distance between the China-appropriateness measure across pairs of macro-sectors for all countries.

Figure A.9: Within-Country, Sector-Level Variation in Business Appropriateness

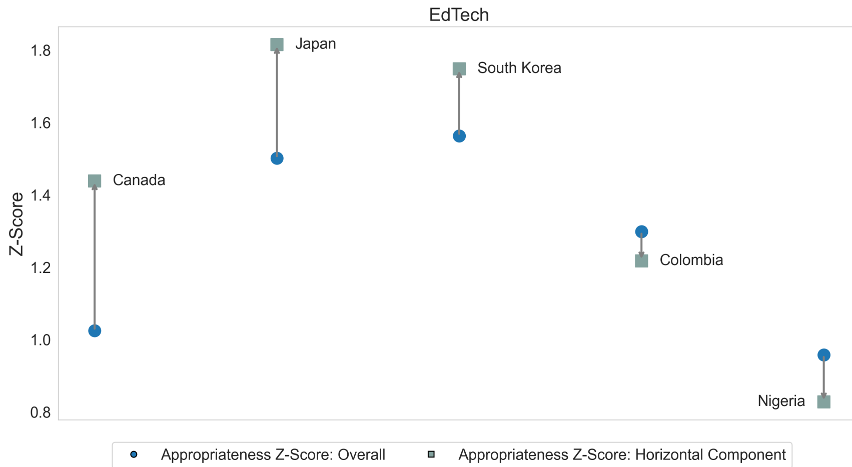
(a) AgTech

(b) FinTech



Note: Figure A.9a displays a histogram of all countries' China-appropriateness in the AgTech macro-sector, after subtracting average China appropriateness across all other macro-sectors. Figure A.9b displays the same for FinTech.

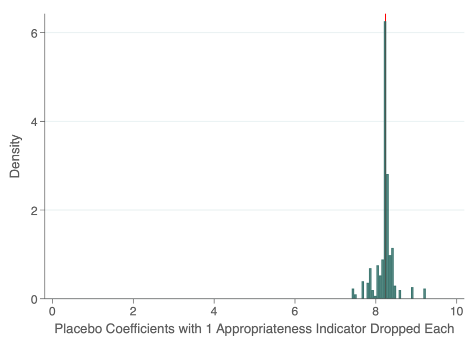
Figure A.10: Horizontal vs. Vertical Appropriateness: Examples



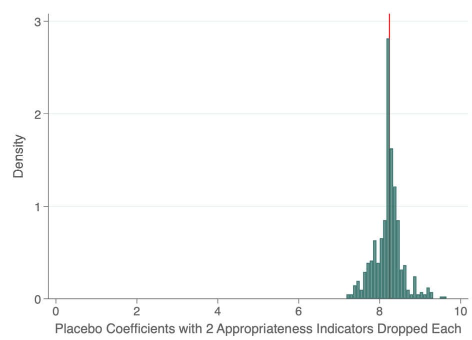
Note: This figure displays the change from baseline appropriateness to horizontal appropriateness for selected countries in EdTech. Horizontal component of the appropriateness is constructed by regressing the appropriateness overall measure on GDP per capita and obtaining the residual component. Both the overall appropriateness and the horizontal component are taken Z-score for better comparison.

Figure A.11: Robustness to Excluding Indicators from Appropriateness Measure

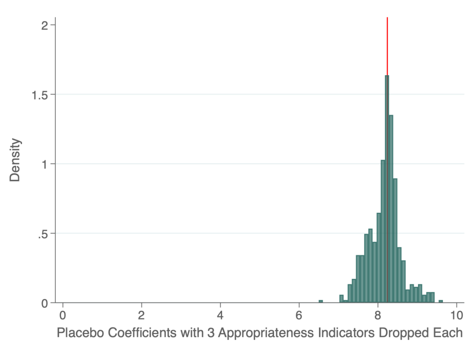
(a) Dropping 1 Indicator



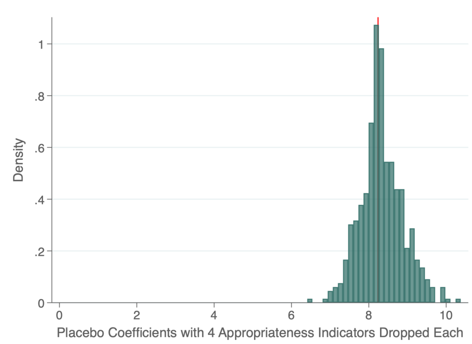
(b) Dropping 2 Indicators



(c) Dropping 3 Indicators

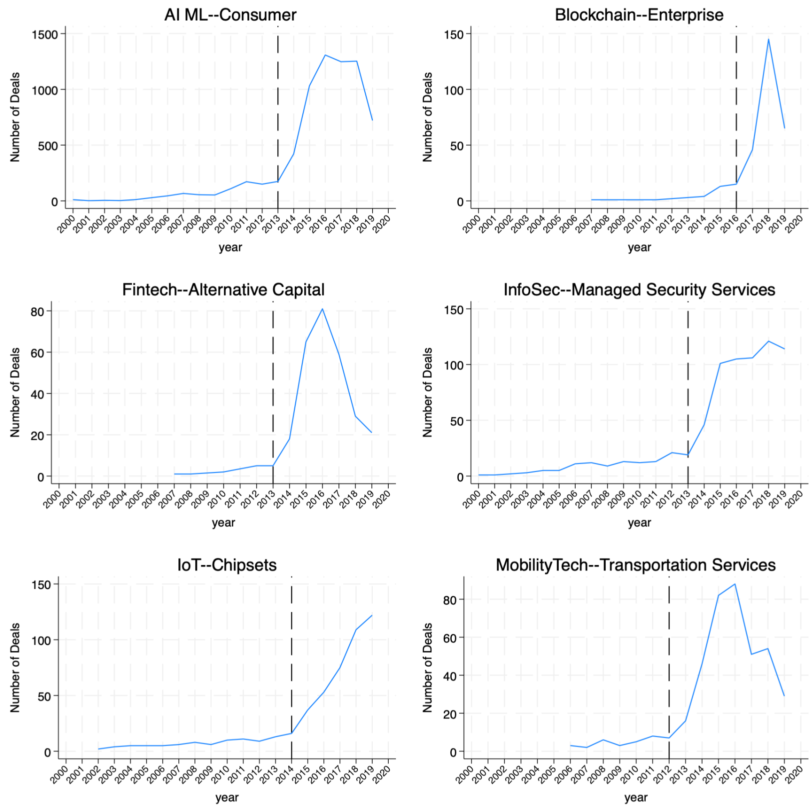


(d) Dropping 4 Indicators



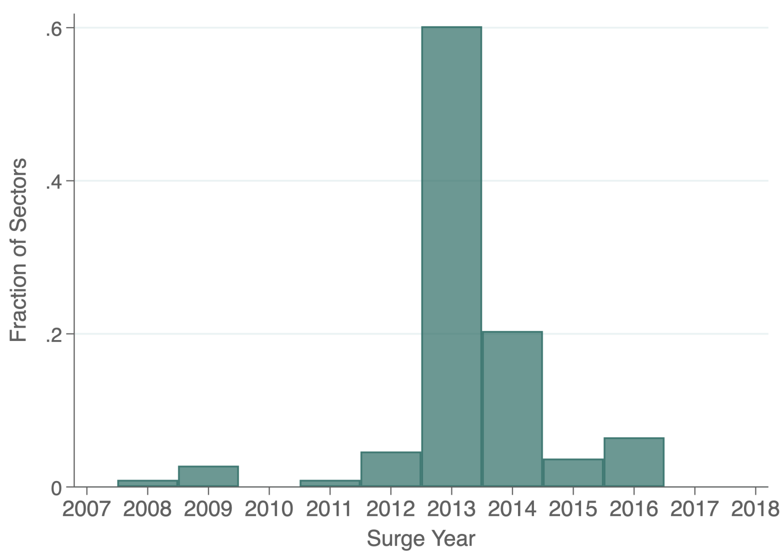
Note: This figure reports histograms of coefficient estimates from a series of estimates of Equation 2, in which $ChinaAppropriateness_{cs}$ is replaced with an alternate appropriateness measure where one, two, three, or four of the indicators used in the appropriateness calculation are dropped, repeated with 500 random simulations each. Our main estimate of β from Equation 2 is displayed with a red vertical line.

Figure A.12: Examples of Sector-Level Surge Years



Note: This figure shows six examples of sector-specific surge years. "Surge year" is defined as the start year of a two-year window in which the number of VC-backed deals received by Chinese companies has the highest growth rate. We restrict attention to two-year windows with at least 10 deals (or 40 for sectors that have more than 300 deals) in order to avoid estimating high growth rates from a very small number of deals. The maximum growth rate has to be larger than 100% to be identified as a "surge year."

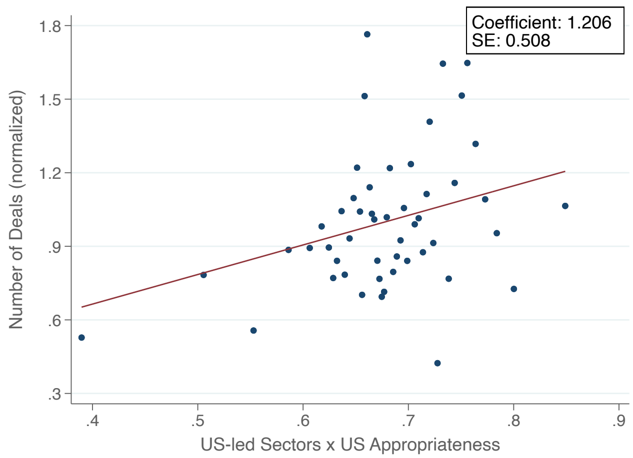
Figure A.13: Distribution of Surge Years Across Sectors



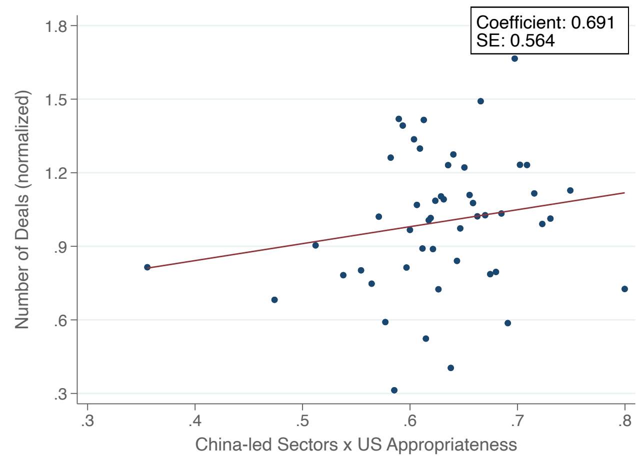
Note: This figure shows the distribution of sector-specific surge years for China-led sectors. "Surge year" is defined as the start year of a two-year window in which the number of VC-backed deals received by Chinese companies has the highest growth rate. We restrict attention to two-year windows with at least 10 deals (or 40 for sectors that have more than 300 deals) at the end in order to avoid estimating high growth rates from a very small number of deals. The maximum growth rate has to be larger than 100% to be identified as a "surge year."

Figure A.14: China vs. US Appropriateness, Before China's Rise

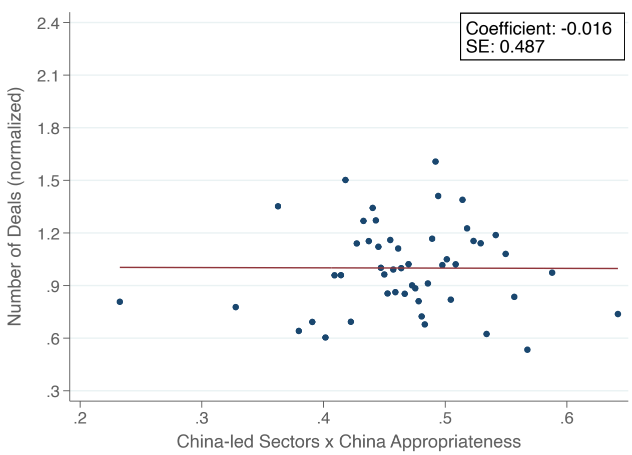
(a) US Appropriateness × US-Led



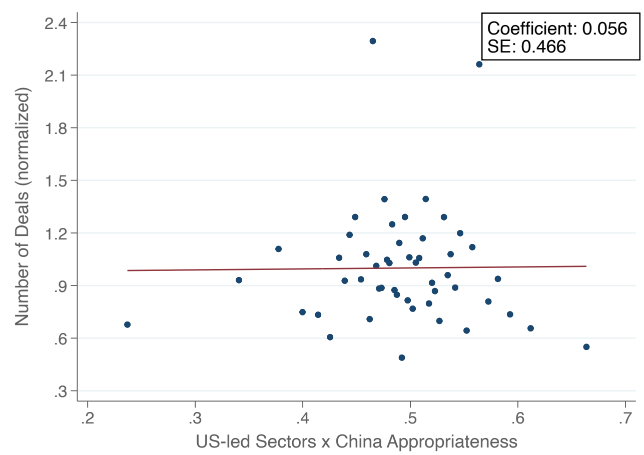
(b) US Appropriateness × China-Led



(c) China Appropriateness × China-Led

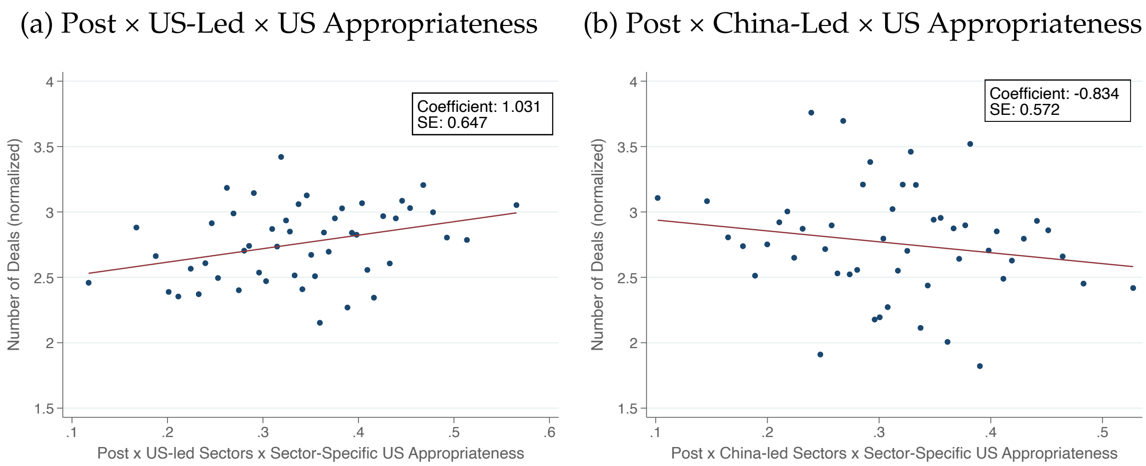


(d) China Appropriateness × US-Led



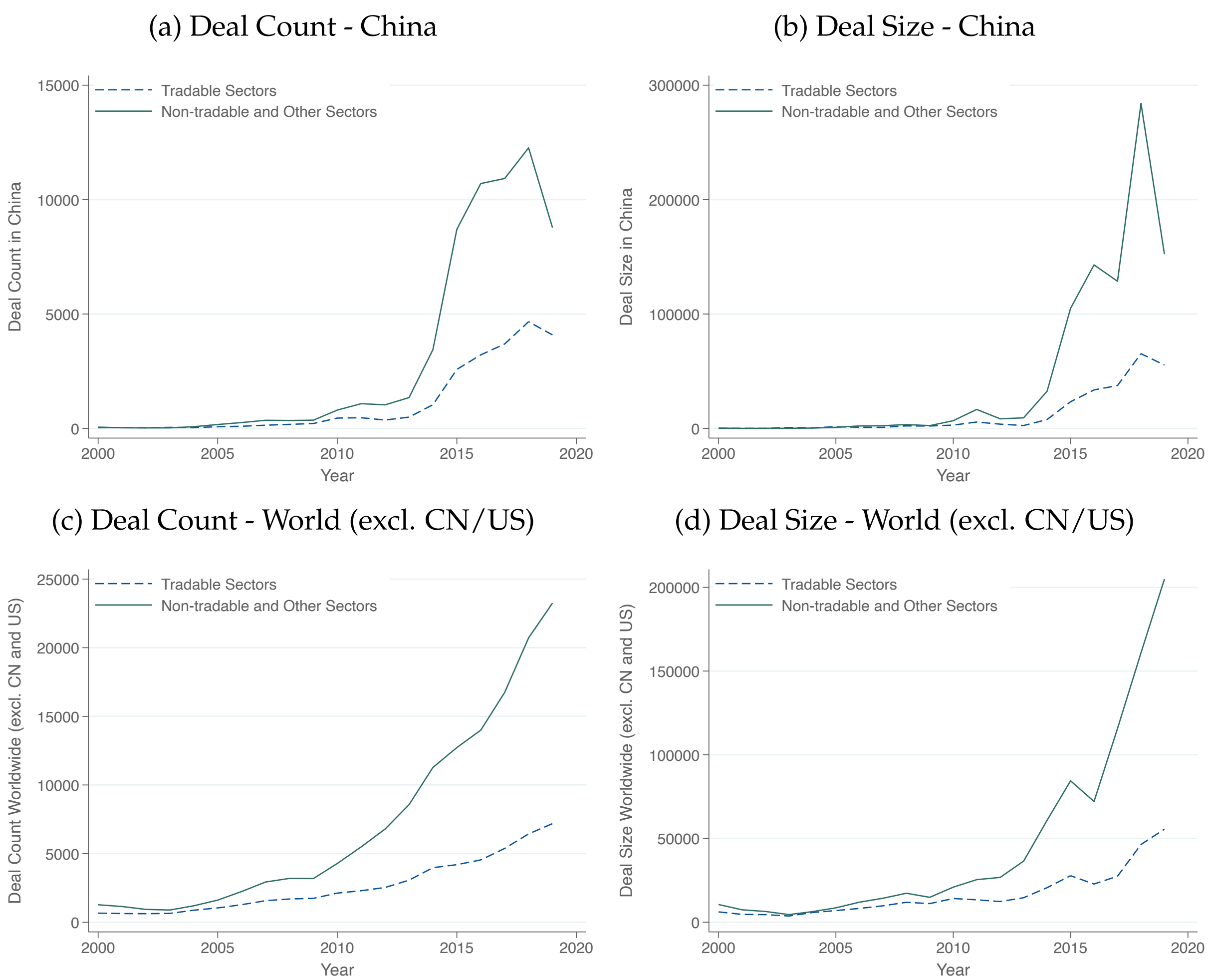
Note: Figure A.14a displays the relationship between pre-2013 deals and $USLed_sUSAppropriateness_{cs}$ and Figure A.14b displays the relationship between pre-2013 deals and $ChinaLed_sUSAppropriateness_{cs}$, both estimated from the same regression. Figure A.14c shows the relationship between pre-2013 deals and $ChinaLed_sChinaAppropriateness_{cs}$ and Figure A.14d shows the relationship between pre-2013 deals and $USLed_sChinaAppropriateness_{cs}$, both estimated from the same regression. The outcome variable is the number of deals, summed from 2000-2012 and normalized relative to the country mean, as described in the main text. All specifications include country and sector fixed effects. The coefficient and standard error for the displayed coefficient is reported in each sub-figure.

Figure A.15: US Appropriateness After China's Rise



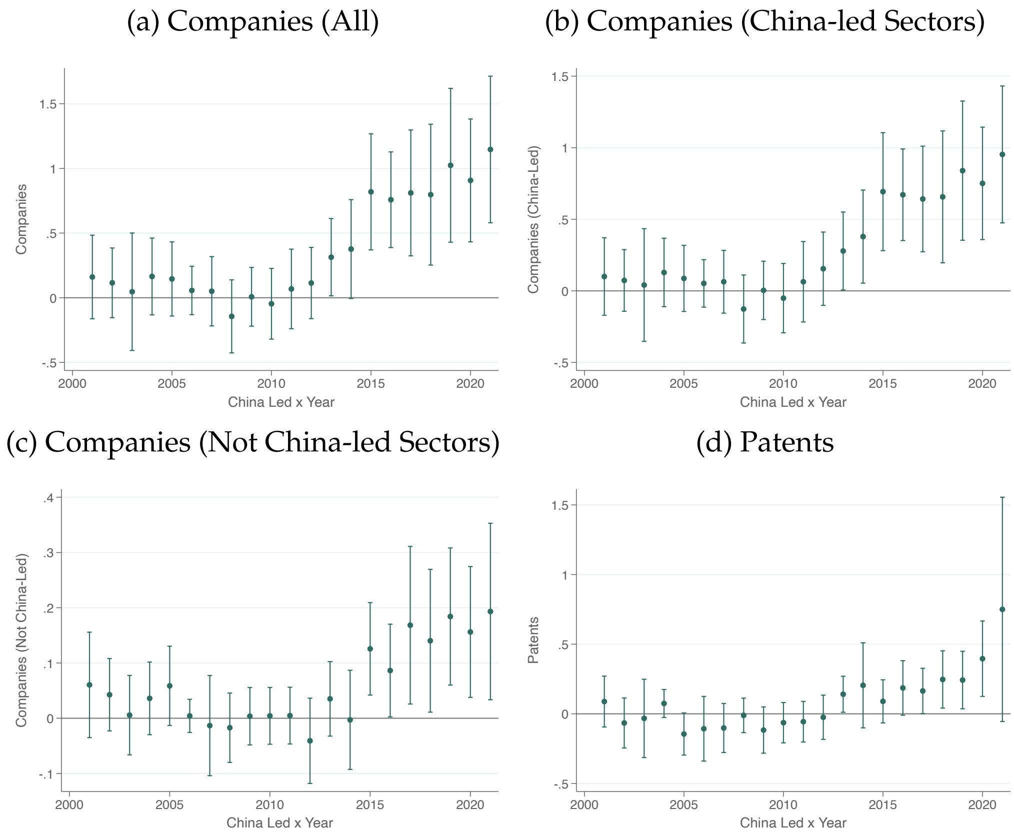
Note: Figure A.15a displays the relationship between normalized deals and $Post_t USLed_s USAppropriateness_{cs}$ and Figure A.15b displays the relationship between normalized deals and $Post_t ChinaLed_s USAppropriateness_{cs}$. Standard errors are clustered at the country level.

Figure A.16: Number of Deals in China by Tradability



Note: This figure demonstrates the trend in deal numbers and deal size for China and our regression sample (world wide excluding China and US).

Figure A.17: China's Rise and City-Level Entrepreneurship: Dynamics



Note: All figures report estimates of year indicators interacted with $ShareChinaLed_i$. The unit of observation is a city-year pair and the outcome variable is listed above each sub-figure. Standard errors are clustered by country and 95% confidence intervals are displayed.

Table A.1: China's VC Status Compared with Other Countries

Country	"Emergence Year"	GDP Per Capita	VC Per Capita	% of World VC	% of World Pubs	% of World R&D	% of US Patents
China	2015	$12,244	$9.10	13.44%	7.71%	20.84%	2.83%
Indonesia	2018	$11,852	$5.29	0.97%	0.87%	0.40%	0.00%
Mexico	2000	$12,613	$1.57	0.28%	0.51%	0.43%	0.05%
Poland	2000	$12,732	$2.60	0.18%	1.33%	0.36%	0.01%
South Korea	1988	$12,040	$0.17	0.04%	0.18%	2.90%	0.12%
Russia	2002	$12,259	$0.03	0.01%	3.41%	2.35%	0.12%
Egypt	2018	$11,957	$0.12	0.01%	0.53%	0.50%	0.02%
South Africa	2014	$12,242	$0.05	0.00%	0.49%	0.46%	0.05%
Brazil	2007	$12,500	$0.01	0.00%	2.03%	2.11%	0.06%
Israel	1969	$12,310	0	0.00%	N/A	N/A	0.09%
Singapore	1979	$12,521	0	0.00%	0.03%	N/A	0.00%
Chile	1993	$12,297	0	0.00%	0.17%	0.34%	0.01%
Turkey	2003	$12,380	0	0.00%	1.20%	0.41%	0.02%
Iran	2004	$12,404	0	0.00%	0.42%	0.43%	0.00%
Thailand	2006	$12,181	0	0.00%	0.30%	0.16%	0.02%
Japan	1968	$12,725	N/A	N/A	N/A	N/A	2.49%

Note: This table reports venture capital share and innovation measures for selected countries when they are at a similar level in terms of GDP per capita as China was in 2015 (all GDP and VC values are in 2011 US dollars), which we term their "Emergence Year." The sourcing of this table is discussed in Appendix A.

Table A.2: Summary Statistics

	Panel A: VC Deals				
	Total	China	United States	Other EM	Other Non-EM
Number of VC Deals	169,505	28,733	77,897	17,674	45,201
Number of Companies with VC Deals	88,267	15,086	34,946	11,494	26,741
Mean size of VC deals (US$ millions)	13.67	28.95	13.97	13.48	7.01
Mean number of VC deals per company	1.92	1.90	2.23	1.54	1.69
Share of companies with > 1 deal	44.55%	49.66%	52.18%	30.57%	37.69%
	Panel B1: Sectors				
	Mean		Median		SD
Number of companies per sector	1021.14		415.50		1942.41
Number of sectors predicted per company	3.08		3.00		1.64
Number of sectors conditional on >1 sectors	3.51		3.00		1.47
	Panel B2: Sectors, Divided by China and US Led				
	China-led Sectors			US-led Sectors	
Number of company-sector pairs	136,908			134,715	
Number of company-sector pairs (other EM)	19,715			15,110	
Number of company-sector pairs (other non-EM)	40,626			40,995	
Average deal size (US$ millions)	10.42			10.39	
Average deal size (other EM, US$ millions)	8.82			6.56	
Average deal size (other non-EM, US$ millions)	5.43			6.15	

Note: This table reports the main summary statistics. Emerging markets (“EM”) are defined as countries that are not members of OECD by 1980, and developed markets (“Non-EM”) are defined as members of OECD by 1980. “Other EM” excludes China and “Other Non-EM” excludes the US. The time-span for all panels is from 2000 to 2019. Panel A reports summary statistics of venture capital (VC) deals extracted from PitchBook. All deal size information is nominal US dollars. Panel B1 reports summary statistics on sectors. Panel B2 reports summary statistics on China-led sectors and US-led sectors.

Table A.3: Example Indicators for Macro-Sectors

Macro-Sector	**Indicators**
AgTech	Arable land (hectares per person); Cereal yield (kg per hectare); Employment in agriculture, male (% of male employment); Forest area (% of land area); Livestock production index
AI ML	Charges for the use of intellectual property (current US$); Fixed broadband subscriptions (per 100 people); High-technology exports (current US$); Scientific and technical journal articles; Secure Internet servers (per 1 million people)
EdTech	Government expenditure on education, total (% of GDP); Literacy rate, adult total (% of people ages 15 and above); Mobile cellular subscriptions (per 100 people); Pupil-teacher ratio, primary; School enrollment, primary (% gross)
Fintech	Automated teller machines (ATMs) (per 100,000 adults); Depth of credit information index; High-technology exports (current US$); Mobile cellular subscriptions (per 100 people); Secure Internet servers (per 1 million people)
Retail HealthTech	Immunization, DPT (% of children ages 12-23 months); Incidence of tuberculosis (per 100,000 people); Life expectancy at birth (years); Mortality rate, infant (per 1,000 live births); Percentage of People at risk of impoverishing for surgical care

Table A.4: Correlation Matrix of Appropriateness Measures

	Baseline	Restricted	All Assigned	GPT Assigned
Baseline	1.000	0.646	0.596	0.508
Restricted	0.646	1.000	0.562	0.194
All Assigned	0.596	0.562	1.000	0.235
GPT Assigned	0.508	0.194	0.235	1.000

Note: This table reports the correlation across the four assignment measures at the sector-country level.

Table A.5: Appropriateness Measure Validation: Patent Transfer and Similarity

	Between Country Pair	
	(1) Log Number of Patent Families	(2) Mean Pre-Period Patent Textual Similarity
Appropriateness between Country Pairs	0.167**	0.021***
	(0.065)	(0.004)
Country 1 - Macro Sector FE	Yes	Yes
Country 2 - Macro Sector FE	Yes	Yes
Country 1 - Country 2 FE	Yes	Yes
Number of Obs	12812	33686
Mean of Indep. Var	2.273	2.297
SD of Indep. Var	0.454	0.409
Mean of Dep. Var	2.655	0.230
SD of Dep. Var	1.920	0.060
Std Beta Coefficient	0.039	0.147

Note: The unit of observation is a country pair-macro sector. In column 1, the outcome variable is the log of jointly filed patents in a given country pair aggregated by macro sector. Patents are a sample of 50,000 families from all patent families in 2010. In column 2, the outcome variable is the average SBERT cosine textual similarity of patent pairs granted in the pre-period between company pairs in the two countries, taking the average by sector and macro-sector. Patents are from a 100,000 random sample from all patents between 2000 and 2019. Standard errors are clustered by macro-sector and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.6: Appropriateness Measure Validation: Citations to China

	(1) EM Country Citations to China	(2) EM Country Citations to US
Appropriateness	1.904**	0.128
	(0.952)	(0.207)
Country Fixed Effects	Yes	Yes
Marcro-Sector Fixed Effects	Yes	Yes
Citation to World Control	Yes	Yes
Number of Obs	94	445
Mean of Dep. Var	1.766	3.272
SD of Dep. Var	1.498	2.204

Note: The unit of observation is a country-macro sector. EM countries are defined as countries not included in the OECD as of 1980. All regressions control for the log citations to all patents. Outcome variables are the log number of citations to patents with Chinese first grantee and US first grantee, respectively. Patents are drawn from a random sample from 100,000 non-China non-US patents from 2000 to 2019 granted in the US. Only citations to patents granted in the US are included for the consistency of quality. Robust standard errors are in parentheses and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.7: Appropriateness and Entrepreneurship: Robustness to Income Controls

	Dependent Variable: Number of Deals (Normalized)				
	(1)	(2)	(3)	(4)	(5)
China-Led Sector × Post × Appropriateness	8.030***	7.408**	7.620**	7.504**	8.025***
	(2.919)	(2.921)	(2.921)	(3.084)	(2.989)
China-Led Sector × Post × Appropriateness × GDP pc above China (Pre)	-0.925				
	(1.421)				
China-Led Sector × Post × Appropriateness × GDP pc (Pre)		-0.518			
		(0.421)			
China-Led Sector × Post × Appropriateness × GDP pc (Post)			-0.457		
			(0.421)		
China-Led Sector × Post × Appropriateness × GDP pc (Below China and above 50%)				1.411	
				(1.931)	
China-Led Sector × Post × Appropriateness × GDP pc (Below China and above 75%)					1.396
					(2.772)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	547040	547040	552300	552300
Mean of Dep. Var	3.588	3.609	3.609	3.588	3.588
SD of Dep. Var	44.979	45.139	45.139	44.979	44.979

Note: The unit of observation is a country-sector-year. In addition to the main triple-interaction, the specifications in this table also include interactions with functions of each country's GDP per capita (or GDP per capita relative to China) on the right hand side of each regression. From left to right, the columns include interactions with (1) an indicator if pre-period GDP per capita was above China's, (2) log of pre-period GDP per capita, (3) log of post-period GDP per capita, (4) an indicator that equals one if a country is above the 50th income percentile among countries with pre-period income below China's, and (5) an indicator that equals one if a country is above the 75th income percentile among countries with pre-period income below China's. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.8: Top Countries for Appropriateness-Based Simulated Deals

Panel A: Simulated Deals			
Simulated Country	Mean Simulated Deals	Mean Simulated Country-led Effect	Percentage Increase Compared with No Effect
Pakistan	9721.96	2473.80	34.13%
Indonesia	9365.35	2327.25	33.07%
Nigeria	9437.21	2251.97	31.34%
India	7519.49	1769.10	30.76%
Brazil	8973.93	2105.13	30.65%
Egypt	9351.10	2125.60	29.42%
Iran	9364.68	2100.65	28.92%
Germany	9343.99	2079.96	28.63%
South Africa	9194.68	2041.56	28.54%
Algeria	9331.49	2069.10	28.49%
China (Actual Estimate)	9130.00	1865.98	25.69%
Panel B: GDP Adjusted Simulated Deals			
Simulated Country	Mean Simulated Deals	Mean Simulated Country-led Effect	Percentage Increase Compared with No Effect
China (Actual Estimate)	9130.00	1865.98	25.69%
Japan	7931.98	667.95	9.20%
Germany	7835.62	571.59	7.87%
India	6108.98	358.59	6.24%
United Kingdom	7654.93	390.91	5.38%
France	7636.05	372.03	5.12%
Brazil	7143.88	275.09	4.00%
Italy	7543.67	279.64	3.85%
Canada	7488.21	224.18	3.09%
South Korea	6009.35	175.31	3.00%
Russia	7419.07	205.18	2.84%

Note: This table reports the top 10 countries in terms of simulated deals in our counterfactuals where we assume each country rises to VC leadership. It also reports the actual estimates from our main specification using China. In Panel A, all countries are assumed to lead the same number of sectors (69), whereas in Panel B the number of sectors that a country can lead is proportional to its GDP as a fraction of China.

Table A.9: Appropriateness and Entrepreneurship: Western-Backed Deals in China

	Number of Deals (Normalized)	
	(1)	(2)
China-Led × Post × Appropriateness	8.414***	
	(2.951)	
Western LP China-Led × Post × Appropriateness		9.507**
		(3.892)
Sector × Country FE	Yes	Yes
Country × Year FE	Yes	Yes
Sector × Year FE	Yes	Yes
Suitability × Year FE	Yes	Yes
Number of Obs	552300	552300
Mean of Dep. Var	3.588	3.588
SD of Dep. Var	44.979	44.979

Notes: The unit of observation is a country-sector-year. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.10: Beyond Venture Capital Investment: Angels, Private Equity, and Corporate Deals

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log($/deal)
Panel A: Angel Deals, Baseline China-led					
China-Led × Post × Appropriateness	6.431	6.412	0.149**	0.117	0.368
	(7.044)	(8.866)	(0.065)	(0.071)	(0.242)
Panel B: Angel Deals, Strict China-led					
China-Led (Strict) × Post × Appropriateness	14.294**	16.318**	0.195***	0.150***	0.138
	(6.170)	(8.066)	(0.049)	(0.056)	(0.287)
Number of Obs	478660	475020	478660	478660	35619
Mean of Dep. Var	7.873	10.245	0.180	0.082	-1.671
SD of Dep. Var	75.056	87.409	0.600	0.417	1.662
Panel C: PE Growth/Expansion Deals, Baseline China-led					
China-Led × Post × Appropriateness	1.678	2.696**	0.018*	0.052**	-0.544**
	(1.017)	(1.358)	(0.009)	(0.024)	(0.219)
Panel D: PE Growth/Expansion Deals, Strict China-led					
China-Led (Strict) × Post × Appropriateness	2.059**	2.803**	0.011	0.010	-0.940***
	(0.869)	(1.087)	(0.012)	(0.029)	(0.203)
Number of Obs	678540	634680	678540	678540	10118
Mean of Dep. Var	1.644	2.489	0.045	0.069	2.195
SD of Dep. Var	30.362	37.126	0.252	0.552	1.875
Panel E: Corporate Deals, Baseline China-led					
China-Led × Post × Appropriateness	2.058	3.087	0.015	0.025	0.177
	(1.396)	(2.716)	(0.013)	(0.033)	(0.982)
Panel F: Corporate Deals, Strict China-led					
China-Led (Strict) × Post × Appropriateness	2.767**	3.327	0.026***	0.076**	2.480***
	(1.386)	(2.298)	(0.008)	(0.035)	(0.577)
Number of Obs	547040	484640	547040	547040	2382
Mean of Dep. Var	1.684	2.706	0.022	0.025	1.644
SD of Dep. Var	36.225	46.356	0.155	0.333	2.483
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes

Note: The unit of observation is a country-sector-year. Panels A and B report our main specification results using angel investments only, Panels C and D using PE growth/expansion deals only, and Panels E and F using corporate investments only. Panels A, C, E present results using our baseline China-led sector measure, where a sector is defined as China-led if it has an above-median ratio of the number of deals received by Chinese companies to that of US companies from 2015 to 2019. Panels B, D, F use a stricter China-led measure, where a sector is defined as China-led only if the number of deals received by Chinese companies are strictly higher than that of US companies during the same period. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. We omit country-sector pairs which have no observation across all years, and countries might have different level of coverage across different types of deals, therefore the differences in the number of observations across panels and across columns. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.11: Appropriateness and Entrepreneurship: Extended Sample Period

	Deal Count			Deal Size	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Weighted	asinh	asinh	log($/deal)
Panel A: Baseline China-led measure, 2000-2021					
China-Led Sector × Post × Appropriateness	9.499**	11.954**	0.113**	0.236**	0.308**
	(3.723)	(4.742)	(0.048)	(0.100)	(0.127)
Panel B: Strict China-led measure, 2000-2021					
China-Led Sector (Strict) × Post × Appropriateness	12.292***	16.421***	0.144***	0.336***	0.557***
	(3.997)	(5.505)	(0.033)	(0.088)	(0.136)
Number of Obs	607530	591360	607530	607530	45410
Mean of Dep. Var	5.103	6.878	0.159	0.223	1.017
SD of Dep. Var	57.020	67.300	0.555	0.905	1.539
Panel C: Baseline China-led measure, 2000-2024					
China-Led Sector × Post × Appropriateness	10.809*	11.261	0.131*	0.249*	0.315***
	(6.027)	(7.054)	(0.068)	(0.135)	(0.116)
Panel D: Strict China-led measure, 2000-2024					
China-Led Sector (Strict) × Post × Appropriateness	15.217***	17.458***	0.171***	0.372***	0.533***
	(5.064)	(6.615)	(0.043)	(0.112)	(0.118)
Number of Obs	745500	656250	745500	745500	61827
Mean of Dep. Var	7.952	11.948	0.180	0.254	1.065
SD of Dep. Var	81.394	101.517	0.599	0.981	1.570
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes

Note: The unit of observation is a country-sector-year and the sample period is extended to 2000-2021 (Panels A-B) and 2000-2024 (Panels C-D). Panel A and C presents results using our baseline China-led sector measure, where a sector is defined as China-led if it has an above-median ratio of the number of deals received by Chinese companies to that of US companies for the period of 2015 to 2019. Panel B and D uses a stricter China-led measure, where a sector is defined as China-led only if the number of deals received by Chinese companies are strictly higher than that of US companies during the same period. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.12: Appropriateness and Entrepreneurship: China-Led Defined Relative to the World

	Deal Count			Deal Size	
	(1)	(2)	(3)	(4)	(5)
	Baseline	Weighted	asinh	asinh	log($/deal)
(World) China-Led Sector × Post × Appropriateness	8.836***	11.698***	0.087**	0.161**	0.142
	(2.583)	(3.552)	(0.035)	(0.063)	(0.125)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479

Note: The unit of observation is a country-sector-year. A sector is (World) China-led if the ratio of the number of deals received by Chinese companies to that of companies in the *rest of the world* for the period of 2015 to 2019 is above median. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.13: Appropriateness and Entrepreneurship: Sensitivity Tests for Appropriateness Measure

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log($/deal)
Panel A: "Partial-Freedom" Indicator Assignment					
China-Led Sector × Post × Appropriateness	8.325***	10.813***	0.086**	0.170**	0.264**
	(2.865)	(3.715)	(0.042)	(0.083)	(0.105)
Number of Obs	547040	532480	547040	547040	35407
Mean of Dep. Var	3.596	4.878	0.137	0.186	0.927
SD of Dep. Var	45.171	53.161	0.508	0.806	1.479
Panel B: "No-Freedom" Indicator Assignment					
China-Led Sector × Post × Appropriateness	10.350**	13.406**	0.140***	0.306**	0.507*
	(5.123)	(6.583)	(0.052)	(0.122)	(0.260)
Number of Obs	541780	527360	541780	541780	35282
Mean of Dep. Var	3.599	4.885	0.138	0.187	0.924
SD of Dep. Var	45.214	53.218	0.509	0.808	1.479
Panel C: Dropping Countries with >20% Missing					
China-Led Sector × Post × Appropriateness	9.402***	11.896***	0.128***	0.249***	0.275*
	(3.154)	(4.082)	(0.043)	(0.085)	(0.154)
Number of Obs	541780	527360	541780	541780	34188
Mean of Dep. Var	3.581	4.859	0.133	0.181	0.916
SD of Dep. Var	45.329	53.341	0.502	0.796	1.481
Panel D: Dropping Countries with >30% Missing					
China-Led Sector × Post × Appropriateness	8.285***	10.508***	0.108**	0.210**	0.280**
	(2.930)	(3.811)	(0.044)	(0.086)	(0.138)
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479
Panel E: Dropping Indicators with >15% Missing					
China-Led Sector × Post × Appropriateness	8.573***	10.905***	0.104**	0.202**	0.299**
	(2.954)	(3.826)	(0.044)	(0.086)	(0.121)
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479
Panel F: Dropping Indicators with >25% Missing					
China-Led Sector × Post × Appropriateness	8.040**	10.063**	0.112**	0.213**	0.283*
	(3.121)	(4.066)	(0.044)	(0.088)	(0.146)
Number of Obs	552300	537600	552300	552300	35507
Mean of Dep. Var	3.588	4.869	0.136	0.184	0.927
SD of Dep. Var	44.979	52.936	0.506	0.803	1.479
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes

Note: The unit of observation is a country-sector-year. In Panel A, the appropriateness measure uses the assignment of indicators to macro-sectors in which coders were given only "partial freedom" to exclude indicators, and in Panel B "no freedom." In Panel C, countries for which more than 20% of indicators were missing in all years 2003-2013 were excluded from the sample, and in Panel D, 30%. In Panel E, indicators for which more than 15% of countries were missing in all years 2003-2013 were excluded from the sample, and in Panel F, 25%. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.14: Appropriateness and Entrepreneurship: GPT-Assigned World Bank Indicators

	Deal Count				Deal Size		
	(1) Baseline	(2) Baseline	(3) Weighted	(4) asinh	(5) asinh	(6) asinh	(7) log($/deal)
Panel A: Baseline China-led measure							
China-Led × Post × Appropriateness	8.414***				0.209**		
	(2.951)				(0.086)		
China-Led × Post × Appropriateness (GPT)		4.693***	5.995***	0.064***		0.122**	0.185*
		(1.410)	(1.838)	(0.021)		(0.051)	(0.109)
Panel B: Strict China-led measure							
China-Led × Post × Appropriateness	11.009***				0.279***		
	(3.339)				(0.083)		
China-Led × Post × Appropriateness (GPT)		5.667***	7.377***	0.094***		0.201***	0.261**
		(1.637)	(2.188)	(0.021)		(0.056)	(0.104)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	547040	532480	547040	552300	547040	35282
Mean of Dep. Var	3.588	3.570	4.846	0.136	0.184	0.185	0.924
SD of Dep. Var	44.979	45.115	53.091	0.507	0.803	0.804	1.479

Note: The unit of observation is a country-sector-year. Appropriateness (GPT) denotes the appropriateness constructed using GPT-assigned indicators. Panel A presents results using our baseline China-led sector measure, where a sector is defined as China-led if it has an above-median ratio of the number of deals received by Chinese companies to that of US companies for the period of 2015 to 2019. Panel B uses a stricter China-led measure, where a sector is defined as China-led only if the number of deals received by Chinese companies is strictly higher than that of US companies during the same period. The outcome variable and parameterization changes across specifications and is noted at the top of each column. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.15: Appropriateness and Entrepreneurship: Controls for Internet Penetration

	Dependent Variable: Number of Deals (Normalized)				
	(1)	(2)	(3)	(4)	(5)
China-Led Sector × Post × Appropriateness	8.238***	7.823**	8.085***	7.577**	8.344***
	(2.902)	(2.986)	(2.744)	(3.112)	(3.023)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	No	No	No	No	Yes
Internet Penetration x Sector FE	No	Internet %	Cellular	Internet %	Internet %
Number of Obs	552300	544936	550196	544936	544936
Mean of Dep. Var	3.588	3.602	3.592	3.602	3.602
SD of Dep. Var	44.979	44.918	44.977	44.918	44.918

Note: The unit of observation is a country-sector-year. EM countries are defined as countries not included in the OECD as of 1980. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels. For internet penetration, columns 2, 4, and 5 control for the interaction between sector fixed effects and individuals using the internet (% of population) at country-year level from WDI data. Column 3 controls for the interaction between sector fixed effects and mobile cellular subscriptions (per 100 people) at country-year level from WDI data.

Table A.16: Appropriateness and Entrepreneurship: Trade with China

	Dependent Variable: Number of Deals (Normalized)				
	(1)	(2)	(3)	(4)	(5)
Regression Sample:	Baseline	Export Low	Export High	Import Low	Import High
China-Led Sector × Post × Appropriateness	8.238***	8.607**	8.780**	6.570	9.080**
	(2.902)	(4.220)	(3.823)	(4.334)	(3.758)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	241960	310340	220920	331380
Mean of Dep. Var	3.588	3.848	3.385	2.799	4.113
SD of Dep. Var	44.979	47.129	43.229	36.420	49.869

Note: The unit of observation is a country-sector-year. “Export Low” denotes countries whose value of exports to China as a percentage of the country’s total exports during the *entire analysis period* is below median among countries. “Export High”, “Import Low”, and “Import High” are similarly defined. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.17: Appropriateness and Entrepreneurship: Trade with China

	Normalized Number of Deals			
	(1)	(2)	(3)	(4)
China-Led Sector × Post × Appropriateness × High Export (pre)	0.950			
	(1.342)			
China-Led Sector × Post × Appropriateness × High Import (pre)		2.136*		
		(1.241)		
China-Led Sector × Post × Appropriateness × High Export (all)			-0.363	
			(1.411)	
China-Led Sector × Post × Appropriateness × High Import (all)				2.019
				(1.241)
Sector × Country FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes
Number of Obs	552300	552300	552300	552300
Mean of Dep. Var	3.588	3.588	3.588	3.588
SD of Dep. Var	44.979	44.979	44.979	44.979

Note: The unit of observation is a country-sector-year. “Export High” denotes countries whose value of exports to China as a percentage of the country’s total exports during the *pre-2013 period* is above median among countries. “Import Low”, and “Import High” are similarly defined. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.18: Appropriateness and Entrepreneurship: Controlling for Sector-Level Growth Trends

	Dependent Variable: Number of Deals (Normalized)					
	(1)	(2)	(3)	(4)	(5)	(6)
China-Led Sector × Post × China Appropriateness	8.238***	6.527***	7.735***	7.087***	6.338**	6.375**
	(2.902)	(2.483)	(2.804)	(2.500)	(2.560)	(2.567)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year × EM Fixed Effects	No	No	No	No	Yes	No
Suitability × Year Fixed Effects	No	No	No	No	No	Yes
EM Growth x Country FE x Year FE	No	#Deals	Deal Size	#Deals excl. CN	#Deals	#Deals
Number of Obs	552300	512400	491400	495600	512400	512400
Mean of Dep. Var	3.588	3.859	3.999	3.983	3.859	3.859
SD of Dep. Var	44.979	46.621	47.501	47.365	46.621	46.621

Note: The unit of observation is a country-sector-year. EM countries are defined as countries not included in the OECD as of 1980. "EM Growth" measures the percentage increase of the average number of deals per year post-2013 and pre-2013 for emerging markets for each sector. Column 2 uses the number of deals to calculate EM growth. Column 3 uses the average total deal size instead of average number of deals. Column 4 excludes China's deals when calculating growth. Column 5 further adds sector by year by EM fixed effects in addition to Column 2, and Column 6 adds suitability by year fixed effects in addition to Column 2. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.19: Policy Constraints and Affected Sectors

Policy Description	Affected Sectors	Sources
Ban or strict restrictions on genetically modified animal and genetically modified products	AgTech | Ag biotech | Animal biotech FoodTech | Bio-engineered foods | Cultivated protein FoodTech | Bio-engineered foods | Fermented protein	Caixin
Ban or strict restrictions on genetically modified crops and genetically modified products	AgTech | Ag biotech | Plant biotech FoodTech | Bio-engineered foods | Future food forms FoodTech | Bio-engineered foods | Novel ingredients FoodTech | Bio-engineered foods | Plant-based protein	Caixin
Weather/meteorology data not open to individual and commercial use	Carbon and Emissions Tech | Land Use | Climate/Earth Data Carbon and Emissions Tech | Land Use | Ecosystem Health and Monitoring	Stanford, Jiemian
Policy restriction on clinical trial (explicit consent needed, rather than automatic consent after a certain period)	Enterprise Health | Clinical Trial Technology | Clinical Trial Management (CTM) & Electronic Data Capture (EDC) Systems Enterprise Health | Clinical Trial Technology | Clinical Trial Technology Enterprise Health | Clinical Trial Technology | Electronic clinical outcome assessment (eCOA) Enterprise Health | Clinical Trial Technology | Patient recruitment and retention	Caixin1, Caixin2
Restrictions on online (internet) prescriptions	Enterprise Health | Prescription Technology | E-Pharmacy	NBD, iFeng
Restrictions on the number of financial institutions involving lending	Fintech | Alternative Lending | Microlending	Caixin
Constraints on housing mortgages by having harsh requirement on second house	Fintech | Alternative Lending | Real Estate Lending	Fang, Caixin
Ban on crypto currency and decentralized finance	Fintech | Digital Assets | Cryptocurrency Wallets and Exchanges Fintech | Digital Assets | Decentralized Finance	Gov.cn
Strict restriction on foreign exchange or cross border payment	Fintech | Payments | B2B Payments Fintech | Payments | Cross Border and FX	Caixin
High entry requirements for insurance agents or brokers	Insurtech | Distribution and Intermediation | Agent & Broker Tech Insurtech | Distribution and Intermediation | Marketplaces	Yicai
Car insurance prices are government capped or controlled	Insurtech | Property and Casualty | Auto	PCAuto
Ban or strict air control on low space air usage	MobilityTech | Advanced Air Mobility | Advanced Air Mobility Aircrafts and Parts MobilityTech | Advanced Air Mobility | Air Mobility Services	Caixin
Personalized testing firms have to have to be medical institutions with a certain number of qualified docters and nurses	Retail HealthTech | Personalized Medicine & Testing | Ad-hoc Personalized Testing Retail HealthTech | Personalized Medicine & Testing | Bioinformatics Retail HealthTech | Personalized Medicine & Testing | Genomic Testing Retail HealthTech | Personalized Medicine & Testing | Personalized Medicine & Testing	Caixin, MoleChina, Gov.cn
Restrictions for online healthcare to certain (periphery) areas	Retail HealthTech | Virtual Health | Concierge specialty & primary care clinics Retail HealthTech | Virtual Health | Digital Therapeutics Retail HealthTech | Virtual Health | telemedicine	CE.cn, Caixin
Conflicts between railway departments and other transportation authorities in different regions	Supply Chain Tech | Freight tech | Marine, rail & port logistics	CB.com

Table A.20: Policy IV Validation: Excluding Markets with Related Policies

	EM Has Similar Policy	Number of Deals (Normalized)	
	(1)	(2)	(3)
		IV Baseline	No Other EM
Appropriateness	0.0161		
	(0.0147)		
$\widehat{\text{China-Led}}$ Sector × Post × Appropriateness		11.0908**	14.5812**
		(5.1531)	(6.8053)
Country FE	Yes	-	-
Sector FE	Yes	-	-
Sector × Country FE	-	Yes	Yes
Country × Year FE	-	Yes	Yes
Sector × Year FE	-	Yes	Yes
Number of Obs	30771	552300	552300
Mean of Dep. Var	0.011	3.588	3.588
SD of Dep. Var	0.106	44.979	44.979

Note: The unit of observation is a country-sector for column 1 and a country-sector-year for columns 2 and 3. Dependent variables are reported at the top of the respective columns. Columns 1 reports the correlation of appropriateness score to China and whether an emerging market has similar policy constraint or not. "EM Has Similar Policy" is a dummy variable that equals one if the given country has similar policy constraint as China's in the given sector and zero otherwise. Column 2 reports the baseline IV results. In column 3, the policy constraints used have to only appear in China but no other EM countries. The triple interaction term is instrumented by the not-policy-constrained sectors interacted with post and appropriateness. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.21: Balance Test of Policy Constrained Sectors and Others

	(1)	(2)	(3)	(4)
	Level Difference	Growth Rate Diff.	Level Diff. (FE)	Growth Diff. (FE)
Panel A: All Countries				
Deal count	13.097	0.019	27.430	-0.011
	(21.357)	(0.151)	(20.166)	(0.163)
Deal size	235.629	8.386	356.874	8.829
	(224.937)	(9.651)	(220.152)	(10.490)
Unique companies	12.250	0.008	25.712	-0.022
	(19.993)	(0.137)	(18.885)	(0.147)
Unique countries	0.269	-0.086	1.049	-0.114
	(1.521)	(0.085)	(1.320)	(0.092)
Panel B: Emerging Markets				
Deal count	-0.058	-0.135	1.598	-0.136
	(1.927)	(0.116)	(1.814)	(0.126)
Deal size	-4.174	-116.416	1.416	-28.801
	(13.989)	(120.957)	(17.106)	(48.070)
Unique companies	-0.074	-0.136	1.530	-0.127
	(1.843)	(0.112)	(1.732)	(0.120)
Unique countries	0.087	-0.070	0.416	-0.068
	(0.525)	(0.100)	(0.486)	(0.103)
Panel C: China				
Deal count	0.476	-0.151	1.429	-0.120
	(0.935)	(0.112)	(0.905)	(0.136)
Deal size	3.074	1.444	5.337	1.505
	(9.461)	(1.332)	(11.974)	(1.254)
Unique companies	0.414	-0.133	1.338	-0.081
	(0.883)	(0.115)	(0.855)	(0.128)

Notes: This table reports the mean difference between Chinese policy constrained sectors and other sectors. Columns 1 and 2 report the Level and Growth differences without macro-sector fixed effects. Columns 3 and 4 report the differences with macro-sector fixed effects included. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.22: Appropriateness and Entrepreneurship: Sector-Specific Surge Year

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(deal)
Panel A: Baseline China-led					
China-Led Sector × Sector-Specific Post × Appropriateness	8.823**	10.252**	0.105**	0.173**	0.068
	(3.445)	(4.275)	(0.043)	(0.084)	(0.126)
Panel B: Strict China-led					
China-Led Sector × Sector-Specific Post × Appropriateness	11.534***	14.107***	0.122***	0.236***	0.305*
	(3.708)	(4.859)	(0.032)	(0.083)	(0.155)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	537600	736400	736400	35551
Mean of Dep. Var	3.588	4.869	0.102	0.139	0.926
SD of Dep. Var	44.979	52.936	0.442	0.700	1.481

Note: The unit of observation is a country-sector-year. Unlike earlier analyses, the post-period indicator is defined separately for each sector, based on when that sector took off in China. Panel A presents results using our baseline China-led sector measure, where a sector is defined as China-led if it has an above-median ratio of the number of deals received by Chinese companies to that of US companies for the period of 2015 to 2019. Panel B uses a stricter China-led measure, where a sector is defined as China-led only if the number of deals received by Chinese companies are strictly higher than that of US companies during the same period. In column 2, the regression is weighted by the log of number of total deals in the sector during the pre-period. In column 3, the outcome is the inverse hyperbolic sine transformation of the number of deals. In column 4, the outcome is the inverse hyperbolic sine transformation of total investment value and in column 5 it is the log of the average investment value per deal. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.23: Textual Similarity by LP

	Text similarity to existing Chinese companies in the sector		Text similarity to existing Western Backed Chinese companies in the sector		Text similarity to existing Non-Western Backed Chinese companies in the sector	
	(1) Mean Similarity	(2) 90th Percentile Similarity	(3) Mean Similarity	(4) 90th Percentile Similarity	(5) Mean Similarity	(6) 90th Percentile Similarity
China-Led Sector × Post	0.0103**	0.0137***	0.0116**	0.0132**	0.0119**	0.0127**
× China Suitability	(0.0047)	(0.0047)	(0.0050)	(0.0061)	(0.0052)	(0.0050)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	42536	42536	39273	39273	41519	41519
Mean of Dep. Var	0.506	0.614	0.500	0.599	0.507	0.606
SD of Dep. Var	0.094	0.099	0.101	0.110	0.096	0.099

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Only Chinese companies existed before a given company are considered. Western-Backed company is defined as a company with any deal that has western LP investor or investor based outside China and Hong Kong. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.24: The Effect of Political Alignment

	Dependent Variable: Number of Deals (Normalized)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Top Quartile UN Vote Similarity	Bottom 3 Quartiles UN Vote Similarity	Top Quartile Polity Score Similarity	Bottom 3 Quartiles Polity Score Similarity	Govt Prioritized Sectors	Not Prioritized Sectors
China-Led × Post	11.734**	7.459**	9.949*	7.732***	2.600	9.751***
× Appropriateness	(5.743)	(3.120)	(5.542)	(2.774)	(2.600)	(3.616)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	139127	411332	118613	380824	174300	378000
Mean of Dep. Var	4.514	3.289	3.350	3.130	4.628	3.108
SD of Dep. Var	54.283	41.465	46.049	40.832	51.643	41.540

Notes: The unit of observation is a country-sector-year. Each regression is estimated on a different sample, noted at the top of each column. In columns 1-4, some countries are excluded from each specification, and in columns 5-6, some sectors are excluded from each specification. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.25: Results After Controlling for Political Alignment

	Dependent Variable: Normalized Number of Deals			
	(1)	(2)	(3)	(4)
China-Led Sector × Post × Appropriateness	8.238***	8.573***	7.359***	7.969***
	(2.902)	(2.635)	(2.774)	(2.597)
China-Led Sector × Post × Polity Score Mismatch with China		-0.206**		-0.143
		(0.102)		(0.109)
China-Led Sector × Post × UN Voting Mismatch with China			-2.369***	-1.290*
			(0.816)	(0.768)
Sector × Country FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes
Number of Obs	552300	499963	551511	499174
Mean of Dep. Var	3.588	3.179	3.592	3.183
SD of Dep. Var	44.979	42.107	45.011	42.140

Note: The unit of observation is a country-sector-year. In addition to the main triple-interaction, the specifications in this table also include interactions with country-level political characteristics on the right hand side of each regression. Polity score mismatch with China denotes the distance between a country's polity score and China's polity score. UN Voting mismatch with China denotes the distance between a country's UN voting history and China's. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.26: Appropriateness and Entrepreneurship: Vertical versus Horizontal Components

	Number of Deals (Normalized)		
	(1)	(2)	(3)
China-Led × Post × Appropriateness	8.414***		
	(2.951)		
China-Led × Post × Appropriateness Z-score		2.286***	
		(0.802)	
China-Led × Post × Appropriateness Z-score (GDP pc)			1.325***
			(0.471)
China-Led × Post × Appropriateness Z-score (Residual)			1.666**
			(0.827)
Sector × Country FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes
Appropriateness × Year FE	Yes	Yes	Yes
Number of Obs	552300	552300	547040
Mean of Dep. Var	3.588	3.588	3.609
SD of Dep. Var	44.979	44.979	45.139

Notes: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Appropriateness (GDP pc) is obtained by regressing appropriateness on average GDP per capita during the sample period and using the predicted value, whereas Appropriateness (Residual) is obtained by using the residual. We take Z-score of our baseline appropriateness measure, GDP pc component and residual component for better comparison. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.27: Appropriate Entrepreneurship and Socioeconomic Outcomes

	Outcome is the average of development indicator z-scores (x1000)	
	(1)	(2)
	All Countries	EM Countries
Panel A: Baseline		
Predicted China-Induced Deals	0.073***	0.119***
(Appropriateness Z-score)	(0.025)	(0.032)
Number of Obs	2100	1755
Mean of Dep. Var	27.533	-29.374
SD of Dep. Var	259.532	229.547
Panel B: From Appropriateness GDP pc		
Predicted China-Induced Deals	-0.012	-0.049
(GDP pc Component Z-score)	(0.024)	(0.040)
Number of Obs	2085	1740
Mean of Dep. Var	30.502	-26.306
SD of Dep. Var	258.029	228.060
Panel C: From Appropriateness Residual		
Predicted China-Induced Deals	0.106***	0.153***
(Residual Component Z-score)	(0.031)	(0.034)
Number of Obs	2085	1740
Mean of Dep. Var	30.502	-26.306
SD of Dep. Var	258.029	228.060
Country FE	Yes	Yes
Macro Sector FE	Yes	Yes

Note: The unit of observation is a country-macro-sector. The independent variable is the sum of predicted China-driven deals (normalized) for the post period. Z-scores are multiplied by 1000. Panel B uses predicted China-Induced deals from Appropriateness GDP pc component as discussed in Table **??** and Panel C using residual component. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.28: Appropriate Entrepreneurship and Socioeconomic Outcomes: Agriculture, Education, Health

	Outcome is the average of development indicator z-scores (x1000)			
	All Macro-Sectors		Agriculture, Education, and Health	
	All Countries	EMs	All Countries	EMs
Predicted China-Induced Deals	0.073***	0.119***	1.080***	1.087***
	(0.025)	(0.032)	(0.227)	(0.219)
Country FE	Yes	Yes	Yes	Yes
Macro Sector FE	Yes	Yes	Yes	Yes
Number of Obs	2100	1755	560	468
Mean of Dep. Var	27.533	-29.374	43.490	-13.610
SD of Dep. Var	259.532	229.547	278.398	255.758

Note: The unit of observation is a country-macro-sector. EM country is defined as countries that are not in the OECD as of 1980. Agriculture, Education, and Health denotes the macro sectors of AgTech, EdTech, Enterprise Health, and Retail HealthTech. The independent variable is the sum of predicted China-driven deals (normalized) for the post period. Z-scores are multiplied by 1000. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.29: China's Rise and City-Level Entrepreneurship

	All Companies	China-Led Sectors	Non-China-Led Sectors	All Companies	Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
Regression sample:	EM	EM	EM	Full	EM	Full
Share China-Led × Post	0.734***	0.615***	0.119***	0.084**	0.321***	0.072
	(0.164)	(0.142)	(0.030)	(0.039)	(0.098)	(0.052)
Share China-Led × Post × EM				0.650***		0.249**
				(0.167)		(0.110)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × EM FE	-	-	-	Yes	-	Yes
Number of Obs	1150	1150	1150	5139	1150	5139
Mean of Dep. Var	0.153	0.132	0.021	0.048	0.077	0.026
SD of Dep. Var	0.243	0.214	0.044	0.135	0.205	0.107

Note: The unit of observation is a city-year. EM countries are defined as countries not included in the OECD as of 1980. *Share of China-Led* denotes the share of VC-backed companies in the city that are in one of the China-led sectors during the pre-analysis period. Cities with at least 20 companies founded during the pre-analysis period were included in the analysis. Column 1 reports our result for EM countries. In column 2, the outcome is constructed using only companies classified into at least one China-led sector. In column 3, the outcome is constructed using only companies classified into no predicted China-led sectors. Columns 4 reports the result for all countries, with the interaction term for EM. In columns 5 and 6, we examine the number of patents awarded to inventors living in each city as the dependent variable, for EM and all countries with the interaction term for EM. Standard errors are double-clustered by city and year×country, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.30: China's Rise and City-Level Entrepreneurship: Robustness

	All Companies	China-Led Sectors	Non-China-Led Sectors	All Companies	Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
Regression sample:	EM	EM	EM	Full	EM	Full
Panel A: Inverse Hyperbolic Sine						
Share China-Led × Post	1.883***	1.533***	1.177**	0.403	0.579	0.071
	(0.598)	(0.562)	(0.561)	(0.328)	(0.581)	(0.324)
Share China-Led × Post × EM				1.480**		0.508
				(0.677)		(0.659)
Number of Obs	1150	1150	1150	5139	1150	5139
Mean of Dep. Var	2.187	1.989	0.814	1.901	3.274	4.241
SD of Dep. Var	1.218	1.230	0.963	1.181	2.623	2.025
Panel B: Log Outcome						
Share China-Led × Post	1.762***	1.686***	1.730***	0.352	1.132**	0.052
	(0.553)	(0.526)	(0.524)	(0.321)	(0.538)	(0.315)
Share China-Led × Post × EM				1.411**		1.080*
				(0.634)		(0.617)
Number of Obs	1097	1051	602	4714	914	4852
Mean of Dep. Var	1.548	1.425	0.761	1.317	3.400	3.789
SD of Dep. Var	1.199	1.174	0.861	1.137	2.309	1.812
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × EM FE	-	-	-	Yes	-	Yes

Note: The unit of observation is a city-year. EM countries are defined as countries not included in the OECD as of 1980. *Share of China-Led* denotes the share of VC-backed companies in the city that are in one of the China-led sectors during the pre-analysis period. Cities with at least 20 companies founded during the pre-analysis period were included in the analysis. Column 1 reports our result for EM countries. In column 2, the outcome is constructed using only companies classified into at least one China-led sector. In column 3, the outcome is constructed using only companies classified into no predicted China-led sectors. Columns 4 reports the result for all countries, with the interaction term for EM. In columns 5 and 6, we examine the number of patents awarded to inventors living in each city as the dependent variable, for EM and all countries with the interaction term for EM. In Panel A, all outcomes are parameterized using the inverse hyperbolic sine transformation and in Panel B, they are parameterized using the log transformation. Standard errors are clustered by city and year×country, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.