Appropriate Entrepreneurship? The Rise of China and the Developing World

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Abstract

Global innovation and entrepreneurship has 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 data on global venture activities, 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 variation in sector-specific policy constraints in China that shifted the likelihood of entrepreneurial take-off. 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 in innovation outside of the traditional frontier.

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1 Introduction

Global investment in innovation and entrepreneurship has traditionally been concentrated in a small set of high-income countries. 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 of 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 business models and technology that is suited to the factor endowments, tastes, geography, or culture of the rich 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 new parts of the world.

We investigate this question by studying the rapid rise of innovation in China, focusing in particular on high-growth entrepreneurship and venture capital (VC) investment. We study this area for three reasons. First, the rise of VC investment in China was dramatic, faster than China's rise in other areas of innovation, providing stark time-series variation. While in 2001, 88% 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. Anecdotally, this transformation has already 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" (Schroeder, 2023). Second, global data on VC investment and firm outcomes make it possible to systematically measure entrepreneurship and its consequences around the world. Finally, idiosyncratic variation in Chinese investment across sectors, along with country-by-sector

[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 (2023) studies inappropriate technology in agriculture.

differences in the potential "appropriateness" of Chinese technology, make it possible to isolate the international consequences of China's rise as an R&D hub independently from global, country-specific, or sector-specific trends in entrepreneurship.

Using this global database of entrepreneurial activity and novel measure 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 particularly suitable. The rise in investment is fueled by investments by local investors, rather than US or China-based firms, and by the creation new firms that closely resemble pre-existing counterparts in China. Moreover, it had far-reaching economic impacts, leading to a rise in serial entrepreneurship and in broader measures of innovation and development. 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 and Measurement Venture capital (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.[3] While VC investment was heavily concentrated in the US for much of its history, the last decade has witnessed a dramatic rise in China, unparalleled by any other country. 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 (e.g., due to uncertainty and information asymmetries), 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, and is particularly pronounced in contexts where contract enforcement are less well established (e.g. Gompers and Lerner, 1999; Lerner and Schoar, 2005). However, business models suitable for the US may not be appropriate elsewhere, and those that would thrive in other regions might not have suited the US market in the first place. This misalignment could be particularly pronounced in low- and middle-income countries.

A range of qualitative evidence—in areas ranging from education technology to social commerce and "super apps"—suggests that China's rise as a counterpoint to the US has

[3]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.

reshaped entrepreneurship across emerging markets (Lerner et al., 2024b, 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 any other context.

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.[4] 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 "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 the 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., educational attainment is 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. On average, the measure is higher in developing countries than in developed countries. There is also substantial within-country variation in appropriateness across sectors, which we exploit in our empirical analysis. Thus, our main analysis fully absorbs any trends in country-specific

[4] Pitchbook includes a description of each company and the size and capital providers of each financing round. It has become the industry gold standard for the analysis of global venture transactions. Data are gathered through firm/fund contacts, news stories, and regulatory filings (see Section 3).

(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.

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 ecosystem monitoring — and show that they substantially limit entrepreneurship and investment in China. Importantly, such domestic policies are plausibly independent from potential investment success or investment opportunities 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 a 214% increase in venture investment deals among China-led sectors. Aggregating these estimates across all country-sector pairs implies that the rise of China increased overall emerging market venture activity outside of China by 42%. The estimates are similar if we focus only within developing countries or control directly for trends in sector-specific growth in developing countries. The effects are predominately driven by *local* investors, rather than investors from China or the US.[5]

We next investigate whether the results are consistent with a causal effect of China's emergence as an entrepreneurial hub. Given the fixed effects included in the baseline specification, the main concern is a spurious correlation between *trends* in the appropriateness measure at the country-sector level and trends in some omitted characteristic that causes entrepreneurial take-off. To help rule out this possibility, we exploit idiosyncratic domestic policy variation that constrained certain investment sectors in China but are likely independent from potential investment success elsewhere in the world. In these

[5]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.

sectors — where Chinese investment never took off — we detect no relationship between our appropriateness measure and entrepreneurial activity elsewhere in the world. 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 falsification test rules out the possibility that spurious correlation drives the result, so long as the omitted characteristic is not correlated itexclusively with socioeceonomic similarity to China.

Turning to dynamics, we find no evidence of pre-existing trends. 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, similarity to China becomes a strong predictor of venture activity, particularly in sectors that China comes to dominate. Similarity 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. Using Natural Language Processing tools to measure similarity in business description across company pairs, we show direct evidence of firm-level mimicry of Chinese businesses. The rise of China was accompanied by an increase in textual similarity between descriptions of new firms and descriptions 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 emulating their Chinese predecessors.

We then 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.

Finally, 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. In fact, the results are substantially weaker after restricting attention to the strategic sectors, indicating that investment growth driven by explicit political considerations may have had weaker global spillovers.

Broader Impacts Finally, we study the broader economic consequences of our main results. We first focus on firm-level effects and, using data on company outcomes, find large positive effects on the number of firms that are acquired or go public but no effect on firms that have failed. Thus, our estimates are not driven by failures or short-run fads. Next, we document an increase in the number of serial entrepreneurs — individuals who found multiple startups and are particularly important for the growth of local centers of entrepreneurship (e.g. Mallaby, 2022). Moreover, we show that these serial entrepreneurs start subsequent companies in sectors that are *not* led by China. The initial growth in entrepreneurship following the rise of China thus had positive cross-sector spillover effects by generating a pool of serial entrepreneurs who branched out from the China-dominated sectors in which they started.

Next, 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 document 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 activity after the rise of China. While more pronounced in sectors led by China, the effects are also present in sectors with few existing Chinese firms. This is consistent with the cross-sector spillover effects driven by serial entrepreneurship and indicates that city-level effects extended beyond the transmission of business ideas directly from China. All of these patterns are driven by cities in emerging markets.

Last, 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.

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, 2023). These studies have focused on the consequences of innovation that is directed disproportionately toward the characteristics of high-income countries. 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 local focus of Chinese entrepreneurship, which builds existing work documenting innovation "home bias" in other areas (e.g., Costinot et al., 2019; Moscona and Sastry, 2023). Finally, while a broad range of existing studies have identified important mechanisms of technology transfer — including role of governments (Giorcelli, 2019), academia (Aghion et al., 2023), and supply chains (Bai et al., 2022)—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 VC investment, 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 study the consequences of the recent growth in Chinese innovation, focusing on its impact on entrepreneurial activity beyond China's borders.

Finally, we build on the small existing set of work on venture capital in emerging economies, such as Lerner and Schoar (2005) and Colonnelli et al. (2024). 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 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 China's venture investment 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 of that take-off: venture-backed firms and start-ups.[6] Panel A of Figure 1 displays the changing distribution of VC investment around the world between 2001 and 2021. Panel B 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).[7] 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 take-off of China's venture sector had numerous drivers, including the return of seasoned Chinese entrepreneurs and investors from abroad, the willingness of global investors to contribute both capital and expertise to local managers, and favorable government policies (such as the creation of robust public markets).

Chinese ventures have demonstrated genuine innovative accomplishments, not merely copying business models from elsewhere. Many Chinese companies feature "recombinant innovations" — a term coined by Weitzman (1998) but dating back to Poincaré and Schumpeter — 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.

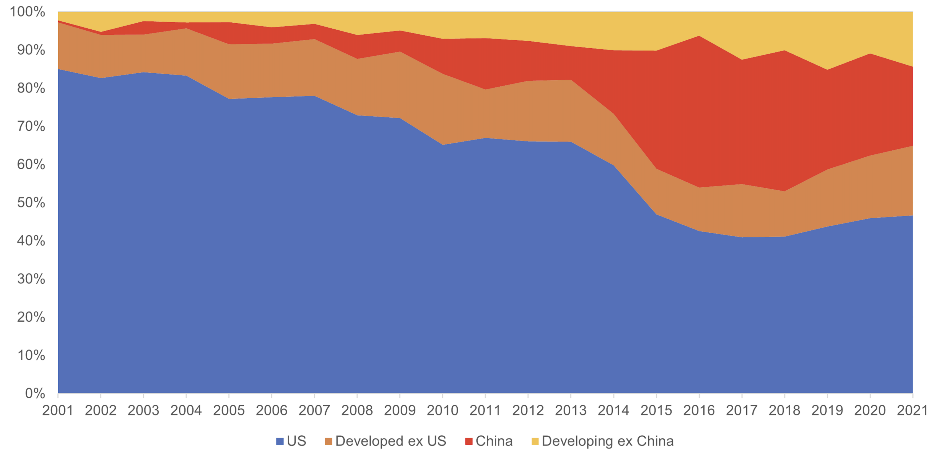
The size of China's venture industry is unprecedented and unique among emerging economies. This makes it an exciting natural experiment to study the consequences of an emerging economy rising as a new center of global innovation. To convey this point, we fix China's GDP per capita at its 2015 level (US$ 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

[6] 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.

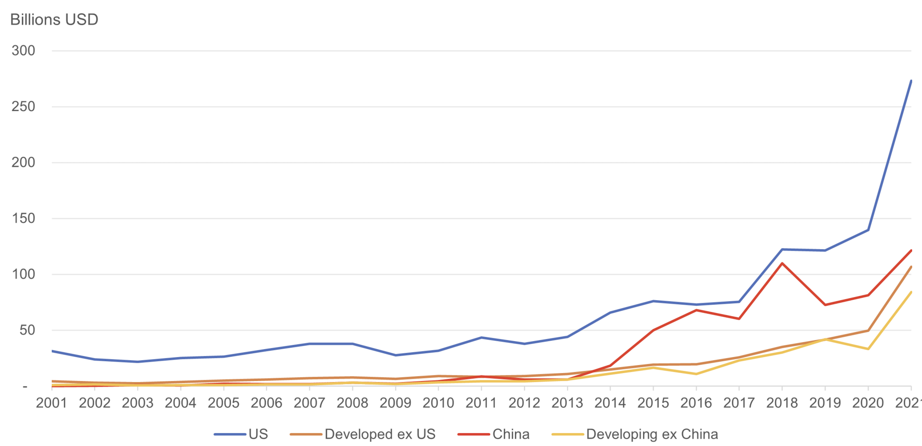
[7] Figure A.2 shows the same plot expressed in total number of unique deals instead of deal value. The pattern is very similar except that the timing of China's rise shifts slightly earlier.

Figure 1: Venture Investment Overview

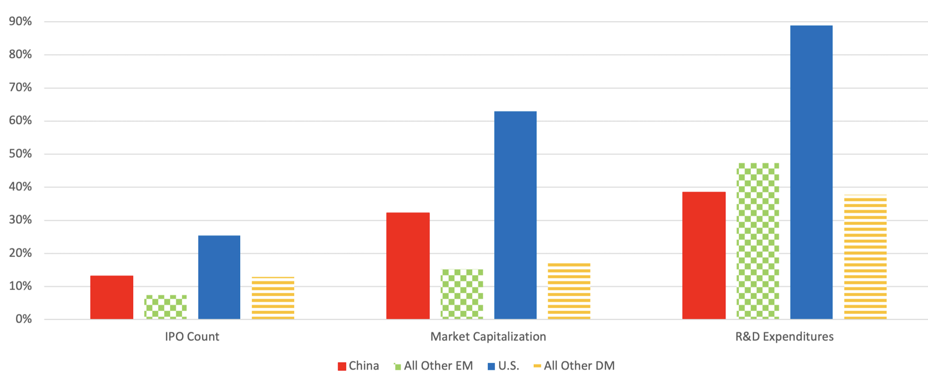
(a) Share of Global VC Investment



(b) Value of Global Investment



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



Note: 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. Figure 1a and Figure 1b are from Pitchbook; the data sources for Figure 1c are discussed in Appendix A.

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.

2.2 Venture capital in other emerging economies

In recent years, venture investment has begun to play an increasingly important role among firms in emerging markets more broadly. The growing role of VC for global R&D makes it important to understand the drivers of VC investment in these contexts.

To make this point systematically, we follow Lerner and Nanda (2020)'s methodology for the US and identify the share of young, publicly traded firms headquartered in each country that are VC-backed. Young and public firms are likely to be a key source of economic dynamism (Haltiwanger et al., 2013; Ayyagari et al., 2017). We identify these offerings using S&P's Capital IQ, from which we also obtain data on their market capitalization and R&D spending (see Appendix A for details). Figure 1, Panel C, presents the results for the US, China, and all other developed and emerging markets. About 10% of the young, publicly listed firms in emerging markets outside of China are venture-backed, and they represent 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 in these countries more generally, we examine US patents awarded between 2013 and 2022 to all institutional (non-individual) assignees based in emerging markets outside of China.[8] 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. (2024a), the weighted share rises to 41.66%. Thus, venture-backed companies represent a substantial share of overall innovation in low- and middle-income countries.

[8]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.

2.3 Emulating Chinese ventures

In recent years, Chinese firms have been increasingly emulated, particularly in emerging markets (Lerner et al. (2024b) 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, driven 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 (e.g., for a video game designer, fast video-processing semiconductors) 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 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 price and pitch products to one another. This model soon attracted imitators in developing markets, particularly 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 (Pinduouo, in this case) precedes the take-off of similar ventures in other emerging markets.

There are other ample 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, particularly the subset geared toward elementary and secondary education, have been particularly influential in India.

These examples of business emulating the 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.

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.[9] From its founding in 2007, Pitchbook was designed to have a world-wide focus. The information in the PitchBook 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.[10,11]

In Table 1, Panel A, we present a series of summary statistics. The compiled data

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

[10]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.

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

Table 1: 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" denotes all EM countries excluding China, and "Other Non-EM" denotes all non-EM countries excluding 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. A sector is defined to be China led if the ratio of the number of VC deals received by Chinese companies to the total number of deals received by Chinese and US companies for 2015-2019 is above the median among all sectors. US-led sectors are sectors that are below the median of the aforementioned ratio.

cover 88,267 companies from 152 countries that received 169,505 venture deals in total for the period 2000-2019. 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 constitute a venture capital transaction.[12] 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 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 (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.

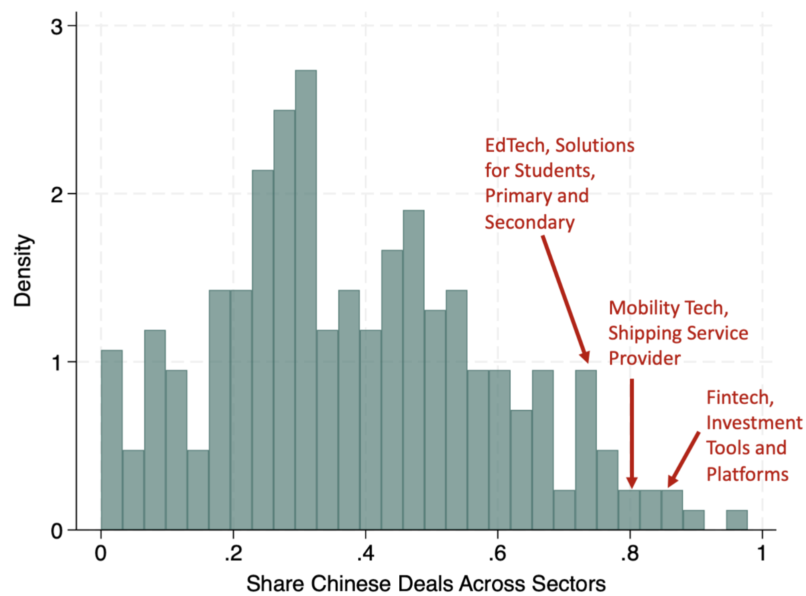
PitchBook analysts have assigned 26,524 companies to these sectors by hand. To assign the remaining companies, we fine-tune Bidirectional Encoder Representations from Transformers (BERT) models for each sector using these human classifications and the paragraph-long text that describes each company's business mission, business model, and area of business as the training set.[13] 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 1, 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, and conditional on being categorized into multiple sectors, the average number of sectors is 3.51.

[12] 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.

[13] 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: China's Share of Venture Deals Across Sectors

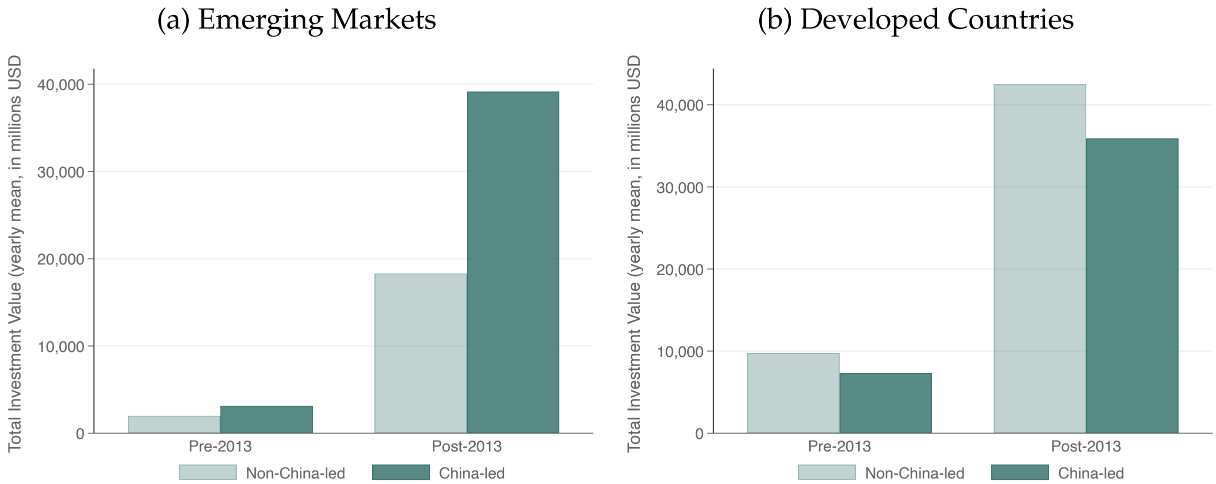


Note: This figure plots a histogram of the ratio of the number of venture deals for Chinese companies to the total number of venture deals for Chinese and US companies in each sector from 2015 to 2019. Values for three example sectors are marked in red.

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 2 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 2.3, 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. As an alternative definition, we define China-led sectors as those where the total number of venture investment 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 2. By construction, half of the sectors are China-led following the baseline definition. A smaller but still substantial

Figure 3: Investment Trends in Emerging vs. Developed Markets



Note: Figure 3a shows the total VC investment for emerging markets (defined as countries not in the OECD by 1980), separated by China-led sectors. Figure 3b displays the total VC investment for developed markets (defined as countries in the OECD by 1980), separated by China-led.

number (69) are China-led following our stricter definition.[14]

The rise of China and and its focus on very different technology areas led to a sharp re-direction of overall entrepreneurship across these two "benchmark countries." Figure A.5a 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.5b 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, driven by growth in new areas and with no evidence of a contraction in other areas.

Global investment trends: emerging vs. developed markets Moving beyond investment in China or the US, and consistent with the cases outlined in Section 2.3, the rise of China was followed by a dramatic increase in business formation *other* developing countries, driven by sectors in which China led the US. Figure 3a displays the total value of venture investment in developing countries (excluding China) in China-led and US-led sectors,

[14]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 two features of VC investment. First, outside of the US and China, no single country represented a substantial share of global investment. Second, there is a large amount of case study evidence, some of which is 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 define China's sector-level leadership based on its share of global deals.

both before and after the rise of China. There was a dramatic increase in investment in China-led sectors — including companies like Indonesia's Super and Brazil's Facily — 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 3b). If anything, the pattern is the opposite. Table 1, Panel B.2, presents a broader set of summary statistics, all consistent with China's rise coinciding with greater investment in other emerging economies.

In the next section, we introduce the building blocks of our strategy to investigate whether the international diffusion of Chinese entrepreneurship was driven by its "appropriateness" in other parts of the world.

3.3 The appropriateness of Chinese entrepreneurship

To investigate the hypothesis that venture investments in China-led sectors shape global investment in places where Chinese technology is most 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.[15] 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 supply of particular technology) and features of demand (i.e., characteristics that affect 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 shape business diffusion, that is beyond the scope of this paper.

Members of our team assigned indicators to macro-sectors using three methods, with

[15]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.

different levels of coder freedom.[16] In a first method (our baseline), coders were fully free not to assign indicators that they deemed of limited relevance to none of the macro sectors. In a second method, 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.[17]

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 $Appropriateteness_{cs}$.

Variation in appropriateness The appropriateness measure captures variation both across countries (it is constructed using country-level indicators) and across macro-sectors within countries (only certain indicators are assigned to each macro-sector). Figure A.6a displays the average appropriateness 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. For example, most of sub-Saharan Africa has a relatively low measure of potential appropriateness. In Figure A.6b, each country is color-coded based on the *difference* between its average China-appropriateness and its average US-appropriateness, calculated in an analogous manner. Non-OECD countries are 0.565 standard deviations more similar to China than they are to the US, suggesting that developing countries 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, there is a large gap in appropriateness between the most and least appropriate sectors (Figure A.7). Zooming in on specific markets, Figure A.8 displays histograms of appropriatness of Chinese R&D for AgTech (A.8a) and FinTech (A.8b), after subtracting average appropriateness across all other sectors. While Figure A.6a shows that India is very similar to China on average, Figures A.8a and A.8b document that the appropriateness measure is

[16] In Appendix C, we describe in greater detail the indicator assignment processes used in the analysis.

[17] Table A.2 gives examples of the indicators chosen for specific macro-sectors. While the first method allows for the highest amount of freedom, the final method allows us to make sure that the results are not driven by including (or not) specific indicators in the measure.

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.

Validation To validate that this measure captures the applicability of Chinese technology to each country-sector, we show that it predicts the extent to which innovators working in each market cite Chinese technology using patent data.[18] Table A.3, columns 1-2, shows that appropriateness is positively correlated with citations to Chinese patents, conditional on both country and macro-sector fixed effects, as well as total backward citations. The effect is stronger restricting attention to emerging market assignees (column 2). Appropriateness of Chinese R&D is not, however, correlated with patent citations to US patents (columns 3-4), a reassuring falsification exercise.

4 Main results

4.1 Empirical strategy

In this section, wee 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.

Before introducing our main empirical specification, we return to two of the countries highlighted in the motivating cases described in Section 2, India and Indonesia, also two of the largest emerging markets. We trace the number and total size of venture deals received by Indian and Indonesian enterprises, distinguishing between sectors led by China and those not, and whether these sectors exhibit high or low appropriateness of Chinese enterprise (see Figure A.9). The pattern illustrated in the cases holds more broadly across India and Indonesia: local venture activities in China-led sectors sharply rise after 2013 — when China took off — and this is driven by the specific sectors in these countries that have a high level of measured appropriateness of Chinese enterprise.

[18] We link VC-backed companies to USPTO's patent data and train BERT models using each patent's abstract and the sectors its assignee is in to predict 100,000 random patents granted in the US from 2000 to 2019 by countries other than the US and China to one (or multiple) of the sectors in Pitchbook. We then compile the results at the macro-sector level. We focus on a random subset of patents due to computational constraints that make it very costly to predict the universe of patents during our sample period.

In order to investigate these patterns systematically, 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:

$$y_{cst} = \beta\left(ChinaLed_s * Post_t * Appropriateteness_{cs}\right) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + X'\Gamma + \epsilon_{cst}, \quad (1)$$

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. $Appropriateteness_{cs}$, 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.[19] 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 Chinese benchmark companies could lead to a rise in global entrepreneurship, especially in markets where Chinese business ideas and technology are most suited (high $Appropriateteness_{cs}$). 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 trends in countries' entrepreneurial environments, their evolving ties to China, etc. These will capture, for instance, shifts in country-level growth rates or connections to China, as long as these changes do not disproportionately affect the specific sectors in which Chinese VC investment specialized. Second, $sector * year$ fixed effects control for global trends in entrepreneurship for each sector. This will capture any sector-specific trends (e.g., the rise of AI), so long as they affect all countries similarly. 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. This would 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 across country-

[19]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 4.4, 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.

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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year × EM Fixed Effects	No	Yes	No	No	No
Appropriateness × Year Fixed Effects	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.

sector pairs within developing countries. 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 $Appropriateteness_{cs}$ and that disproportionately affects 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, we control directly for a range of potential drivers of common sector-country trends in entrepreneurship, including the sector-specific effect of internet penetration, trade openness, and trade with China. 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 shock or trend.

4.2 Main estimates

Table 2, columns 1-2, present the baseline estimates of Equation 1. 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. 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.[20] 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 $Appropriateteness_{cs}$ in Equation 1 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 $Appropriateteness_{cs}$. While we showed above that entrepreneurship in China-led sectors increased substantially in developing countries following China's take-off (Figure 3a), 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 terms of total investment value rather than the number of investment rounds (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 a 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).[21]

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 shaping its diffusion around the globe.

Magnitudes To assess the effect of China's rise on overall entrepreneurship in emerging markets, we use Equation 1 to predict the total number of deals, both with and without the effect of China captured by β (see Appendix D for details).[22] We find that the rise of

[20] Table A.4 further makes this point by controlling for $ChinaLed_s * Post_t$ interacted with measures of country-level income (or income relative to China). In all cases, the effect of the income interactions are insignificant and their inclusion does not attenuate our coefficient of interest. These results are consistent with a view of technological appropriateness based on "horizontal" differentiation, and inconsistent with a mechanism in which technology appropriateness is only "vertically" differentiated by development stage.

[21] Table 3 also shows that the findings are similar using alternative strategies to parameterize the dependent variable, including the inverse hyperbolic sine transformation.

[22] This exercise relies on three assumptions. The first 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. The second is that there is no effect in country-sector pairs where appropriateness

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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	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.

China increased emerging market venture deals by 42%.

What might have been the impact if another country grew over the past decade in China's place? Answering this question could help benchmark the effect of China *per se* against the potential effect of growth in other emerging markets, which may also have generated businesses more suited to developing contexts. To do this, we use estimates of β and the fixed effects from Equation 1, combined with country-sector level measures of appropriateness with respect to all other countries.[23] To incorporate the potential scale of innovation in each country, we also report results after scaling the number of sectors in which each country can specialize by its GDP relative to that of China. Without scaling

takes value zero, and we adjust our appropriateness measure so that this is the case for the minimum value of the appropriateness measure within each macro-sector. The third is that fixed effect estimates are held constant in the counterfactual without the rise of China.

[23]To facilitate cross-country comparisons, we focus on the strict China-led measure. Since we do not know which sectors might have been "led" by each country, we randomly select 500 sets of sectors and compute the mean predicted deal count across all simulations.

by GDP, the country whose rise would have the largest impact is Pakistan, followed by Indonesia and Nigeria. These countries are the most "similar" to the highest number of other emerging market country-sector pairs, meaning that their entrepreneurial success would have had the largest potential international spillover effect. When we scale by GDP, however — taking into account the fact that China's dominance across so many sectors was, in part, due to its size — China is at the top of the list (see Table A.5).

Robustness and sensitivity analysis We conduct a range of sensitivity analyses, all reported in the Appendix. We show that the results are similar after including the years 2020 and 2021 (Table A.6) and using the number of sector-level deals in China relative to the rest of the world, rather than relative to the US, to define the "China-led" indicator (Table A.7). The results are robust to a range of sensitivity checks of our construction of the appropriateness measure (see Appendix C for details), including alternative strategies for assigning indicators to macro sectors (Panels A to B, Table A.8); using different thresholds for dropping countries or indicators with high amounts of missing data (Panels C to F of Table A.8); and randomly dropping sets of indicators from the analysis to show the results are not driven by any small set of country characteristics (Figure A.10).

Most importantly, we repeat our baseline analysis except rather than use VC deals to construct the outcome variable, we use all *non*-VC deals in the PitchBook database (Table A.9). One potential concern with our baseline analysis is that non-VC investment could substitute for VC investment; if this were the case, it might suggest that we were over-estimating the effect of China on emerging market entrepreneurship. However, we find no evidence of this pattern: the estimates are all positive and half are statistically significant. If anything, the direction of non-VC financing reinforces our baseline results.

4.3 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 these sectors. For this to affect the causal interpretation of β in Equation 1, these reasons would also need to be spuriously correlated with trends in country-sector-level appropriateness.

4.3.1 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 networks and trade networks, we can control for these observed features directly. Specifically, we control for internet penetration rate (Table A.10), trade with China during the pre-period (Table A.11), trade with China during the entire sampling period (Table A.12), and the triple-difference term interacting with the trade volume (Table A.13). Our baseline estimates remain qualitatively and quantitatively very similar. As a more hands-off strategy to account for common trends, we also control directly for the sector-level growth rate during the sample period across all emerging markets, interacted with country-by-year fixed effects (Table A.14). The coefficient of interest remains very similar, indicating that common-sector level growth trends, and even the potentially heterogeneous consequences of these trends across countries, do not affect the results.

4.3.2 Policy shocks to Chinese take-off in specific sectors

The possibility remains, however, that our results are biased by some unobserved differential trend specific to China-led sectors in country-sector pairs with high $Appropriateness_{cs}$. To directly address this issue, we examine specific regulatory policies implemented by Chinese leadership and bureaucracy that limited growth in some sectors. While 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 in other countries in these sectors that were constrained by government policy. If we *do* observe an effect, it would suggest that our estimates could be driven by spurious trends.

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. This process is explained and documented in more detail in Appendix E. For example, a range of reports highlight policies in China that restricted access by individuals and commercial companies to basic hardware facilities for meteorological data, limiting potential firm growth in climate/earth data and ecosystem monitoring.[24] 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.[25] Overall, we identify constraints in 33 sectors (Table A.15 describes all the policies).

Importantly, these policies are largely specific to China's administrative, bureaucratic, and political environment. We search for the presence of each policy that we identify in all other emerging markets, and we find that the median policy is present in only 7 out of

[24]For instance, Felix Wu, founder of Seniverse, said in an Stanford GSB China interview, "Due to the closure of China's commercial meteorological market ... the value of natural big data such as meteorology and environment is difficult to apply to industries and enterprises in the Chinese market, hindering the refined operation and efficient growth of enterprises." Source: `http://gsbchina.stanford.edu/æůśåžęèő¿èřĹ/çĆźçĞČäÿŞèő¿-å¿Čç§ěåďĺæřŤåĹŻåğŃäžžåŘťéčđïijŽåĄŽäÿŋåŻ¡çŽĎ-weather-comp/` (in Chinese).

[25]As Caixin recently reported (`https://weekly.caixin.com/m/2024-04-12/102185327.html?originReferrer=caixinsearch_pc` (in Chinese)), "The biggest obstacle [to any development of low-space technology firms] is the high degree of control of low-altitude airspace.".

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

117 emerging market countries in our sample. Moreover, the presence of similar sector-constraining policies in other countries is *not* associated with socioeconomic similarity to China (Table A.16, column 1).

Our findings that exploit sector-specific policy constraints in China are all consistent with a causal interpretation of our main results. The estimates are reported in 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). Second, we estimate Equation 1, but using the presence of a policy constraint instead of the China-led sector indicator (columns 3-4). We find a strong and consistent negative coefficient on the triple interaction term, indicating that venture activity growth is substantially lower if a constraint exists in China. Columns 5-6 report consistent estimates from an instrumental variable specification where the China-led sector indicator is instrumented with the absence of constraining policies in China and hence cross-sector variation in Chinese take-off is only due to domestic policy variation. The results also hold if we exclude policies that appeared in other emerging markets from the instrument (columns 2-3 of Table A.16).

Thus, policy constraints that affected sector-specific growth in China but are 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.

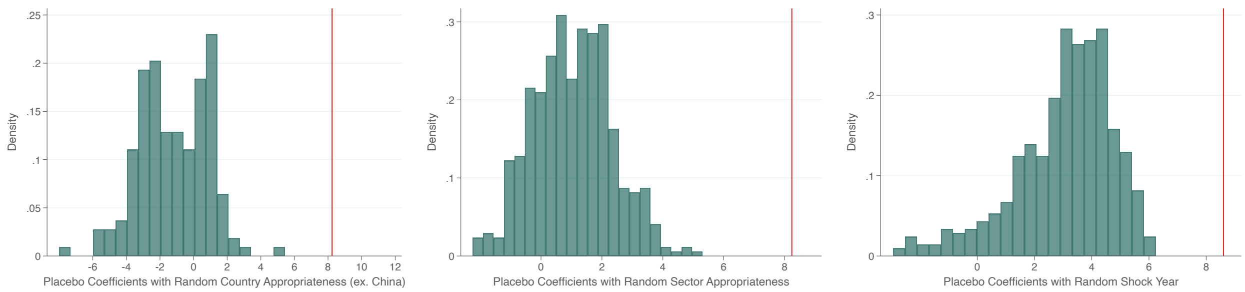
4.3.3 Falsification tests

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 rather than the rise of China itself, then 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 successively compute socio-economic similarity of each $country * sector$ to its counterpart in every other country. We then successively re-estimate Equation 1 in which we replace $Appropriateness_{cs}$ with the analogous appropriateness measure for every other country. Figure 4a 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 main estimate is the largest, consistent with our results capturing the causal effect of China's take-off. Only the appropriateness of Chinese R&D predicts entrepreneurial growth in the sectors that rose across emerging markets.

A second potential concern is that our measure of appropriateness may be very similar for all sectors in each country. The results may consequentially not be capturing differences

Figure 4: Falsification Tests

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



Note: Figure 4a reports a histogram of coefficient estimates from a series of estimates of Equation 1, in which $ChinaAppropriateness_{cs}$ is replaced with an analogous appropriateness measure for each other country. Our main estimate of β from Equation 1 is displayed with a red vertical line. Figure 4b reports a histogram of coefficient estimates from a series of estimates of Equation 1, in which the sector component of $ChinaAppropriateness_{cs}$ is drawn at random each time. Our main estimate of β from Equation 1 is displayed with a red vertical line. Figure 4c reports a histogram of coefficient estimates from a series of estimates of Equation 1, 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.

in the sector-specific appropriateness of Chinese entrepreneurship within each country and instead capturing largely cross-country differences. To address this, we again estimate a series of placebo versions of Equation 1, now randomizing the sectoral component of $Appropriateness_{cs}$ within each country.[26] Figure 4b presents the histogram of these placebo coefficients and our baseline coefficient estimate as a vertical red line. 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, cross-sector differences in similarity to China across investment sectors.

4.4 Dynamics

To this point, our analysis has focused on how the rise of China reshaped global entrepreneurship after 2013. We next examine the patterns of entrepreneurial activities prior to the rise of China and how they changed over time.

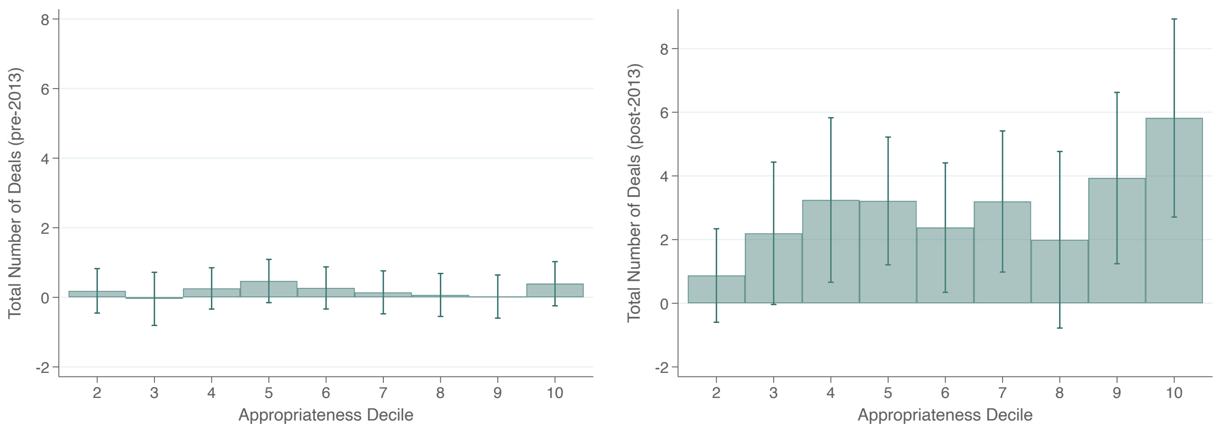
Figure 5 reports the relationship between the China-led sector indicator and venture deals, separately for each decile of our appropriateness measure, both for the pre-period (before 2013) and post-period (after 2013). The results in each sub-figure are from a single regression in which the first decile is the excluded group and all bars display estimates of the interaction between $ChinaLed_s$ and the appropriate decile indicator. There is no

[26] E.g., for AgTech in Pakistan, we assign Pakistan's China appropriateness score of one of the other macro-sectors at random and repeat this for all country-sector pairs in each randomization.

Figure 5: Effect of Appropriateness by Decile: Pre vs. Post Period

(a) Pre-period (before 2013)

(b) Post-period (2013 and after)



Note: Figure 5a 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 5b 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.

difference between country-sector pairs with different values of the appropriateness index prior to the rise of China: the effect of each decile is small in magnitude and statistically indistinguishable from zero (Figure 5a). 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 5b).

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.[27] While the modal surge year is 2013, which is why we use this year in our baseline analysis, there is also variation across different sectors (Figure A.12).[28] Estimates of Equation 1 using a sector-specific post-period definition are slightly larger than our baseline results (Table A.17). Moreover, if we randomize the surge year across sectors and re-estimate the regression, our main estimate larger than all other estimates (Figure 4c). The global spread of entrepreneurship in China-led sectors thus exactly followed the sector-level timing of growth in China.

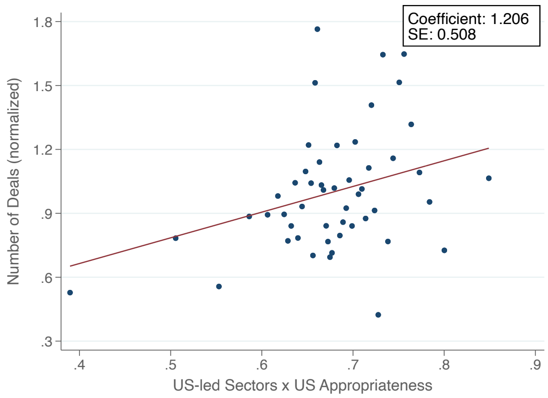
We next study the role of the US during the pre-period. We construct a country-by-sector measure of similarity to the US, analogous to the measure of $Appropriatness_{cs}$. We

[27]Figure A.11 shows the number of Chinese deals over time for several example sectors, with the surge year marked by a vertical line. We restrict attention to two-year windows with at least 10 deals at the end of the two-year window in order to avoid estimating high growth rates from a very small number of deals.

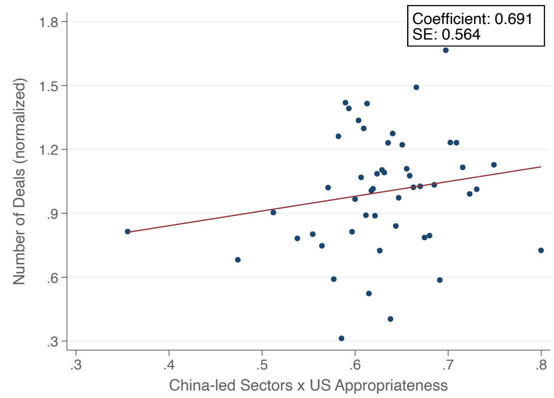
[28]2013 also satisfies the requirements used to determine the sector-specific surge year for the full sample.

Figure 6: China vs. US Appropriateness, Before China's Rise

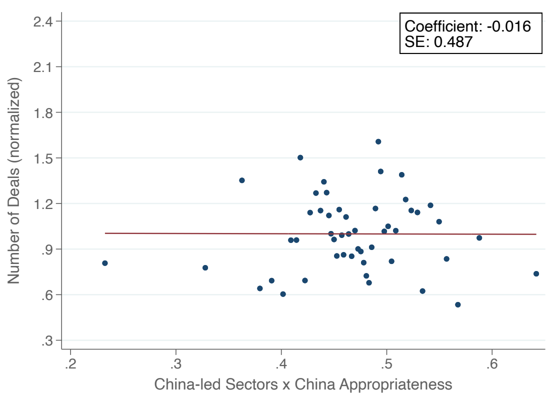
(a) US Appropriateness × US-Led



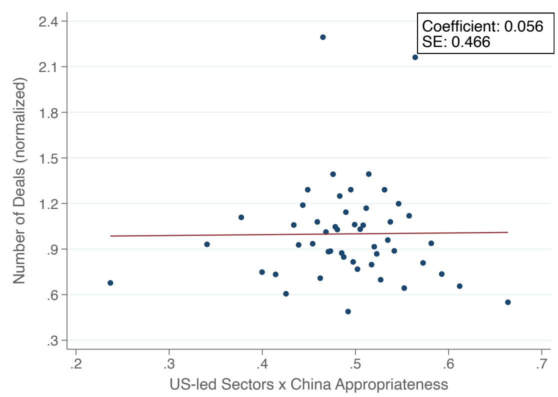
(b) US Appropriateness × China-Led



(c) China Appropriateness × China-Led



(d) China Appropriateness × US-Led



Note: Figure 6a displays the relationship between pre-2013 deals and $USLed_s \times USAppropriateness_{cs}$ and Figure 6b displays the relationship between pre-2013 deals and $ChinaLed_s \times USAppropriateness_{cs}$, both estimated from the same regression. Figure 6c shows the relationship between pre-2013 deals and $ChinaLed_s \times ChinaAppropriateness_{cs}$ and Figure 6d shows the relationship between pre-2013 deals and $USLed_s \times ChinaAppropriateness_{cs}$, 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.

then examine whether similarity to the US predicts entrepreneurship at the country-by-sector level prior to the rise of China. Focusing on years before 2013, we estimate:

$$y_{cs} = \phi_1(Appropriateness^{US}_{cs} * USLed_s) + \phi_2(Appropriateness^{US}_{cs} * ChinaLed_s) + \alpha_c + \gamma_s + \epsilon_{cs} \tag{2}$$

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

Our estimate of ϕ_1 is positive and significant (Figure 6a), 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 with similar socioeconomic conditions to the were more likely to invest in start-ups. Our estimate of ϕ_2 is about half the magnitude of ϕ_1 and statistically indistinguishable from zero (Figure 6b), consistent with there being less activity in these sectors by US firms even prior to the rise of China. Moreover, Figures 6c and 6d report estimates of Equation 2 in which the appropriateness of US R&D is replaced with the appropriateness of Chinese R&D. The estimates are insignificant and close to zero, again showing that socioeconomic similarity to China did not predict entrepreneurship *prior* to the rise of China.

Finally, we investigate whether the global diffusion of entrepreneurship from the US changed after 2013. Figure A.13 reports the difference in the effect of $(USAppropriateness_{cs} * USLed_s)$ and $(USAppropriateness_{cs} * ChinaLed_s)$ between the pre and post-periods.[29] If anything, the effect of US appropriateness increases during the post period 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 suited to different socioeconomic contexts.

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 emulation of Chinese companies, we use Natural Language Processing tools to measure similarity in business description across all company pairs within each sector.[30] 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

[29] We estimate this difference from a single regression, a version of Equation 2 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.

[30] We use SentenceTransformer, a framework for state-of-the-art sentence embeddings, with pre-trained BERT models 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 while also being more efficient than directly using BERT.

Table 5: Increasing Business Model Similarity to China

	Text similarity to existing 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. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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 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 90th percentile of the similarity distribution, to capture the fact that companies may closely follow a small number of Chinese companies in the sector (or even a single company) but not be similar to others. We then estimate versions of Equation 1 with these within-sector measures of companies' similarity to China as the dependent variables.

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 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. For a given level of socioeconomic similarity, the estimates suggest that businesses in China-led sectors became roughly 0.15 standard deviations more similar to recent Chinese companies, compared to business in sectors not led by China.

5.2 Investors and deal types

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

Table 6, columns 1-3, reports estimates in which the dependent variables are the number of deals with an investor from China (column 1), with an investor from the US (column 2), and with a local investor (column 3)[31]. While we estimate positive coefficients across specifications, the largest effect is for local investors. These estimates indicate that the growth of Chinese venture capital promoted local investment in emerging markets.

Next, we split the deals in the sample between those that are a company's first deal and those that are follow-on deals. In principle, both could be affected by the rise of Chinese venture capital. One possibility is that new start-ups are founded by entrepreneurs learning from businesses and technology developed in China. This would lead the effect to concentrate on early-stage deals. Alternatively, the findings may be concentrated in later-stage deals, perhaps as more sophisticated investors "pile in" to finance existing firms once there is a proven benchmark in China.

Table 6, columns 4 and 5, reports 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.

5.3 Is it the politics, stupid?

So far, our results have focused on the development and diffusion of Chinese entrepreneurship driven by its "appropriateness," but they have been silent about the role of 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 of the business models that end up diffusing to other emerging markets.

[31]We define the VC to be "local" if its headquarter is the same as the firm.

Table 6: Deal Types, Investors, and Company Outcomes

	Outcome is (normalized) number of deals from investors from			Outcome is (normalized) number of		Outcome is (normalized) number of deals for companies that end up		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	China	US	Own Country	First deals	Follow-on deals	Failing	Acquired or IPO	Neither (yet)
China-Led × Post × Appropriateness	0.880	1.087	4.455***	5.295***	2.943**	0.525	1.204**	6.510***
	(0.565)	(1.295)	(1.604)	(2.006)	(1.201)	(0.791)	(0.557)	(2.241)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	552300	552300	552300	552300	552300	552300	552300
Mean of Dep. Var	0.079	0.803	1.716	2.772	0.816	0.507	0.496	2.584
SD of Dep. Var	4.150	19.497	26.571	39.463	17.930	16.311	13.803	38.142

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

To investigate these issues, we develop two proxies for political closeness to China: *(i)* voting similarity on UN resolutions, which captures countries' international political stance;[32] and *(ii)* the similarity of political regime as measured by the Polity Project, which captures countries' political institutions by amalgamating key features such as checks and balances on the executive and the competitiveness of elections.[33] We also compile lists of strategic technologies from two high-profile technological blueprints laid out by the Chinese government: *(i)* "Made in China 2025" (published in 2015), a national strategic plan for industrial policy as part of China's Thirteenth and Fourteenth Five-Year Plans; and *(ii)* "China's Stranglehold Technologies" (published in 2018). We then hand-linked each of the technologies on these lists to one or more of the sectors in our baseline analysis.

To understand whether politics shapes our baseline results, we estimate versions of Equation 1, restricting the sample to countries that are either aligned or not aligned with China in terms of UN voting and regime characteristics, and restricting the sectors to strategic or non-strategic technologies.

Table 7 reports these estimates. In the first two columns, we report the baseline result focusing on countries that are in the top quartile in terms of UN voting similarity to China (column 1) and countries that are in the bottom three quartiles (column 2). The coefficient of interest is larger in column 1, suggesting that the effects are more pronounced for China's allies; nevertheless, they remain positive, significant, and similar in magnitude to our baseline estimates in column 2. Columns 3 and 4 split the sample based on the similarity of the Polity score to China and tell a very similar story.

In columns 5 and 6, we split the sample based on whether the sector is one of the strategic sectors or not. We find substantially smaller effects for the government-prioritized sectors (column 5) and larger effects for the non-prioritized sectors (column 6). While suggestive, these findings indicate that "top-down" entrepreneurship is less likely to lead to businesses that spread around the world. The sectors that grew in China with limited government involvement, however, had large spillovers on 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 1 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.18). The coefficient on both terms is negative – countries more politically aligned with China are more likely to invest in China-led sectors – but our main coefficient of interest are unaffected.

[32]This measure is based on an "ideal point scale" derived from voting behavior in the UN General Assembly, as documented by Bailey et al. (2017). Countries' ideal points are recovered from the recorded votes for a wide range of issues that appear in the General Assembly in the period from 1946 to 2012.

[33]Polity scores each country's institutions from from -10 (authoritarian) to 10 (full democracy).

Table 7: 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 × Appropriateness	11.734**	7.459**	9.949*	7.732***	2.600	9.751***
	(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

: 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.

6 Broader impacts

In this section, we investigate the broader economic impacts of this rise in emerging market entrepreneurship. More appropriate entrepreneurial models may make new ventures more successful and impactful; however, if entrepreneurs are simply substituting one successful model of venture activity for another, the broader implications could be limited.

6.1 Firm outcomes

As a first test, we investigate outcomes at the firm-level. Are the main results driven by investment in companies that end up failing (as most startups do)? Or are they driven by businesses that end up being successful? We use PitchBook data on firm outcomes and, in each sector-year, count the number of funding rounds for firms that end up failing, firms that end in an acquisition or IPO (a rough but frequently used proxy for investment success), and firms that have not yet exited.

Table 6, columns 6-8 present estimates of Equation 1 in which the dependent variables are the (normalized) number of deals associated with each exit type (or no exit). In column 6, the outcome is the number of deals associated with companies that fail, and the coefficient estimate is small in magnitude and statistically indistinguishable from zero. In column 7, the outcome variable is the number of deals associated with "successful" companies: those that ended in acquisition or IPO. We find a positive and significant effect. Finally, in column 8, the outcome is the number of deals associated with companies that have not yet exited as of mid-2022. 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). The coefficient is again positive and significant. These estimates suggest that our findings are not driven by firms that fail, or by short-run fads. That said, the story of many of these companies remains to be written.

6.2 Serial entrepreneurs and cross-sector spillovers

Next, we move beyond the firm level and investigate local entrepreneurial ecosystems. Regional 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 due to the development of reputational capital and accumulation of local knowledge (Gompers et al., 2010). Qualitative work has also pointed to serial entrepreneurship as an important contributor to regional entrepreneurial success (e.g., Mallaby, 2022).

Building on this set of ideas, we investigate whether our findings are accompanied by repeat entrepreneurship and investment. We then investigate whether these serial entrepreneurs and investors were able to take greater risks and operate more independently from international trends by investigating whether they branched out from the China-led sectors that they initially followed.

We estimate the following augmented version of our baseline specification:

$$y^X_{cst} = \beta\,(ChinaLed_s * Post_t * Appropriateness_{cs}) + \alpha_{cs} + \gamma_{ct} + \delta_{st} + \epsilon_{cst}, \tag{3}$$

where y^X_{cst} is the number of serial founders whose *first* company was in sector s, and who became a serial founder in year t.[34] To measure founders' behaviors in their follow-on entrepreneurship, we also break down each serial entrepreneur's second company based on the sector(s) that it falls into. We separately estimate the effect on serial entrepreneurs whose second company falls into sector grouping X, where X includes (i) only China-led sectors, (ii) at least one sector that is not China-led, (iii) all sectors that are not China-led.[35]

Table 8 reports estimates of Equation 3. Column 1 shows that the rise of China led to a larger group of serial entrepreneurs. Moreover, these effects are driven by serial entrepreneurs entering sectors that are *not* led by China. In column 2, the outcome is the number of serial entrepreneurs whose subsequent company (or companies) fell into China-led sectors. The coefficient estimate is very close to zero. In column 3, the outcome variable is the number of entrepreneurs whose second company falls into at least one sector that is not led by China, and the estimate is positive and significant. Finally, in column 4, the outcome variable is the number of entrepreneurs whose second company falls *exclusively* into sectors that are not led by China. The coefficient is again positive and significant. We observe a similar pattern in columns 5-8, where the outcome variable is an indicator for the presence of any serial entrepreneur in the relevant category.

Thus, the rise in entrepreneurship around the world documented in the main results was accompanied by the emergence of serial entrepreneurs. These entrepreneurs ended up exploring sectors in which Chinese firms were *not* dominant players and hence, where there is less likely to be a clear Chinese benchmark. These cross-sector spillovers and rise of flexible, independent entrepreneurs could be an important part of the overall effect of China's rise on emerging markets.[36]

[34] If no contact is listed by Pitchbook as the founder, we define the founder as the CEO during the first deal.

[35] Focusing on each serial founder's second company's sector is largely without loss, since 93% of serial founders have founded exactly two companies. Results using the number of companies founded by serial entrepreneurs (rather than the number of serial entrepreneurs) as the dependent variable are similar.

[36] We repeat this analysis focusing on serial investors (Table A.19). While the coefficient estimates are again all positive, they are less precise. Nevertheless, when we focus on serial investments in companies that fall into sectors that are not led by China (columns 4 and 8), we estimate positive and significant effects. Investors who first gained experience by investing in business models developed in China may also extend their investments in subsequent years to local businesses in other areas.

Table 8: Serial Entrepreneurs

	Number of Serial Entrepreneurs				Serial Entrepreneur Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Only CL Sectors	Any non-CL Sectors	Only non-CL Sectors	All	Only CL Sectors	Any non-CL Sectors	Only non-CL Sectors
China-Led $\times$ Post $\times$ Appropriateness	0.019**	0.005	0.014**	0.006*	0.012***	0.005*	0.009**	0.005*
	(0.008)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Sector $\times$ Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	552300	552300	552300	552300	552300	552300	552300
Mean of Dep. Var	0.007	0.002	0.005	0.002	0.006	0.002	0.004	0.002
SD of Dep. Var	0.105	0.049	0.085	0.050	0.076	0.043	0.066	0.040

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), as "any non-CL sectors" if her second company falls into at least one non-China-led sector, and as "only non-CL sectors" if her second companies fall exclusively in non-China-led sectors. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

6.3 City-level effects and geographic spillovers

So far, we have documented that country-by-sector-level exposure to the rise of Chinese VC led to growth in entrepreneurial activity. However, there is a large body of work emphasizing the importance of local research spillovers and the geographic clustering of entrepreneurship (Jaffe et al., 1993). Was the rise in entrepreneurship accompanied by the growth of geographic hubs of entrepreneurship and innovation in emerging markets?

To measure the exposure of each city to the rise of China, we measure the share of their VC-backed companies in one of the China-led sectors during the pre-analysis period. We then investigate whether the rise of China increased both the number of new firms and broader measures of innovative activity in these locations that were best able to capitalize the growth of China. We estimate:

$$y_{it} = \gamma(ShareChinaLed_i * Post_t) + \alpha_i + \delta_t + \epsilon_{it} \tag{4}$$

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 as well as the number of patents assigned to firms in each city, in order to investigate whether the greater city-level VC activity was accompanied by more innovation.[37] The findings are reported in Table 9.

We first restrict attention to cities in emerging economies. In Table 9, column 1, the outcome is the number of new companies and γ is positive and significant.[38] The result from column 1 could be entirely driven by the growth of sectors in which inspiration could be drawn directly from China. However, if there are local geographic spillovers, we may also find positive effects on companies that are not in sectors led by China. In columns 2 and 3, we separately estimate the effect on companies that are in one of the China-led sectors and companies that are not. While the effect size is larger for companies in China-led sectors (column 2), it remains positive for companies outside China-led sectors (column 3). These findings dovetail with the results from the previous section, which documented the rise of serial entrepreneurs who branched out from the sectors that had clear Chinese predecessors. In column 4, we use the full sample of countries and investigate whether, as in the country-by-sector-level analysis, the positive effect on overall entrepreneurship is larger in developing compared to developed countries. We find that the city-level effect

[37]We geo-locate the headquarters of all PitchBook companies using SimpleMaps, supplemented with Opendatasoft, and use patents' location information from disambiguated assignee locations compiled by PatentsView. We link both to the nearest populated city from Natural Earth and restrict attention for our analysis to cities with at least 20 companies during the pre-analysis period.

[38]In Table 9, the outcome is parameterized as the normalized level of deals or patents; however, the results are very similar if we instead use the inverse hyperbbolic sine or log transformation (see Table A.20).

Table 9: 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. 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. In columns 5 and 6, we examine the number of patents awarded to inventors living in each city as the dependent variable. Standard errors are double-clustered by city and year×country, and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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. In column 5, we restrict attention to emerging economies and the outcome is the number of patents assigned to firms in the city. The estimate of γ is positive and significant. In column 6, we again use the full sample of countries to investigate whether the effect of the rise of China on innovation is stronger in developing countries. Consistent with all preceding analysis, we find that the effects are much larger in developing countries.

Figure A.14 reports event study estimates corresponding to the specifications from columns 1, 2, 3, and 5 of Table 9. In all cases, we see no evidence of different pre-existing trends in more-exposed compared to less-exposed cities. The trends begin to diverge around 2014 or 2015 and the gap widens thereafter.

These estimates suggest that the rise of Chinese entrepreneurship had impacts beyond the companies that it directly inspired. In cities that were initially best positioned to follow China, there was substantial business formation, including in sectors that were *not* dominated by China. There was also a large increase in overall innovative activity.

6.4 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 productive innovation ecosystems. However, the effects of a rise in entrepreneurship may extend beyond the innovation economy. After all, greater investment in education technology start-ups may be beneficial not only because it fuels innovation and entrepreneurship in education technology, but also because it leads to improved educational outcomes. The same is true for health technology investment and health outcomes, agricultural technology investment and agricultural productivity, etc.

While identifying a clear link between VC investment and economic outcomes is challenging, particularly over our relatively short sample period, we present suggestive evidence that the rise in entrepreneurship documented in the first parts of the paper had positive economic consequences. First, we 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 (2013-2019). 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.

Second, we use the coefficient estimates from Equation 1 to predict the total number of deals in each country-sector pair during our post-period induced by the rise of China. We then 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:

$$y_{cm} = \phi PredictedDeals_{cm} + \alpha_c + \delta_m + \epsilon_{cm}, \tag{5}$$

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. Finding that $\phi > 0$ would indicate that the rise in entrepreneurship was associated with improved socioeconomic well-being.

Estimates of Equation 5 are reported in Table A.21. The first column includes the full sample and suggests that higher predicted entrepreneurship is associated with a small, positive increase in socioeconomic well-being. A one standard deviation increase in predicted entrepreneurship is associated with a 0.02 standard deviation improvement in socio-economic outcomes. Column 2 restricts the sample to emerging markets, and the coefficient estimate increases by 60%. Columns 3-4 repeat the specifications from columns 1-2, restricting 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.

These estimates suggest that the China-led rise in emerging market entrepreneurship, documented throughout the paper, may indeed have had a discernible, positive effect on development outcomes. That said, these results are only suggestive and more work would need to be done to fully understand the causal relationship between entrepreneurship and socioeconomic development.

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 the 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. Understanding the consequences of Chinese entrepreneurial success for “soft power” is an important question.

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.

Finally, is the diffusion of business ideas to the developing world accelerated by the growth of venture capital-funded entrepreneurship itself? Successful start-ups 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 atvarious 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]

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

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.

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://ncse` s.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 market (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 i 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/inno` vation-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 nation of the fund location).

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% adjustment 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 to be 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 the ability to pick-and-choose 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.8, 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.8, 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 1) 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 the our measure of appropriateness with respect to the country X. We assume the same coefficients we obtained from the baseline specification 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.5, 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.16, 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.

References Not Cited in the Main Text

Fei, Celine Y., "Linking different data sources of venture capital and private equity in China," *Unpublished Working Paper, University of North Carolina*, 2018, `https://ssrn.com/abstract=3524066`.

Lerner, Josh and Amit Seru,"The use and misuse of patent data: Issues for finance and beyond," *Review of Financial Studies*, 2022, *35* (6), 2667–2704.

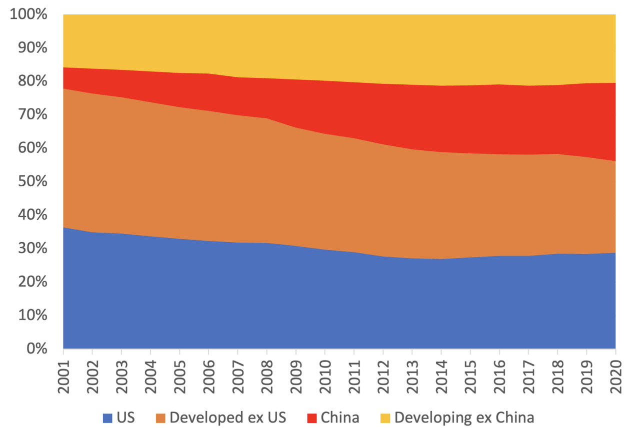
Li, Jinlin, "Government as an equity investor: Evidence from Chinese government venture capital through cycles," *Unpublished Working Paper, Harvard University*, 2022, `https://ssrn.com/abstract=4221937`.

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

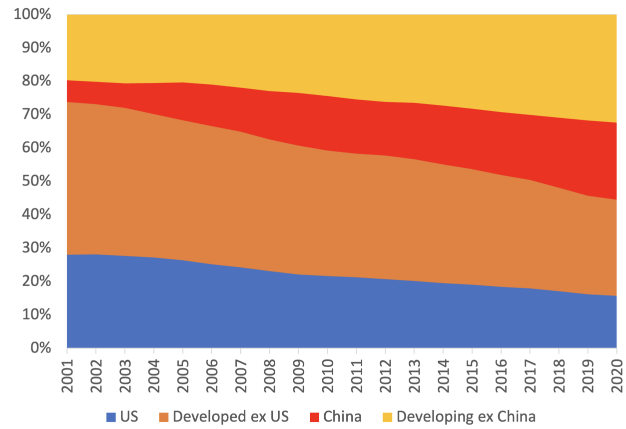
Appendix F Additional Figures and Tables

Figure A.1: Global Innovation Overview

(a) Share of Global R&D Investment

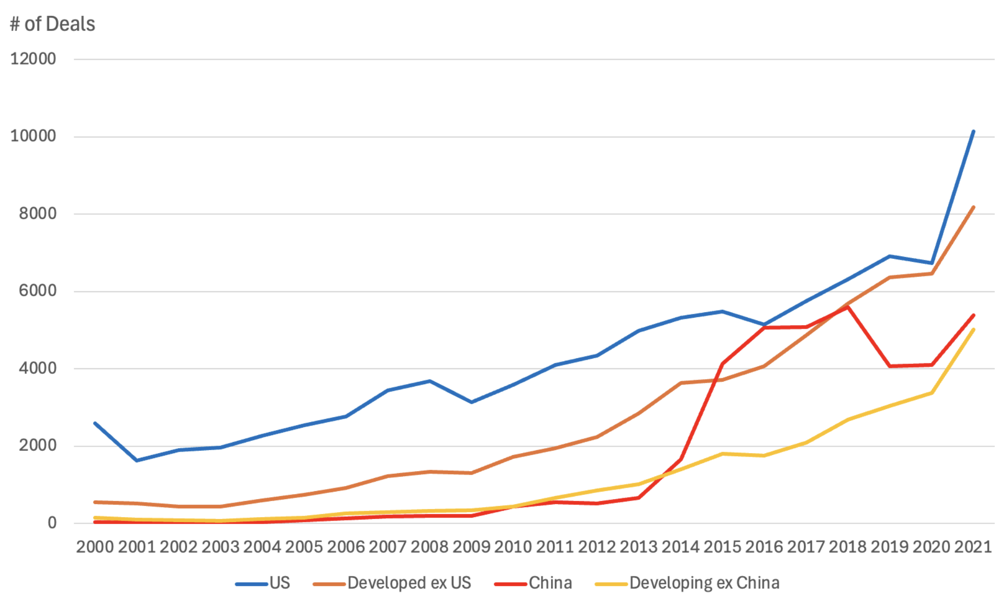


(b) Share of Global Scientific Publications



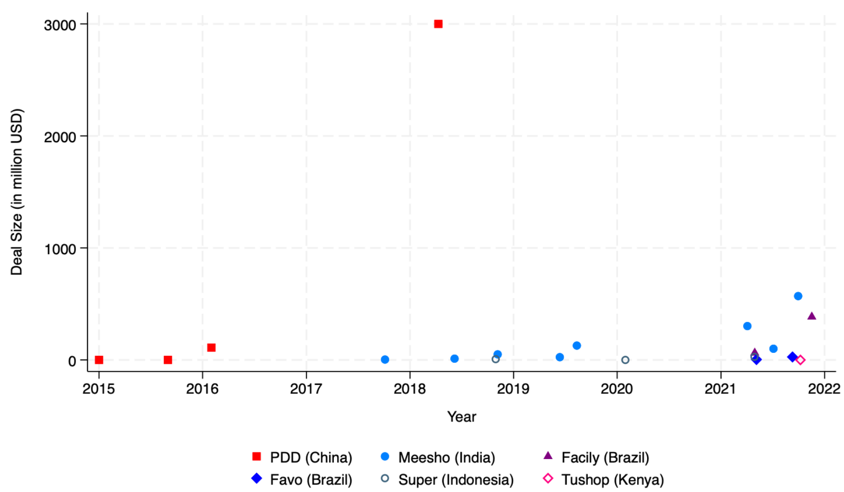
Note: Figure A.1a shows the changing mixture of global R&D investment. Figure A.1b displays the changing mixture of scientific publications. The data sources for this figure are discussed in Appendix A.

Figure A.2: Venture Investment Overview - Deal Numbers



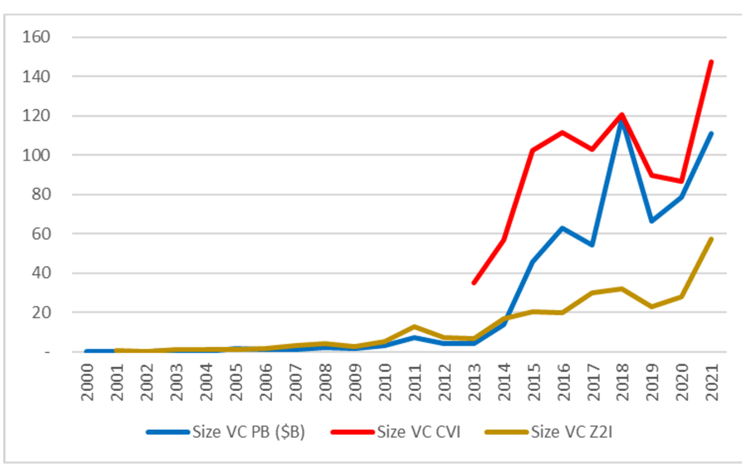
Note: This figure shows the global VC landscape in terms of deal numbers. The data source is Pitchbook.

Figure A.3: Example Sectors: Scatter Plot of Deal Size and Deal Date, Social Commerce



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.

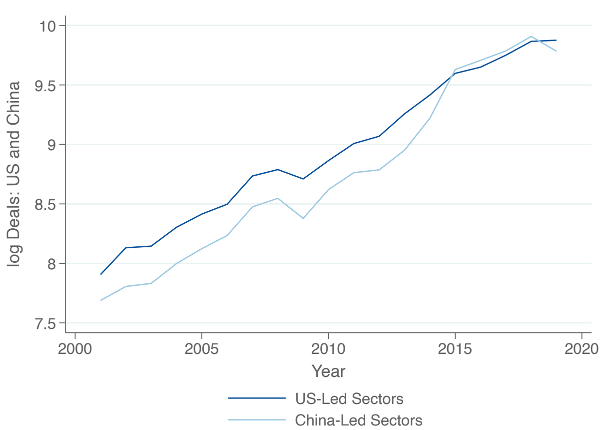
Figure A.4: Cross Validation of Chinese VC Data



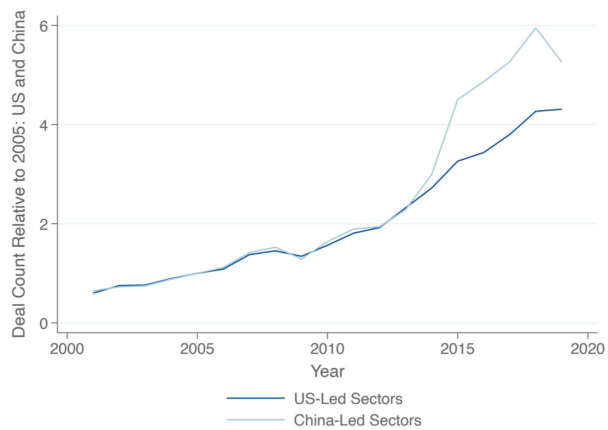
Note: This figure shows VC transactions in China for three sources: PitchBook, Zero2IPO, and China Venture Institute. Further discussion of the data validation process is in Appendix B.

Figure A.5: Re-direction of Entrepreneurship Toward China-Led Sectors

(a) log Deal Count



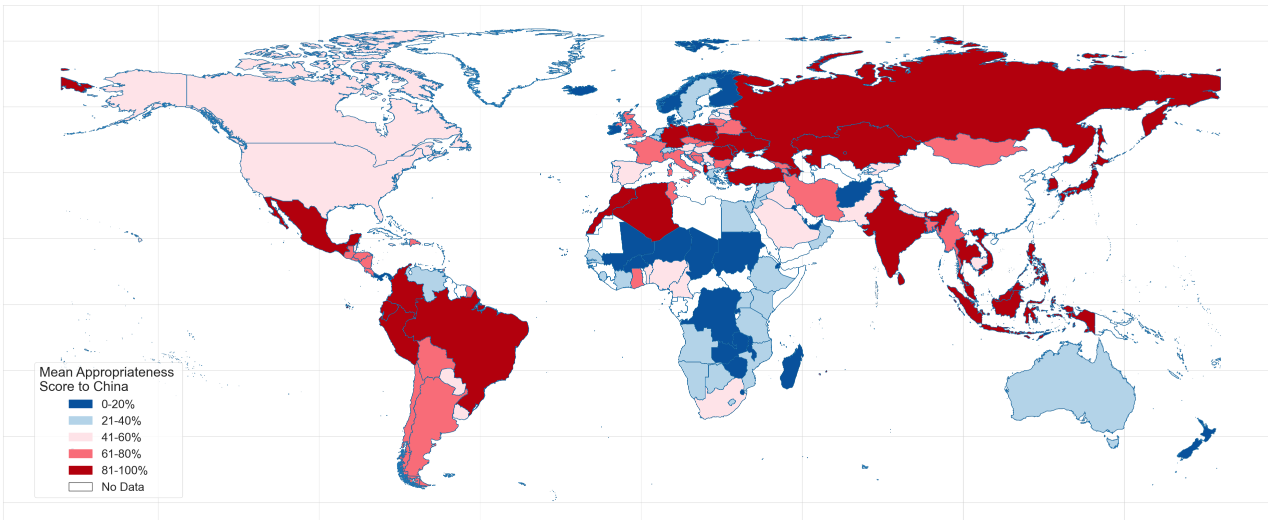
(b) Deal Count Relative to 2005



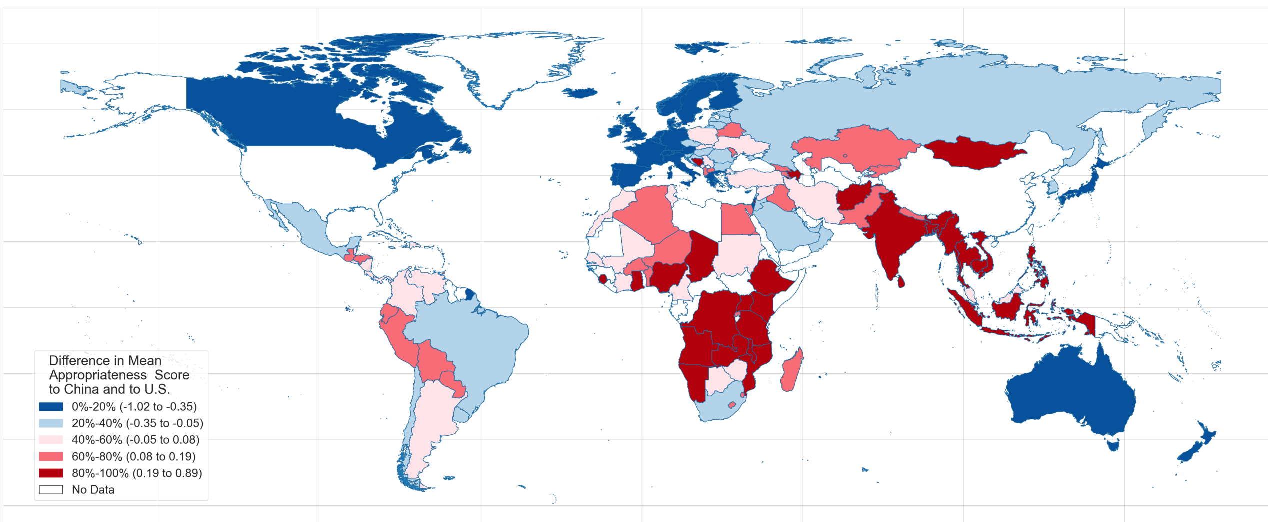
Note: Figure A.5a displays the log of the total number of deals in China-led and US-led sectors in both China and the US, over time. Figure A.5b the total number of deals in China-led and US-led sectors in both China and the US, relative to the total number of deals in 2005, over time.

Figure A.6: Country-Level Variation in Business Appropriateness

(a) Average China Appropriateness

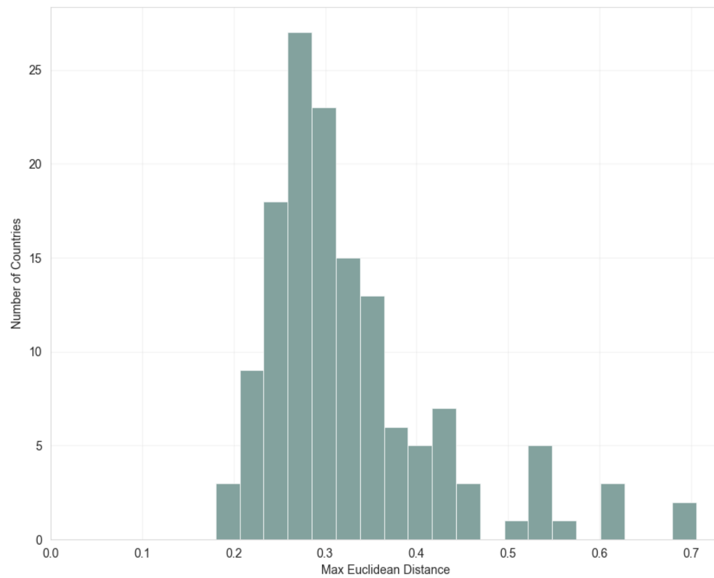


(b) Difference Between Average China Appropriateness and Average US Appropriateness



Note: Figure A.6a 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. Darker-colored countries are in higher quintiles of the China-appropriateness distribution. Figure A.6b 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).

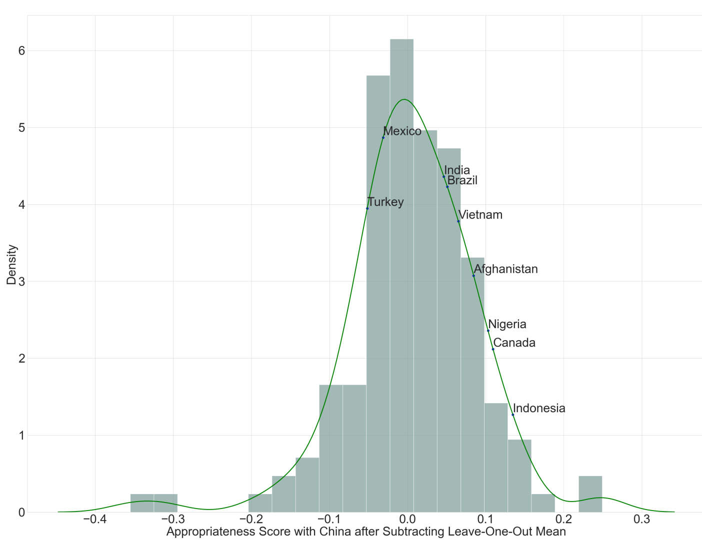
Figure A.7: Maximum Appropriateness Score Distance between Sectors within Countries



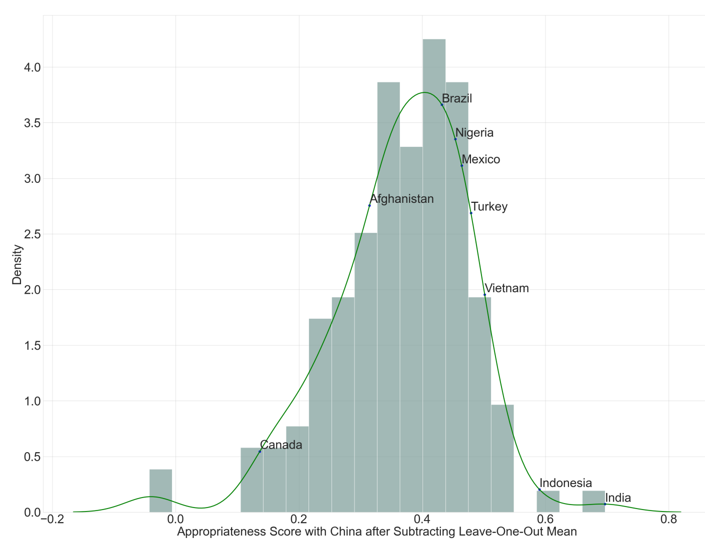
Note: This figure displays a histogram of the maximum distance between the China-appropriateness measure across pairs of macro-sectors for all countries.

Figure A.8: Within-Country, Sector-Level Variation in Business Appropriateness

(a) AgTech



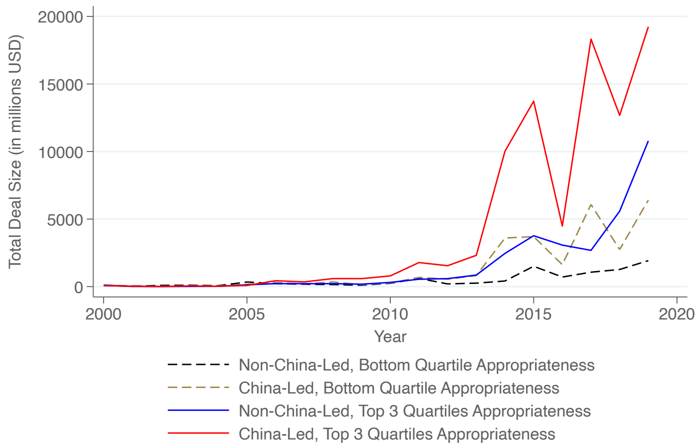
(b) FinTech



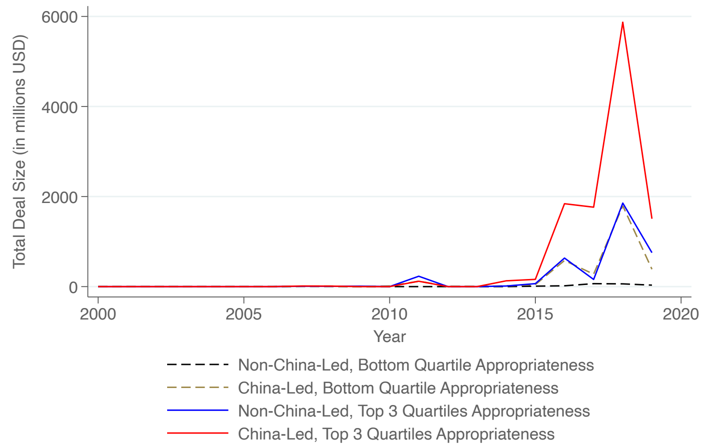
Note: Figure A.8a displays a histogram of all countries' China-appropriateness in the AgTech macro-sector, after subtracting average China appropriateness across all other macro-sectors. Figure A.8b displays the same for FinTech.

Figure A.9: Raw Trends Examples: India and Indonesia

(a) India, Total Investment



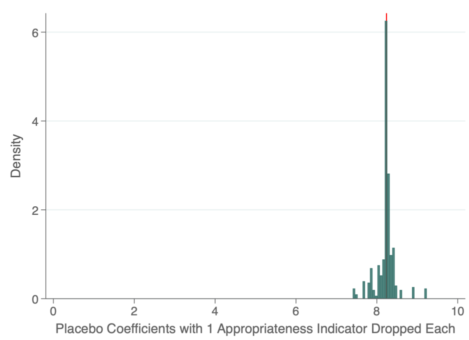
(b) Indonesia, Total Investment



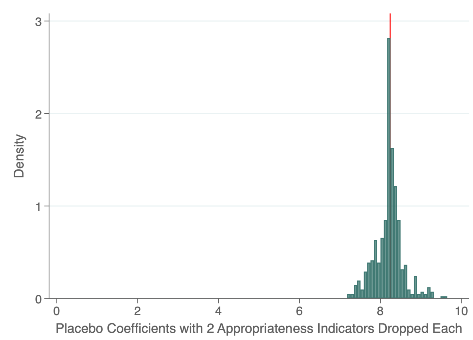
Note: This figure reports the raw trends of total investment in India and Indonesia, separated by appropriateness score with respect to China and whether the sector is a China-led sector.

Figure A.10: Robustness to Excluding Indicators from Appropriateness Measure

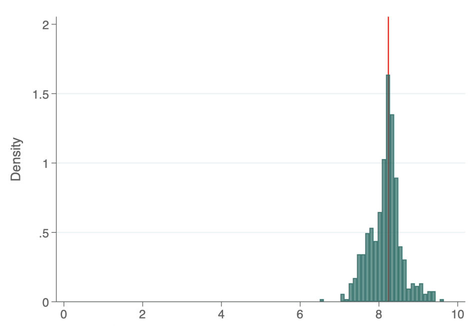
(a) Dropping 1 Indicator



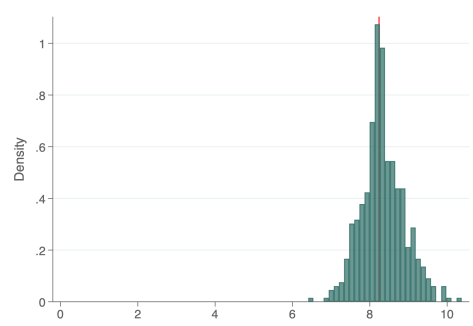
(b) Dropping 2 Indicators



(c) Dropping 3 Indicators

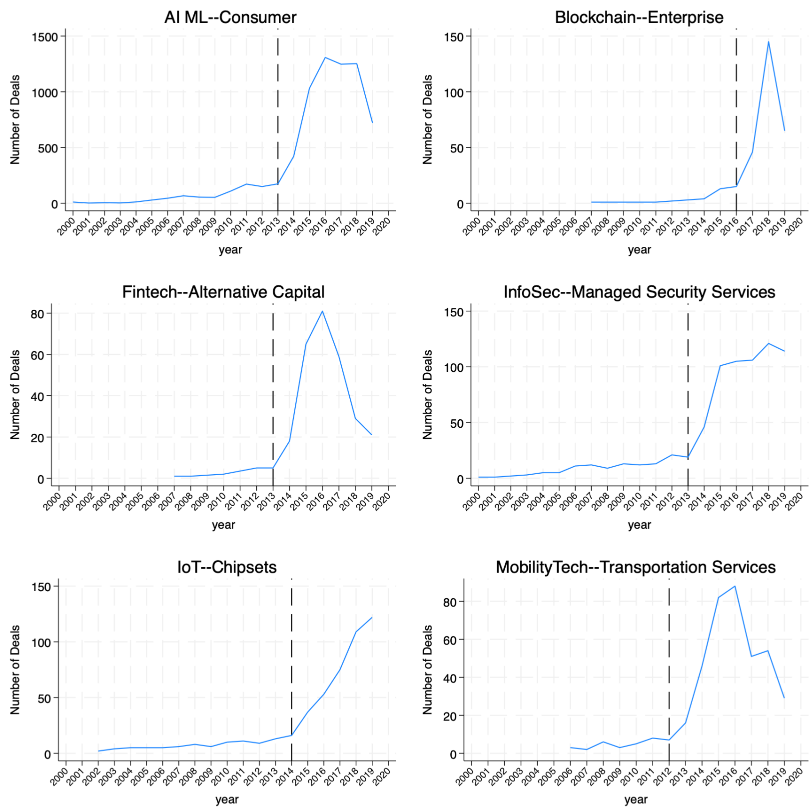


(d) Dropping 4 Indicators



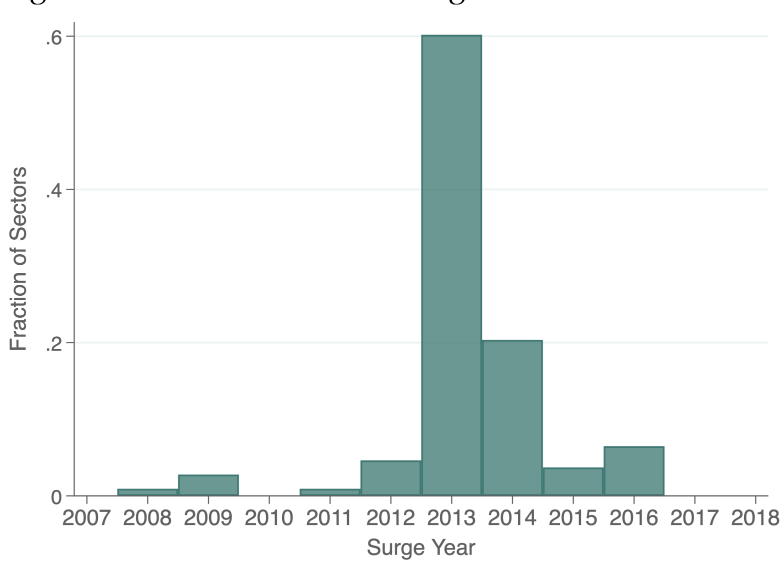
Note: This figure reports histograms of coefficient estimates from a series of estimates of Equation 1, in which $ChinaAppropriateness_{cs}$ is replaced with an alternate appropriateness measure where one, two, three, or four of the indicators used in the appropriateness calculation are dropped, repeated with 500 random simulations each. Our main estimate of β from Equation 1 is displayed with a red vertical line.

Figure A.11: 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."

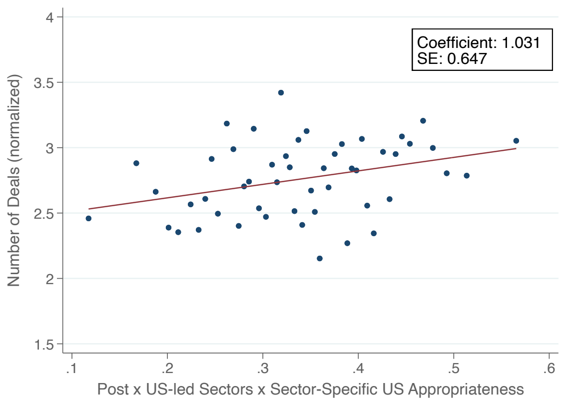
Figure A.12: Distribution of Surge Years Across Sectors



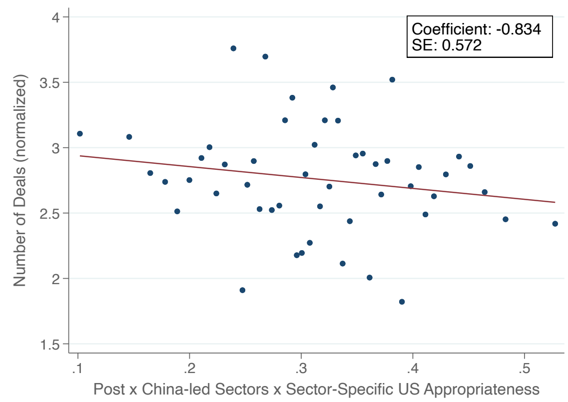
Note: This figure shows the distribution of sector-specific surge years for China-led sectors. "Surge year" is defined as the start year of a two-year window in which the number of VC-backed deals received by Chinese companies has the highest growth rate. We restrict attention to two-year windows with 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.13: US Appropriateness After China's Rise

(a) Post × US-Led × US Appropriateness



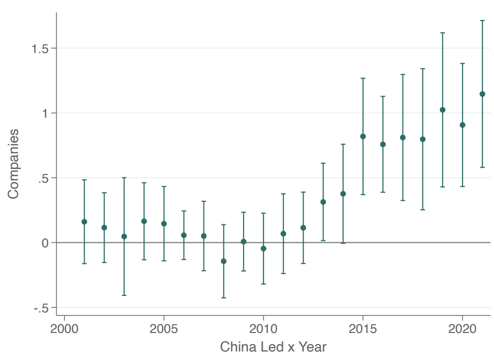
(b) Post × China-Led × US Appropriateness



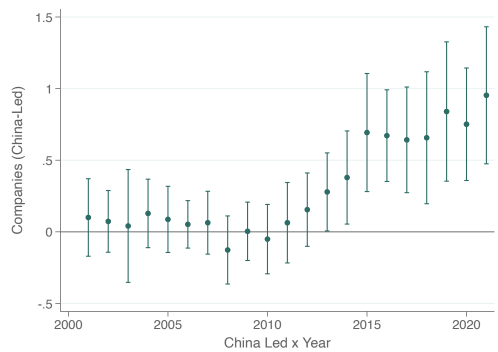
Note: Figure A.13a displays the relationship between normalized deals and $Post_t \times USLed_s \times USAppropriateness_{cs}$ and Figure A.13b displays the relationship between normalized deals and $Post_t \times ChinaLed_s \times USAppropriateness_{cs}$. Standard errors are clustered at the country level.

Figure A.14: China's Rise and City-Level Entrepreneurship: Dynamics

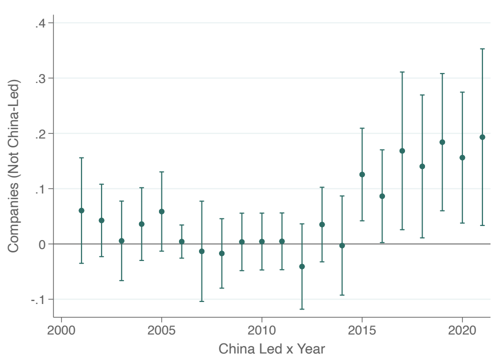
(a) Companies (All)



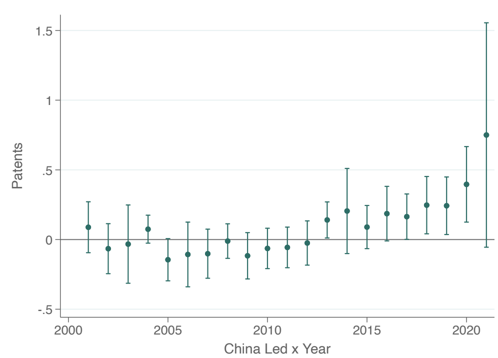
(b) Companies (China-led Sectors)



(c) Companies (Not China-led Sectors)



(d) Patents



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	% of World VC	% of World Pubs	% of World R&D	% of US Patents
China	2015	$12,244	13.44%	7.71%	20.84%	2.83%
Indonesia	2018	$11,852	0.97%	0.87%	0.40%	0.00%
Mexico	2000	$12,613	0.28%	0.51%	0.43%	0.05%
Poland	2000	$12,732	0.18%	1.33%	0.36%	0.01%
So. Korea	1988	$12,040	0.04%	0.18%	2.90%	0.12%
Russia	2002	$12,259	0.01%	3.41%	2.35%	0.12%
Egypt	2018	$11,957	0.01%	0.53%	0.50%	0.02%
So. Africa	2014	$12,242	0.00%	0.49%	0.46%	0.05%
Brazil	2007	$12,500	0.00%	2.03%	2.11%	0.06%
Israel	1969	$12,310	0.00%	N/A	N/A	0.09%
Singapore	1979	$12,521	0.00%	0.03%	N/A	0.00%
Chile	1993	$12,297	0.00%	0.17%	0.34%	0.01%
Turkey	2003	$12,380	0.00%	1.20%	0.41%	0.02%
Iran	2004	$12,404	0.00%	0.42%	0.43%	0.00%
Thailand	2006	$12,181	0.00%	0.30%	0.16%	0.02%
Japan	1968	$12,725	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 values in 2011 US dollars), which we term their "Emergence Year." The sourcing of this table is discussed in Appendix A.

Table A.2: 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

Note: This table presents examples of indicators assigned to five example macro-sectors.

Table A.3: Appropriateness and Citation Patterns

	Log citations to China		Log citations to US	
	(1)	(2)	(3)	(4)
	All	EM	All	EM
Appropriateness	1.170*	2.430**	0.150	0.226
	(0.595)	(1.039)	(0.136)	(0.207)
Country Fixed Effects	Yes	Yes	Yes	Yes
Marcro-Sector Fixed Effects	Yes	Yes	Yes	Yes
Citation to World Control	Yes	Yes	Yes	Yes
Number of Obs	293	88	726	416
Mean of Dep. Var	1.948	1.828	4.624	3.284
SD of Dep. Var	1.314	1.509	2.681	2.204

Note: The unit of observation is a marco sector-country. EM countries are defined as countries not included in the OECD as of 1980. All regressions control for the log citations to all patents. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.4: Results After Controlling for Income and Relative-Income Interactions

	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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	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.5: 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.6: Appropriateness and Entrepreneurship: Robustness for 2000-2021 Sample

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(deal)
Panel A: Baseline China-led measure					
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					
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)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
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

Note: The unit of observation is a country-sector-year and the sample period is extended to include all years from 2000-2021. 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.7: Appropriateness and Entrepreneurship: Robustness for *Relative to the World* Measure

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(deal)
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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	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. The table 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 companies in the rest of the world for the period of 2015 to 2019. 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.8: Appropriateness and Entrepreneurship: Sensitivity Tests

	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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	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.9: Appropriateness and Entrepreneurship: Non-VC Deals

	Deal Count			Deal Size	
	(1) Baseline	(2) Weighted	(3) asinh	(4) asinh	(5) log(deal)
Panel A: Baseline China-led measure					
China-Led Sector × Post × Appropriateness	3.027	3.552	0.133**	0.121	0.065
	(4.299)	(4.796)	(0.052)	(0.113)	(0.209)
Panel B: Strict China-led measure					
China-Led Sector (Strict) × Post × Appropriateness	2.647*	3.010*	0.179***	0.158*	-0.015
	(1.589)	(1.728)	(0.041)	(0.085)	(0.229)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Obs	715360	707200	552300	552300	67812
Mean of Dep. Var	3.103	4.151	0.343	0.447	0.984
SD of Dep. Var	41.496	48.143	0.847	1.541	3.069

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 from 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. All outcome variables are constructed using only non-VC deals. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.10: Appropriateness Robustness: 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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	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.11: Appropriateness and Entrepreneurship: by Trade with China in the Pre-Period

	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***	4.982	10.578**	4.772	9.316**
	(2.902)	(3.675)	(3.980)	(4.421)	(3.808)
Sector × Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	252480	299820	220920	331380
Mean of Dep. Var	3.588	3.503	3.659	2.932	4.025
SD of Dep. Var	44.979	46.832	43.358	43.834	45.722

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 *pre-2013 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.12: Appropriateness and Entrepreneurship: by Trade with China for the Entire Period

	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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	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.13: Appropriateness and Entrepreneurship: by 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 Fixed Effects	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	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.14: Appropriateness Robustness: Sector-Level Growth

	Dependent Variable: Number of Deals (Normalized)					
	(1)	(2)	(3)	(4)	(5)	(6)
China-Led Sector × Post × 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
Appropriateness × 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 3 uses the average total deal size instead of average number of deals. Column 4 excludes China's deals when calculating growth. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.15: 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/meteology 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.16: Results Using Policy-Constrained Sectors

	EM Has Similar Policy	Number of Deals (Normalized)	
	(1)	(2) IV Baseline	(3) No Other EM
Appropriateness	0.0161		
	(0.0147)		
$\widehat{\text{China-Led}}$ Sector × Post × Appropriateness		11.0908**	14.5812**
		(5.1531)	(6.8053)
Country Fixed Effects	Yes	-	-
Sector Fixed Effects	Yes	-	-
Sector × Country Fixed Effects	-	Yes	Yes
Country × Year Fixed Effects	-	Yes	Yes
Sector × Year Fixed Effects	-	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 2-3. 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.17: 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 measure					
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 measure					
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 Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Appropriateness × Year Fixed Effects	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. 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. The post-period indicator is defined separately for each sector, based on when that sector took off in China. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.18: 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 Fixed Effects	Yes	Yes	Yes	Yes
Country × Year Fixed Effects	Yes	Yes	Yes	Yes
Sector × Year Fixed Effects	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.19: Serial Investors

	Number of Serial Investors				Serial Investor Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Only CL Sectors	Any non-CL Sectors	Only non-CL Sectors	All	Only CL Sectors	Any non-CL Sectors	Only non-CL Sectors
China-Led × Post × Appropriateness	0.109	0.052	0.056	0.028**	0.012	0.008	0.017*	0.014***
	(0.071)	(0.037)	(0.036)	(0.012)	(0.014)	(0.015)	(0.009)	(0.005)
Sector × Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	552300	552300	552300	552300	552300	552300	552300	552300
Mean of Dep. Var	0.051	0.017	0.034	0.012	0.029	0.013	0.021	0.009
SD of Dep. Var	0.453	0.185	0.327	0.150	0.167	0.114	0.143	0.097

Note: The unit of observation is a country-sector-year. The dependent variable is defined at the top of each column. Investors are coded as "only in CL sectors" if the second company into which they invest falls within China-led sectors, as "any non-CL sectors" if their second company falls into at least one non-China-led sector, and as "only non-CL sectors" their second company falls exclusively in non-China-led sectors. Standard errors are clustered by country and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A.20: Robustness for 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
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. 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. 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.

Table A.21: The Rise of Emerging Market Entrepreneurship and Socioeconomic Outcomes

	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 Fixed Effects	Yes	Yes	Yes	Yes
Macro Sector Fixed Effects	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. 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.